Essays on External Debt and Equity Finance for UK Small Businesses

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Abstract

This thesis presents three empirical studies related to external debt and equity finance for UK small and medium-sized enterprises (SMEs). The first explores the developments in bank credit market conditions over the period 2010-2017. The evidence suggests that business overdrafts and term loans show slightly different trends in the wake of the global financial crisis. Since 2014, rejection rates reduced for both facilities but remained stable in the run-up to the 2016 Brexit referendum and its immediate aftermath, although the overdraft market became tighter for exporting SMEs. Start-ups and micro firms experienced significantly improved credit conditions after 2014, particularly for overdrafts, although the loan market remained tight.

The second study investigates the relationship between awareness of the Enterprise Finance Guarantee Scheme (EFGS), financial literacy and bank borrowing discouragement. Financially literate SMEs appear to be more likely to be aware of EFGS and, in turn, aware SMEs are less likely to be discouraged from borrowing. Empirical findings indicate that raising EFGS awareness could bring all borrowers back to the overdraft market, but only high-risk borrowers back to the loan market. Finally, improving financial literacy encourages low-risk borrowers to take out loans but discourages high-risk borrowers.

The third empirical study examines the role of angels in equity crowdfunding (ECF) dynamics. One prominent example of ECF innovations is the growing role of institutional investors (mainly business angels) who co-invest alongside the crowd. For ECF funding dynamics, the number of investors exhibits a double L-shaped pattern, with the first spike observed at the start in all campaigns and the second after the target capital is reached in successful campaigns. We find a more pronounced L-shape when an angel co-invests, although this effect weakens when information asymmetry is mitigated as in seasoned ECF offerings or after overfunding.

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Chapter 1 Introduction

1.1 Background

Acting as the engine of economic growth (Spence and Rutherfoord, 2003), small businesses or SMEs have attracted lots of attention from both academicians and practitioners. The number of SMEs in the UK has substantially increased (by almost 64%) in the last two decades, from 3.46 million in 2000 to 5.66 million in 2018, as shown in Figure 1.1.[1] One of the crucial issues for small businesses is the availability of external debt and equity finance since without external financing firms may find it difficult to survive and grow, impairing their ability to offer job opportunities and ultimately holding back the economic development.

Bank debt is the most common way for small businesses to raise external finance (Storey and Greene, 2010). The information asymmetry is severe between banks and small businesses, because small businesses are typically much more informationally opaque compared to their larger counterparts, resulting in potential adverse selection and moral hazard problems. To deal with such problems, banks have developed several lending technologies [2] : *relationship lending*, that relies on "soft" information (qualitative information obtained via contacts with firms, owners and the local community) and *transaction lending* relying on "hard" information (quantitative information, such as data derived from balance sheets and/or collateral guarantees). Lending technologies can be applied synergistically by banks when they make decisions on debt applications (Udell, 2015).

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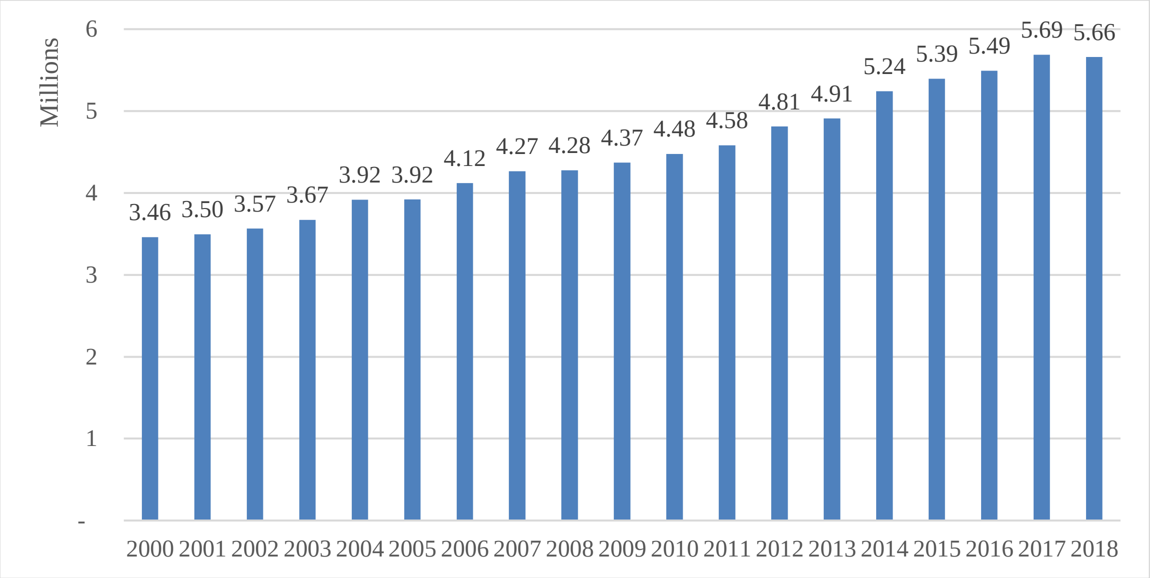
[1] The beginning of 2018 was the first year to witness a decrease in the number, possibly because the uncertainty brought by the 2016 Brexit referendum made fewer businesses commence trading, but more businesses cease trading in 2017.

[2] Berger and Udell introduced the concept of lending technologies in 2002 and proposed an accurate definition in 2006, as "a unique combination of primary information source, screening and underwriting policies/procedures, loan contract structure, and monitoring strategies/mechanisms" (p.2946).

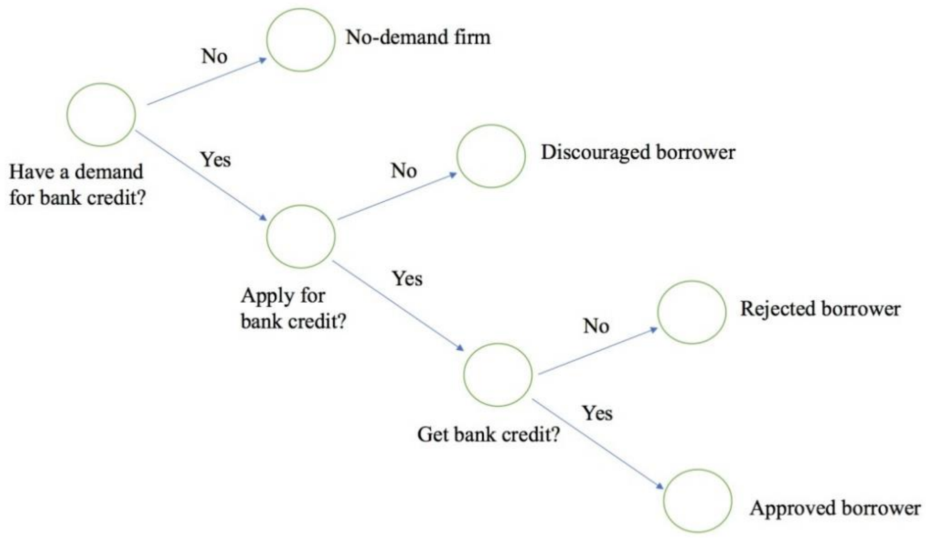
Figure 1.1 Number of Private Sector SMEs in the UK During 2000-2018



Notes: This figure shows the number of UK private sector SMEs in each year from 2000 to 2018. The data are accessed from Department for Business, Energy & Industrial Strategy, Business Population Estimates for the UK and Regions 2018, Table 25.

In relationship lending, banks are able to gather soft information over time and across different products. Considering that soft information is unquantifiable, researchers try to find some proxies, such as the length and distance of the bank-borrower relationship (Udell, 2015). In contrast, credit scoring is one of the transaction-based lending technologies often used by modern banks and is a relatively new technique first adopted by Wells Fargo Bank in the US in the mid-1990s. It resorts to statistical models to predict the probability of default. The variables in the statistical model typically relate to financial ratios (e.g. leverage, liquidity, profitability, coverage and activity/scale/size), credit histories (e.g. financial delinquency), firm characteristics (e.g. size, age, sector, legal status and location) and entrepreneur characteristics (e.g. age, qualification and financial experience).

Figure 1.2 Sequences of SMEs' Bank Lending Activities



Notes: This figure shows the three stages in the process of bank lending activities, which is adopted and modified from Cole and Sokolyk (2016).

For small businesses to access bank credit, the whole process can be divided into three stages (see Figure 1.2). The first two stages are decided by small businesses themselves, but the last stage is decided by banks. Specifically, based on the classical pecking order theory (Myers and Majluf, 1984)[3], a firm will have a demand for bank debt to maintain its daily operations or expand its business, after its internal funds are used exhaustively. In the next stage, the small business with debt demand will contact banks and apply for overdrafts or term loans. However, some small businesses are discouraged from applying for fear of

[3] Postulating that asymmetric information in imperfect capital markets increases the cost of financing, pecking order theory (Myers and Majluf, 1984) claims that firms prefer to use internal funds first, then external debt and finally external equity as a last resort. Another competing capital structure theory is the trade-off theory (Myers, 1984), in which firms need to trade-off the benefits and the costs of debt to find an optimal debt-to-equity ratio, which is also the target debt ratio to maximise firm value. The benefits of debt derive from the tax shield on interest payment and the costs of debt mainly refer to financial distress costs, such as the legal and administrative costs in bankruptcy. Considering information asymmetry plays a key role throughout our whole thesis and most small businesses lack enough knowledge to set a target debt ratio, we apply pecking order theory here, although there is no consensus which theory is better at explaining small businesses' capital structure in previous empirical studies.

rejection, referred to as 'discouraged borrowers' (Kon and Storey, 2003). Lastly, banks will use lending technologies to assess the applications and make decisions to issue all credit required, less credit or no credit at all.

Over the last decade, due to information technology advancement, FinTech has developed a new phase[4], in which non-intermediated financial services are offered to customers. This brings huge challenges to traditional financial intermediaries, such as the growth of peer-to-peer (P2P) lending as an alternative to bank lending. For borrowers, P2P lending has the advantage of no collateral requirement and faster approval process, leading to some borrowers migrating from banks. Despite the rapid growth of P2P lending volumes, bank lending still dominates the market and will not be replaced by P2P in the near future (Thakor, 2019), since banks have a trust advantage.[5]

In the equity market, traditional financing sources are business angel (BA) and venture capital (VC) financing. Business angels refer to high net-worth individuals investing their own money in a firm via an equity stake while venture capitalists raise money from other individuals or institutions and then invest in ventures with high reward potential as well as high risk (Wallmeroth et al., 2018, p.13). They differ in funding sources, company stage, investment frequency, amount and horizon, geographic and industry focus and exit strategy etc. (see a summary in Morrissette (2007).

Several new players also emerged in equity finance (Block et al., 2018), one of which involves the funding of unquoted entrepreneurial firms by the crowd via internet platforms, referred to as *equity crowdfunding* (ECF). Crowdcube is the first large surviving ECF

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[4] Although Fintech is a hot topic nowadays, it has already had a long history which could date back to 150 years ago. Consumers International (2017) classify its evolution into 3 phases: FinTech 1.0 (1866-1967) enabling fast transmissions of financial information, transactions and payments; FinTech 2.0 (1967-2008) introducing electronic payments and clearing systems, ATM machines and online banking; and FinTech 3.0 (2008-present) providing non-intermediated financial services. (p.5)

[5] LendingClub, one of the leading P2P platforms in the US, was accused of changing projects' risk ratings improperly in 2006. Renaud Laplanche, the founder and CEO, departed and the platform was charged a $4 million penalty.

platform founded by Darren Westlake and Luke Lang in 2011, after which more ECF platforms were incorporated. Until 2016, the investment raised on all UK ECF platforms reached £272 million, a huge increase relative to the £1.7 million raised in 2011 (Zhang et al., 2017). Its proportion of total UK equity investment (in seed and venture stage businesses) also increased from 0.35% in 2011 to 17.37% in 2016 (Zhang et al., 2017), reflecting its increasing importance in entrepreneurial finance.

Entrepreneurs can raise money rapidly and cheaply via ECF platforms, pre-test their products' markets and convert their potential customers into investors (Estrin et al., 2018). Another reason why they choose ECF is the general lack of financing after the most recent credit crunch. 70% interviewed ECF fundraisers are found to be discouraged borrowers in the Brown et al. (2018) study and the fundraisers also report that they feel it is "easier to get money from the crowd than from the bank" (p.180). However, because ECF is not a private process, entrepreneurs may worry about the information leakage and the adverse impacts (e.g. damage to reputation) of campaign failure (Estrin et al., 2018).

1.2 Definitions of Small Businesses in the UK Context

There is no single SME definition within the UK government, and different thresholds are defined depending on the purposes, for example, accounting and tax relief etc. In the UK, most banks (such as the Bank of England) adopt the EU definition that came into force on 1 January 2005. SMEs are separated into three groups in the EU definition: medium-sized, small and micro enterprises, with the thresholds provided in Table 1.1.

The European Commission's (EC) first attempt in 1996 employs both quantitative and qualitative criteria, where an enterprise is defined as independent if it is "not owned as to 25% or more of the capital or the voting rights by one enterprise, or jointly by several enterprises" (Recommendation No. 1996/280/EC, p.5). Against a background of positive

Table 1.1 SME Definition Recommended by European Commission (in 1996 and 2003)

		Employees	Annual turnover	or	Total balance sheet	Additional criteria
Medium-sized	2003	<250	≤€50m (≤£34.6m)		≤€43m (≤£29.8m)	-------
	1996	<250	<€40m (≤£33.1m)		<€27m (≤£22.4)	Independence[a]
Small	2003	<50	≤€10m (≤£6.9m)		≤€10m (≤£6.9m)	-------
	1996	<50	<€7m (≤£5.8m)		<€5m (≤£4.1m)	Independence[a]
Micro	2003	<10	≤€2m (≤£1.4m)		≤€2m (≤£1.4m)	-------
	1996	<10	-------		-------	-------

Notes: This table reports the SME definitions recommended by European Commission. The thresholds between each category are reported in €m. Considering this thesis focuses on UK SMEs, the thresholds in £m are reported in parentheses, calculated by the corresponding yearly average exchange rate. The data for exchange rate are accessed from Bank of England. [a]: the enterprise is not owned as to 25% or more of the capital or the voting rights by one enterprise, or jointly by several enterprises (Recommendation No. 1996/280/EC, p.5)

economic growth, the EC amended the recommendation in 2003, increased the thresholds for annual turnover and balance sheet total and also imposed a clear threshold for micro enterprises, which were only defined by the number of employees in 1996. Moreover, the qualitative criteria were removed in the amended definitions.

Another definition comes from the UK Parliament. In the Companies Act (2006), firms generally qualify as small companies if they satisfy two or all of the following three conditions: (1) annual turnover not more than £5.6 million; (2) balance sheet not more than £2.8 million; (3) number of employees not more than 50. The thresholds for turnover and balance sheet are much lower than their counterparts in the EC (2003) definition.

In this thesis, Chapters 2 and 3 use survey data to carry out the empirical analysis. We define SMEs in the same way as the survey: firms with no more than 250 employees and no more than £25 million annual turnovers, slightly lower than the limit set by EC (2003). They should also have the following characteristics to qualify for the surveys: (1) not more than 50% owned by another company and (2) not run as a social enterprise or as a not for profit organization. Chapter 4 explores issues in equity crowdfunding, an established external financing source for UK small businesses. Since the data for all criteria are unavailable, we do not use any definition for small businesses in this chapter and incorporate all fundraisers in our sample. Though, the median (mean) firm age in our sample is 2.9 (4.2) years, in which sense the vast majority are believed to be small businesses.

1.3 Chapter Previews and Contributions to the literature

This thesis investigates three important issues related to small business finance in the next three chapters. Chapter 2 evaluates changes in bank lending conditions focusing on the determinants of bank debt rejections for UK SMEs. Using the UK SMEs Finance Monitor data over 2011-2017, we find slightly different trends for overdrafts and loans, although the factors affecting rejections are similar. The rejection rates decrease after 2014, possibly as a consequence of government programmes for supporting SME financing. The conditions do not change significantly in the run-up and in the year following the 2016 Brexit referendum, but the overdraft market is found to become worse for exporting SMEs during this period. Further, we present robust evidence that firms with female owners and organised as partnerships, and those with a higher initial credit balance are more likely to have their credit application approved while younger, smaller and more innovative SMEs are more likely to be rejected. Finally, among different groups of SMEs, the improved conditions after 2014, especially in the overdraft market, appear to be most significant for start-ups and micro firms.

Chapter 2 makes several contributions to the literature on small business lending where most theoretical and empirical researches are devoted to lending technologies (e.g. Petersen and Rajan, 1994; Berger and Udell, 1995), the effect of bank consolidations (e.g. Petersen and Rajan, 1995; Carbo-Valverde et al., 2009), and credit rationing (e.g. Berger and Udell, 1992; Freel, 2007). Only a handful of studies investigates bank lending conditions under adverse circumstances and most of these focus on the period before and after the global financial crisis up to 2013 (e.g. Fraser, 2012; Armstrong et al., 2013; Cowling, Liu and Zhang, 2016). Extending these studies, this chapter provides an assessment of very recent bank credit market conditions by considering credit availability under a period of great uncertainty and risk prior to and following the Brexit referendum. In addition, the chapter offers insights into identifying which groups of SMEs (by firm size and age) may benefit (or suffer) most from the changed conditions in the aftermath of the global financial crisis and around the Brexit referendum.

Finally, this chapter contributes to the literature investigating the determinants of bank debt rejections. Several firm and owner features are identified as important determinants, such as firm size, age and profitability and owner age and gender (e.g. Fraser, 2009; Cowling et al., 2012; Cole and Dietrich, 2013; Zhao and Jones-Evans, 2017). However, the effect of credit balance is ignored although Mester et al., (2006) claim that credit balance is helpful to banks for monitoring purposes. One plausible reason is that firms are reluctant to answer such questions and therefore a large number of missing values appear in the data set (Lee and Brown, 2017; Rostamkalaei and Freel, 2017). We use the most suitable methodology to cope with missing values and employ multiple imputations, allowing us to test the effect of credit balance on bank debt rejection, which as far as we know, has never been investigated in the prior literature.

Moving one stage backwards in the application process (Figure 1.2), we aim to explore issues on discouraged borrowers in Chapter 3. Specifically, we analyse the relationship between awareness of the Enterprise Finance Guarantee Scheme (EFGS), financial literacy and discouraged borrowers. Using the UK SMEs Finance Monitor Data over 2011-2015, we find a positive relationship between financial literacy and EFGS awareness and a negative relationship between EFGS awareness and bank borrowing discouragement. An in-depth analysis by low- versus high-risk borrowers reveals SMEs aware of EFGS are less likely to be discouraged, no matter what the risk levels for overdraft borrowers are. However, this effect for loans is found among high-risk rather than low-risk SMEs. Moreover, discouragement is found to act as an efficient self-rationing mechanism prior to overdraft or loan application, and financial literacy improves the efficiency in the loan market, since raising financial literacy tends to encourage low-risk borrowers to apply but discourage high-risk borrowers.

The contributions of Chapter 3 are three-fold. The first relates to the literature evaluating the success of UK government schemes proposed to help SMEs to get better access to finance. The Small Firms Loan Guarantee Scheme (SFLGS) sought to mitigate the credit rationing in 1993-1998 (Cowling, 2010) and improve firms' post-loan performance (higher sale and employment growth) in 2006-2008 (Cowling and Siepel, 2013). EFGS, the successor of SFLGS, is estimated to bring a net economic benefit of £1.1 billion in 2009 (Allinson et al., 2013). To the best of our knowledge, this chapter is the first study to show its effectiveness (via awareness) on enhancing SMEs' latent demand for bank lending.

Secondly, it offers insights into the financial literacy literature. Previous studies show that financially literature SMEs are more likely to use various types of financing sources (Delić et al., 2016), have a lower probability of loan rejection (Cowling Liu and Zhang, 2016), have a stronger loan repayment capability (Mutegi et al., 2015) and have a better performance with higher employment growth (Eniola and Entebang, 2016). However, an insignificant effect of financial literacy on loan discouragement is found by Rostamkalaei (2017). Our sub-sample analysis provides an explanation for this insignificance by demonstrating that financial literacy has opposite effects on low- and high-risk borrowers, i.e. encouraging low-risk SMEs to apply but discouraging high-risk borrowers.

Finally, in the literature on discouraged borrowers based upon the Kon and Storey (2003) theoretical model, the majority of empirical studies attempt to investigate their prevalence and trend (e.g. Levenson and Willard, 2000; Rostamkalaei, 2017); characteristics (e.g. Freel et al., 2012; Chakravarty and Xiang, 2013) and creditworthiness (e.g. Han et al., 2009; Cole and Sokolyk, 2016). Han et al. (2009) investigate how to bring discouraged borrowers back to borrowing and find that a longer bank relationship can encourage good borrowers in the US. Nevertheless, the length of the bank relationship has no influence on discouragement in the UK (Fraser, 2009). As far as we are aware, this chapter is the first to empirically answer the 'how' question in the UK context. It shows the role of raising awareness of government schemes and improving financial literacy.

Inspired by the findings in the Brown et al. (2018) study that entrepreneurial firms prefer to raise money from the crowd and most fundraisers in equity crowdfunding (ECF) are discouraged borrowers, we study ECF in Chapter 4. ECF is most developed in the UK (Estrin et al., 2018) where ECF innovations are widespread, one of which is the increasing role of institutional investors (mainly business angels). Using a sample of 21,223 daily observations from 497 campaigns during July 2014 to December 2018, this chapter explores the impact of angels on funding dynamics in ECF campaigns. We observe a double L-shaped dynamic for the number of investors. The first L-shape occurs at the beginning of all ECF campaigns and the second L-shape occurs after the amount raised exceeds the funding target (i.e. overfunding). The L-shaped pattern is pronounced if an ECF campaign attracts angel co-investment at the start, but it becomes less pronounced after overfunding or in seasoned campaigns, where the level of information asymmetry is reduced.

For entrepreneurs in need of money to fund their projects, raising enough funding is their most important objective. Therefore, the mainstream empirical studies in this area explore the determinants of ECF campaign success (e.g. Ralcheva and Roosenboom, 2016, 2019;

Vismara, 2016, 2019 in the UK market) while studies on ECF funding dynamics are still scant. This chapter offers several contributions to the ECF funding dynamics literature (Vulkan et al., 2016; Vismara, 2018; Hornuf and Schwienbacher, 2018a; Nguyen et al., 2019).

Firstly, it offers new insights by discussing different funding mechanisms across UK platforms (business angel co-investment funding model vs standard funding model) and contrasting their impact on the shape of funding dynamics. This has not been investigated previously. It also analyses how this impact responses to the change in information asymmetry. It also sheds new light on the role of angles in the ECF market (e.g. Chen et al., 2016; Hornuf and Schwienbacher, 2016; Kleinert et al., 2018; Wang et al., 2019).

Secondly, Hornuf and Schwienbacher (2018a) is the first study to characterise different ECF funding dynamics: an L-shaped pattern at the campaign start (first seven days) under the first-come first-served mechanism. Confirming the L-shape at the start, Nguyen et al. (2019) explore the pattern at the end of an ECF campaign (last five days) and find a U-shaped pattern. We extend these studies by examining the dynamics after the onset of overfunding. Although more investors are found to be attracted after overfunding in the Hornuf and Schwienbacher (2018a) study, to the best of our knowledge, this is the first study to show the specific pattern after overfunding: a second L-shape which is less pronounced than the first L-shape at the campaign start.

Finally, Chapter 5 concludes with the main findings in this thesis and discusses the limitations as well as some potential avenues for future research.

Chapter 2 What Affects Bank Debt Rejections? Bank Lending Conditions in UK SMEs

2.1 Introduction

SMEs play a key role in virtually every nation primarily because they are the drivers to job creation and local economic growth. In the UK, they constitute 99.3% of all private sector enterprises and contribute approximately 60% of all private sector employment and 51% of all private sector annual turnover (DBEIS, 2017). SMEs rely heavily on bank debt as external financing sources and are more likely to face credit constraints relative to large firms. This is because they are often start-ups and young firms which may not provide sufficient collateral and are thus perceived riskier by banks. Typically, SMEs have limited net wealth and are less informationally transparent than large firms; they also have lower formal reporting needs and less external monitoring (Berger et al., 2005; Armstrong et al., 2013; Udell, 2015). Such reasons make banks more cautious in their lending to small businesses compared with large firms.

Since credit constraint has been recognised as an obstacle to firm growth (Beck and Demirguc-Kunt, 2006), much effort has been devoted to study the credit rationing faced by SMEs (e.g. Berger and Udell, 1992; Freel, 2007). The changes in the bank credit market, especially during the period with high uncertainty and risk, becomes an important issue to both policymakers and SMEs. Extending the literature on small business lending, this chapter attempts to explore (1) what happened to the lending conditions UK SMEs experienced in the recent few years after the global financial crisis and around the Brexit referendum and (2) whether different types of firms experienced same changes in lending conditions.

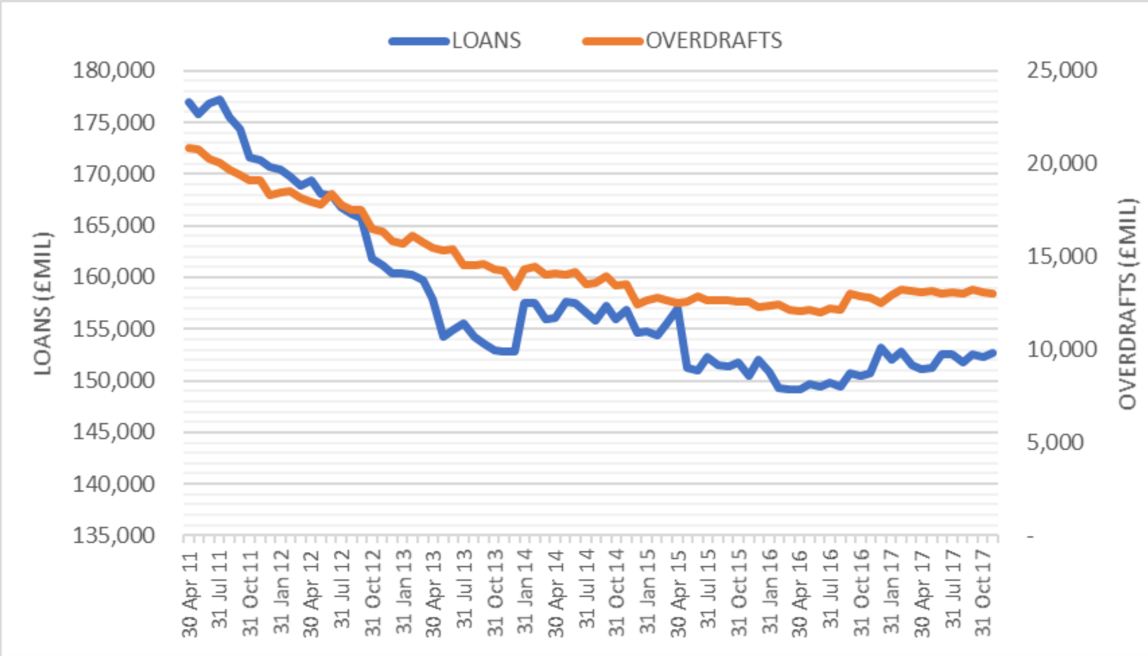
On the supply side, banks' financial conditions and lending capacity have been significantly affected by the global crisis and the economic downturn. Banks had to readjust their balance sheets due to profit reductions, pressures on capital and liquidity problems. They were also required by the updated Basel Committee for Banking Supervision (BCBS) international regulatory framework to hold higher and better-quality capital to increase the resilience of the global financial sector and help promote long-term stability and sustainable growth (BCBS, 2009).[6]

The challenge for regulators is in finding the right balance between reducing risks while at the same time allowing a sustainable credit expansion. In 2014 a capital reduction factor for lending to SMEs (known as SME Supporting Factor or SME SF) recommended by the European Commission was introduced to ensure an adequate flow of credit and increased lending specifically to SMEs but evidence on the success of this measure is still limited.

While new bank capital and liquidity requirements were necessary in the post-crisis phase to mitigate procyclicality and promote macroeconomic and financial stability, SMEs suffered from tight bank credit market conditions, and the impact on the real economy was quite evident. Today, UK SMEs, like many other European SMEs, are still struggling to find adequate funding to survive, invest and grow and, as noted in a recent report from banking group Close Brothers (2016), lenders frequently do not understand their sector. Almost half of UK SMEs have experienced barriers in accessing finance, and a quarter were turned down at the very stage when they looked to grow. Trends in aggregate data since 2011 show a dramatic drop in the use of bank business overdrafts by UK SMEs (-38%), nearly three times higher than that of business loans (-14%), as illustrated in Figure 2.1. This poses major concerns as typically credit lines and working capital are the most

[6] Concerns were soon raised by many (including, e.g. Schizas, 2011) of the potential impact of Basel III's stricter capital rules on banks' ability to lend to small businesses and in fact the issue is still controversial, both in the theoretical and empirical literature.

Figure 2.1 Monetary Financial Intermediaries' All Currency Loans and Overdraft Amounts Outstanding to UK SMEs (Aggregate Data 2011Q1-2017Q3)



Notes: This figure shows the aggregate amount of outstanding loans and overdrafts to UK SMEs during 2011Q1 to 2017Q3, with the blue line for loans and the orange line for overdrafts. The data are accessed from Bank of England (2017), Bankstats Table A8.1.1.

critical financial needs for small businesses.

To alleviate the difficulties faced by SMEs in finding bank credit, the UK government launched several schemes in an effort to facilitate formal bank lending to SMEs, such as the Enterprise Finance Guarantee in 2009; and the Start-up Loan Scheme in 2012. However, the slow economic recovery in the aftermath of the global financial crisis and June 2016's referendum results on Brexit, have triggered a sense of risk and instability for businesses of all sizes and sectors, including banks and financial firms. Among the key concerns are the prospect of leaving the European single market and the uncertainty surrounding the regulatory environment as the UK will have to convert and adapt EU legislation (Filippaios and Stone, 2017). In the worst-case scenario for Britain after Brexit, all businesses will suffer from a shortage of labour, trade restrictions and tariffs that will hinder their profitability and growth opportunities, possibly leading to even higher default rates. With banks being financially constrained themselves, credit may become even harder to get for small riskier businesses.

This chapter offers a significant contribution to the literature by providing an up-to-date evaluation of bank credit conditions and unique insights into the problem of debt rejections for UK SMEs, in the wake of the financial crisis and including the period of great uncertainty in the run-up and immediately after the Brexit referendum in 2016. The focus of the study is on the demand side using a rich firm-level survey data, drawn from the UK SMEs Finance Monitor as the main source for measuring access to finance for small businesses. The breadth of the survey allows us to consider many important aspects in the analysis including ownership and manager characteristics (legal status, male/female); bank relationships and products (including credit balance) and firm demographics (size and age). We conjecture that over the long-time frame for the analysis (2010-2017) the new governmental programmes for supporting SMEs financing had an effect in dropping rejection rates but that was held back by the uncertainty surrounding the Brexit referendum. We distinguish between two types of bank credit, namely business overdrafts facilities and term loans, as firms typically use them for different purposes. Business overdrafts are ideal for firms with fluctuating financing needs, so they are used to ease pressures on working capital and as a back-up for unanticipated expenditures; while term loans are typically used for longer-term purposes and generally firm expansion. Overdraft applicants also have different characteristics compared to loan applicants and the relevant literature has previously indicated that the determinants of overdraft rejections can differ significantly from those of loans' (Armstrong et al., 2013; Lee and Brown, 2017; Zhao and Jones-Evans, 2017).

Second, this chapter offers an in-depth investigation by firm size and age isolating the case of start-ups and younger firms in an attempt to identify which were the most likely to be affected by credit shortages. Start-ups are often very small; nonetheless they give a strong contribution to net employment growth; this was true even during the crisis, as evidenced, for example, in the cross-country study by Criscuolo et al. (2014). Our preferred methodology is a logit model and, in line with the extant literature (Cowling et al., 2012; Fraser, 2012; Armstrong et al., 2013; Cowling, Liu and Zhang, 2016), we test a number of relevant variables in addition to the application date. In particular, we include owner/manager characteristics (like gender and age), type of bank relationships (e.g. multiple suppliers) and firm-specific characteristics (such as size and location). In addition, although in survey data multiple imputation (MI) is a well-developed technique to deal with missing values, this is the first study, to the best of our knowledge, to apply this technique in such a context, allowing us to test the effects of credit balance, which are usually removed in previous studies due to missing values (Lee and Brown, 2017; Rostamkalaei and Freel, 2017).

Our main findings on bank lending conditions indicate that, relative to the years after the global financial crisis (2010-11), the overdraft and loan markets appear to follow slightly different patterns. The rejection rates dropped after 2014 and remained stable in the run-up to the Brexit referendum and its immediate aftermath although the overdraft market became tighter for exporting firms since Brexit. An in-depth analysis of firm size and age shows that micro firms and start-ups experienced significantly improved conditions after 2014, particularly in the case of overdrafts although the loan market is still tight.

As for the determinants of bank debt rejections, we find that SMEs with female owners and organised in partnerships, and with a higher initial credit balance are more likely to be approved, while younger, smaller and more innovative SMEs with lower application amounts are more likely to be rejected both in the case of loans and overdrafts.

The rest of this chapter is organised as follows. Section 2.2 discusses the evolution of UK SME policies since the 1980s. Section 2.3 provides a brief review of the empirical studies on the determinants of bank debt rejection for SMEs and sets out the key research hypotheses. Sections 2.4 describes the data and variables employed in the regressions and presents some descriptive statistics. The empirical results and robustness tests are presented and discussed in Sections 2.5 and 2.6, respectively. Finally, Section 2.7 concludes and provides a discussion of the main related policy issues.

2.2 Evolution of UK SME Policies

Realising the vital role of SMEs in the UK economy, policymakers have designed and implemented a wide range of policies to support entrepreneurs and SMEs in the last 30 years. These policies can be classified into several sub-groups[7] based on the areas they are aimed to influence. This section will discuss the evolution of these policies in chronological order, especially the SME policies on access to finance.

Policymakers first showed interest in small businesses in the 1970s. The Bolton Report[8] in 1973 concentrated on small business management and the first minister for small businesses was appointed in 1977. Despite these facts, the first SME policies came into being at the beginning of the 1980s, with the policy thrust on creating ‘new businesses’ to reduce the unemployment rate (Greene et al., 2008). However, the later evidence indicated that new

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[7] There are six sub-groups: the regulatory framework; R&D and technology; entrepreneurial capabilities; enterprise culture; access to finance and market conditions (Storey and Greene, p.374.)

[8] See the full report at https://api.parliament.uk/historic-hansard/lords/1973/feb/21/small-firms-the-bolton-report

businesses tended to be of poor quality and closed quickly, and the unemployment rate did not reduce as much as policymakers expected (Storey and Greene, 2010).

As new evidence highlighted the importance and potentiality of fast-growth SMEs in bringing benefits to the economy (Jovanovic, 2001), the government shifted the policy thrust from ‘new businesses’ in the 1980s to ‘existing SMEs’ in the 1990s, especially potentially high growth SMEs. Until 2004, the establishment of a wider agenda made ‘access to finance’ as one of the foci in the small business policy.

The global financial crisis in 2008 led to a deterioration of bank lending, and SMEs were found to face greater credit constraints (Fraser, 2012). Thus, the ‘access to finance’ focus became even more crucial after the financial crisis and the government launched various schemes to stimulate bank lending to SMEs (Calabrese et al., 2017), such as the Funding for Lending Scheme (FLS) targeted at banks and the Start-up Loan Scheme (SLS) targeted at early-stage businesses operating for less than 2 years. The FLS provides funding to banks where they can have more funding at lower cost if they perform better in small business lending.

A long-lasting government-backed scheme for SME finance in the UK is the guarantee scheme, the Small Firms Loan Guarantee Scheme (SFLGS). This scheme was initiated in 1981 and targeted at small firms lacking collateral and/or track record when they applied for bank debt. The eligible small firms (with no more than £5.6m turnover) can apply for loans up to £250,000 under this scheme. In response to the difficulties in bank credit availability after the financial crisis, the SFLGS was replaced by the Enterprise Finance Guarantee Scheme (EFGS) which increased the upper limit of loan amount to £1m and extended the eligible SMEs to firms with no more than £25m turnover. In this sense, more SMEs can access more finance under the EFGS scheme.

2.3 Selected Literature Review and Hypothesis Development

Relative to large firms, small firms generally lack a financial track record, are exempted from audited accounts[9], and are less informationally transparent (Armstrong et al., 2013). To overcome this informational opacity problem, banks employ different lending technologies (briefly discussed in Section 1.1) in small business lending. Lending technologies act as "the basic building blocks of the modern research model of small business lending" (Berger, 2015, p.532), which cannot be avoided in an analysis of SME's access to bank credit. Berger (2015) and Udell (2015) provide comprehensive discussions on several lending technologies, such as relationship lending, financial statement lending and credit scoring etc. Despite a combination of soft and hard information used in most lending technologies, a hardening trend, reflected by longer lending distances and less use of personal contacts to underwrite contracts over time (Brevoort and Wolken, 2008), has been uncovered.

On the supply-side, large banks have an advantage, especially a cost advantage, on using hard information because of economies of scale (Stein, 2002) whereas small banks have an advantage on using soft information. The main reason is that soft information can more easily be transmitted credibly within fewer layers of management (Berger and Udell, 2002) and less hierarchical/geographical distance (Liberti and Mian, 2008) as in small banks. In a similar vein, single-market banks, closer to local firms physically, have an advantage on using soft information over multi-market banks (Degryse and Ongena, 2005) and foreign-owned banks, typically large, distant and culturally different, have an advantage on using hard information over domestically-owned banks (Berger and Udell, 2006).

[9] See more details at https://www.gov.uk/audit-exemptions-for-private-limited-companies.

The competition in the banking market is likely to affect small business lending. Theoretically, two competing mechanisms underlying this effect have been proposed. In the information hypothesis (Petersen and Rajan, 1995), banks can internalise the benefits of helping opaque businesses more easily in a low competition market and therefore enhance their credit availability to small businesses. On the other hand, in the market power hypothesis (Carbo-Valverde et al., 2009), reduced competition leads to higher interest rates and greater credit constraints, no matter whether the firm is informationally transparent or opaque. Thus, a positive relationship between banking competition and small business lending is predicted in this hypothesis. Mixed empirical results are found. Several studies (e.g. Marquez, 2002; Han et al., 2009) support the information hypothesis while others (e.g. Chong et al., 2013; Ryan et al., 2014) adduce evidence for the market power hypothesis.

On the demand-side (i.e. firm-side), Stiglitz and Weiss (1981) demonstrate that imperfect information leads banks to restrict lending even when 'good' borrowers are willing to pay higher interest rates than the equilibrium price or to provide more collateral. Inspired by their model, a relatively large body of empirical research ensued that focuses on the analysis of credit rationing for SMEs (e.g. Berger and Udell, 1992; Freel, 2007). For the UK market, lack of sufficient relevant data meant that there are only a handful of papers empirically examining the changes in credit market conditions over recent years. The existing body of literature looks into UK bank lending conditions for SMEs up to 2013, typically focusing on a relatively short time span and ignoring the potential effects of the period of uncertainty in the run-up and following the Brexit referendum on the credit availability (Fraser, 2012; Armstrong et al., 2013).

In this study, we employ a long-time frame for the analysis (2010-2017), and we conjecture that the new governmental programmes for supporting SMEs financing helped reduce the rejection rates. These include initiatives like the Funding for Lending Scheme in 2012, the creation of a British Business Bank and the introduction of the SME Supporting Factor (SME SF) in 2014 to encourage banks to lend to small businesses. This latter initiative is a short-term corrective measure to counterbalance the rise in banks' capital requirement resulting from the cyclical component of Basel III. However, we also expect that the run-up to the Brexit referendum in 2016 triggered widespread uncertainty with investors and firms suffering from unknown trading and/or regulatory environment as the UK decided to leave the European Union. Therefore, our first hypothesis (H1) can be formulated as follows:

> ***H1:*** *Rejection rates diminished thanks to governmental programmes for supporting SMEs financing but increased in the run-up to the Brexit referendum and its immediate aftermath.*

Not all companies suffered from worse credit conditions during and after the Brexit referendum. The uncertainty generated by Brexit resulted in a dramatic drop in the pound sterling's value, imposing a negative effect on the firm performance of exporting SMEs. This was supported by the evidence that exporting SMEs were inclined to regard Brexit as an obstacle to business success (Brown et al., 2019). Exporting activities play a key role in promoting economic growth since approximately 30% of GDP is contributed by exports of goods and service in the UK (OECD, 2019). Exporting SMEs are found to have lower failure rates (Esteve-Perez et al., 2008) and higher sales and asset growth (Beamish and Lu, 2006). However, in such a context, banks will be more cautious and exporting firms in particular likely had the greatest difficulties in accessing bank credit. Therefore, we also hypothesise that:

> ***H2:*** *Export-oriented UK SMEs suffered from tighter credit conditions during and after the Brexit referendum compared to import-oriented firms.*

In terms of factors determining access to bank financing for SMEs, empirical studies tend to include selected owner/manager features, factors related to relationship banking and firm characteristics (e.g. Cole, 1998; Fraser, 2009; Cole and Dietrich, 2013). However, many important variables, such as the presence of a credit balance, are typically omitted due to missing values. In this chapter, we use a technique that allows incorporating this information in the estimated empirical models (see, for the related methodological details, Section 2.4.1).

2.3.1 Owner/Manager Characteristics

The gender of the owner/manager can be an important determinant of bank debt rejection. Compared with male-owned/led SMEs, female-owned/led SMEs tend to be smaller, younger, less profitable (Fasci and Valdez, 1998), slower-growing (Cooper et al., 1994) and less likely to survive (Fairlie and Robb, 2009), suggesting they are potentially riskier and thus more likely to have difficulties in getting funded. Early studies (e.g. Riding and Swift, 1990; Coleman, 2000) provide evidence to this argument; whereas recently, for example, Moro et al. (2017) find no significant difference between access to bank finance of male- and female-owned/led euro area SMEs. Indeed, a cross-country research from Cole and Dietrich (2013) maintain that the situation actually differs from country to country depending on the level of financial development. The authors find that credit suppliers favour female owners/managers in developed countries vs their male counterparts in developing countries. Similarly, Cowling, Liu and Zhang (2016) provide further evidence to Cole and Dietrich (2013)'s argument that female-owned/led SMEs in the UK are less likely to be rejected, although they are found to have lower demand. In addition, owner age (Zhao and Jones-Evans, 2017) and financial qualifications (Cowling, Liu and Zhang, 2016) are usually found to be positively associated with bank credit availability for UK SMEs. Given the above, we propose the following two hypotheses:

H3 (a): *Female-owned/led SMEs are more (less) likely to be rejected when they apply for bank financing.*

H4: *SMEs with experienced and specialised owners/managers are less likely to be rejected when they apply for bank financing.*

2.3.2 Relationship Lending

In relationship lending, banks are able to gather soft information over time and across different products. In this sense, two dimensions in relationship lending are widely discussed in previous literature: duration and concentration. Over time, the collection of the information on firms' creditworthiness builds up, giving SMEs advantages when they apply for bank credit. Similarly, if a bank supplies a bundle rather than a single product to a firm, monitoring is much easier and less costly (Fraser, 2009). The lower information asymmetry should give the bank an incentive to extend credit. Therefore, a longer-term and more concentrated bank relationship is expected to help SMEs get better access to bank credit.

This hypothesis has been supported in several empirical investigations (e.g. Petersen and Rajan, 1994; Berger and Udell, 1995; Hernández-Cánova and Martínez-Solan, 2010). Using information from 101 separate studies during 1970-2010, Kysucky and Norden (2015) carry out a cross-country meta-analysis and find that SMEs can benefit from stronger bank relationships since "long-lasting, exclusive and synergy-creating bank relationships are associated with higher credit volume and lower loan rates" (p. 90). However, concentrating on US small businesses, Cole (1998) estimates multivariate logistic regressions and claims it is the pre-existing relationship, rather than the length of the relationship that has a positive impact on access to credit for SMEs. Employing bivariate probit models for UK SMEs, Fraser (2009) finds that not only the length but also the concentration of banking relationship is insignificant. The information obtained from the applicants' previous suppliers is sufficient for banks to make decisions so that they do not need to establish extra close relationships with SMEs. Our main hypothesis can be formulated as follows:

> ***H5:*** *SMEs with a closer relationship with banks (either long-term or as single lender) are less likely to be rejected when they apply for bank financing.*

As mentioned above, the role of credit balance has not been examined before, mainly due to missing data problems. Credit balance refers to the amount that a firm usually holds in its current and deposit accounts, enabling banks to get better oversight of the cash inflow and outflow and reducing information asymmetry. Account balance has been employed to estimate consumer credit scores (Finlay, 2008). Similarly, the transparent information obtained from firm credit balance becomes particularly useful to assess borrower's ability to generate profits and predict its probability of default, which is even more valuable in the UK where small businesses are exempted from having to audit their annual accounts. Banks can also monitor the changes in the credit balance to get rid of moral hazard problems, especially when the SME has an exclusive relationship with the bank (Mester et al., 2006). Moreover, credit balance makes it easier for banks to uncover borrowers' losses. This can motivate SMEs to take action to generate higher returns (Nakamura, 1991). Therefore, credit balance plays an important role in bank lending to small businesses in the sense that banks can use it as a 'selection' tool during applications, a 'monitoring' tool after applications and a 'buffer' in the event of default. The higher the credit balance, the lower the probability of default, the stronger the 'buffer' and the less likely their applications get rejected.

H6: *SMEs with higher credit balance are less likely to be rejected when they apply for bank financing.*

2.3.3 Firm Characteristics

Firm age and size are deemed to play an important role in the determination of rejection rates for SMEs (Cowling et al., 2012). This could be because older and larger SMEs are usually more able to provide sufficient collateral. They are also more likely to have a track record of business financial information and credit history that reduce the information asymmetry between credit suppliers and firms (Fraser et al., 2015). Since young and small firms, including innovative start-ups, are believed to be more fragile and thus more likely to default, particularly in turbulent times, they might find it harder to access loans as banks' decision is generally based on the applicants' creditworthiness (Fraser, 2009). Several empirical studies have revealed the positive relationship between credit availability and SMEs' age and size (e.g. Coleman, 2004; Armstrong et al., 2013). However, at least for the UK case, the size effect is insignificant in some studies (e.g. Fraser, 2009; Cowling Liu and Zhang, 2016) and the age effect also disappears in others (Fraser, 2012; Lee and Brown, 2017).

Industry sector is another factor that may affect SMEs' access to finance. The rationale is that firms in the same industry are subject to similar market conditions (Freel et al., 2012) and therefore, belonging to a certain industry classification can act as a signal for business risk. Though, based on the evidence drawn in studies by, e.g. Armstrong et al. (2013); and Cowling, Liu and Zhang (2016), it seems to have no significant bearing on bank debt rejection for UK SMEs.

Effects of growth and profitability on bank credit availability are also investigated in the relevant literature. Cole and Dietrich (2013) employ the data from World Bank Enterprise

Survey and argue that banks are more likely to grant credit to SMEs with positive growth, but only for larger SMEs. Subsequent research by Moro et al. (2017) demonstrates the negative effects of both growth and profitability on loan denial for euro area SMEs. However, the effect of profitability disappears when sample selection issues are under control. Focusing on UK SMEs and employing Heckman selection models, Cowling, Liu and Zhang (2016) reveal an insignificant relationship between profitability and access to bank finance. They also find that high growth SMEs are more likely to be denied, suggesting the preference of banks "to incremental (managed) growth than the risk of accelerated growth" (p. 921).

Other significant firm characteristics often found in UK studies include the SMEs' degree of 'innovativeness', their geographic location and degree of international business activity. Although innovative SMEs are more likely to make new applications for overdrafts and loans relative to non-innovative SMEs (Lee and Brown, 2017), they appear to have more difficulties accessing finance after controlling for other risk factors (Freel, 2007; Lee at al., 2015). Concerning location, Lee and Drever (2014) use a composite poverty index to represent geographical variation and find that it has no influence on credit availability. However, employing a proxy for travelling miles between bank headquarters and branches, Zhao and Jones-Evans (2017) highlight the importance of geographical disparities. Given the findings in the most recent previous literature, we formulate the following hypotheses:

> ***H7:*** *Smaller, innovative, younger SMEs and start-ups are more likely to be rejected when they apply for bank financing.*

> ***H8:*** *Profitable SMEs are less likely to be rejected when they apply for bank financing.*

2.4 Data

The dataset used in this study is drawn from the Small and Medium-Sized Enterprise Finance Monitor (SMEFM) accessed from the UK Data Archive (BDRC Continental, 2018), which provides micro firm-level survey data collected from 2011 Q1Q2 to 2017 Q4.[10] Since the survey asks for SMEs' experiences in the previous 12 months, we have information on UK SMEs from 2010. However, applications in 2010 and in 2017 are underestimated because they refer to the previous period.

Around 5,000 different SMEs were interviewed in each wave (27 in total, corresponding to 131,323 observations). The database asks for their experiences of seeking and obtaining external finance in the previous 12 months, future financial needs and barriers for future growth, as well as the characteristics of the SMEs and their owners/managers. The way the survey works is that a company cannot be included in the pool more than once a year. Therefore, the quarterly survey data are in repeated-measured structure, instead of panel structure. Even if we construct a panel sample using some "repeat" participants, they tend to be large SMEs, and this will bias our analysis towards large SMEs and produce misleading inferences.

Unlike in most European countries, UK SMEs demand more credit lines than loans as finance sources (DBIS, 2016). Therefore, we construct and analyse two separate datasets: one for business overdraft and the other for term loan applications. We delete observations with no initial outcome of their applications and those that refer to the year 2009.[11] Our

[10] The first wave survey was performed in February-May 2011 and is specifically denoted by "2011 Q1Q2". Subsequent surveys were undertaken in standard quarter periods (January-March, April-June, July-September and October-December). The survey data can be accessed till wave 27 (i.e. 2017 Q4) on the UK Data Archive (retrieved October 31, 2019, from https://beta.ukdataservice.ac.uk/datacatalogue/studies/study?id=6888). Therefore, the sample period under investigation covers the 2011-2017 period.

[11] Since the survey asks for SMEs' experiences in the previous 12 months, the first wave survey conducted in 2011 should collect information in 2010. Therefore, applications in 2009 (the information before 2010) are regarded as outliers and removed from the sample.

Table 2.1 Reasons for Bank Debt Applications

Panel A – Reasons for overdrafts applications (N=10673)	%
Working capital/Cash flow	81.30
As a safety net	39.24
To cover a short-term funding gap	26.02
To fund growth of the business in the UK	15.42
Purchase of equipment/machinery	11.72
To fund growth of the business overseas	1.99
Panel B – Reasons for loans applications (N=5864)	**%**
To fund growth of the business in the UK	28.89
Purchase of premises	26.67
Purchase of equipment/machinery	25.70
To develop new products/services	13.73
To replace other funding	12.33
Purchase of motor vehicles	12.02
Working capital/Cash flow	6.38
To take over another business	2.81
To fund growth of the business overseas	2.46

Notes: This table reports the reasons for bank debt applications, with Panel A for overdrafts and Panel B for loans. Percentages are calculated out of SMEs which applied for overdrafts/loans during the period 2010-2017. Figures do not add up to 100% because respondents can choose more than one answer.

final sample includes a total of 16,537 observations, split into two separate samples: 10,673 observations for overdraft and 5,864 for loans.

Credit lines are typically shorter term and lower in volume than loans. Table 2.1 illustrates different reasons for overdraft (Panel A) and loan (Panel B) applications. Most SMEs use overdrafts as working capital to help with day to day cash flow management (81%), as a safety net just in case (39%) or to cover short-term gaps until funds are available (26%). On the other hand, 31% of SMEs apply for loans to expand their businesses (29% domestically and 2% overseas), purchase premises (27%) and equipment (26%).

Table 2.2 Business Overdrafts and Term Loans Applications and Rejections by Sub-periods During 2010-2017

Application dates	# of Overdrafts	# of loans	Loans/ overdrafts	% changes overdrafts	% changes loans	Overdrafts Rejections[a] (%)	Loans Rejections[a] (%)
2010	608	350	58%	-	-	18.91	24.29
2011	2227	1103	50%	266%	215%	19.04	27.92
2012	1888	923	49%	-15%	-16%	22.67	29.79
2013	1565	781	50%	-17%	-15%	20.77	29.58
2014	1348	745	55%	-14%	-5%	12.09	20.54
2015	1087	611	56%	-19%	-18%	9.02	16.20
2016	713	367	51%	-34%	-40%	9.82	18.80
2017	523	247	47%	-27%	-33%	8.03	15.38

Notes: This table reports the number of bank debt applications and the rejection rates in each year from 2010 to 2017. Applications in 2010 and 2017 are underestimated due to the way the survey question is formulated (see details in Section 2.4). Reported data only include SMEs which applied for overdrafts/loans over 2010-2017. [a]: Data only include SMEs which applied for overdrafts/loans during 2010-2017.

Table 2.2 displays the number of SMEs which have applied for bank financing by year over the studied period.[12] Overdraft applicants are almost twice as many the number of loan applicants in all years. We saw before that high needs for working capital and day-to-day liquidity are driving overdraft applications. Excluding 2010, Table 2.2 also reveals a dramatic drop (by nearly 2/3) in the number of applications for both overdrafts and loans. Although the number of applications cannot measure bank credit demand accurately due to a likely "discouragement factor" at play, the trend described above is suggestive of a decreasing bank credit demand in the wake of the financial crisis. A report by DBIS (2015) highlights that – excluding SMEs with no employees –, fewer UK SMEs sought finance in 2014 (19%), relative to 2012 (24%) and 2010 (26%). A possible reason is that firms adjust their business plans to slow down their growth during a crisis. This allows firms to accumulate enough internal funds and therefore, do not demand external bank debt after

[12] The data for applications in 2010 and 2017 are incomplete because fewer surveys covered these two periods, compared to other years, due to the way the survey is formulated (see also footnote 10). Specifically, the survey asked SMEs' experiences over the past 12 months, which means applications in 2013 were surveyed from wave 8 (Q1 2013) to wave 15 (Q4 2014). However, applications in 2010 were only surveyed in the first three waves (only three waves were conducted in 2011), and applications in 2017 were only surveyed in the last four waves.

the recession (BBB, 2016). Political and economic uncertainty around Brexit has likely affected firms' investment plans in the most recent years (Brown et al., 2019).

The rejection rate is defined as "the proportion of firms which applied for credit and were either refused outright or received less credit than they requested, as a proportion of firms applying" (Armstrong et al., 2013, p. R41). The last two columns in Table 2.2 illustrate that the bank debt rejection rates during 2010-2017 are higher for loans than overdrafts in every year, reflecting the preference of banks to issuing low volume, contingent short-term finance (see also DBIS, 2016). This could also partially explain the lower number of loan applications in Table 2.2 since, as mentioned earlier, higher rejection rates could subsequently increase discouragement and thus reduce the number of applications. Table 2.2 also shows that for both overdrafts and loans, the rejection rates appear considerably higher in 2010-2013 compared to more recent years. This trend implies a tight credit condition during the great recession until 2013 and seems to hint to a greater banks' propensity to lend in more recent years, both in terms of overdrafts and loans. However, it is possible to note that conditions are slightly tight again, particularly for loans in 2016, the year of the Brexit referendum.

2.4.1 Main Model and Variable Description

We employ a logistic regression model for the empirical investigation. The outcome of the application from the i-th SME (for i=1, 2, …, n) can be described by a Bernoulli random variable Y_i, so that:

$$Y_i = \begin{cases} 1 & if\ the\ i - th\ SME\ is\ rejected \\ 0 & if\ the\ i - th\ SME\ is\ not\ rejected \end{cases} \tag{2.1}$$

where a firm is defined as being rejected if it is either refused outright or receives less credit than it requests. Let π_i represent the probability of bank debt rejection of i-th SME, thus $\pi_i = Pr(Y_i = 1)$. To estimate π_i, consider a covariate vector X_i and a link function $g(.)$ which is monotonic and twice differentiable such that:

$$g(\pi_i) = X_i^T \beta \tag{2.2}$$

where β denotes the unknown parameters vector to be estimated. The link function is the logit link based on the symmetric logistic distribution that can be described as follows:

$$\ln\left(\frac{\pi_i}{1-\pi_i}\right) = X_i^T \beta \tag{2.3}$$

In order to avoid the potential biased and/or inefficient estimated coefficients resulted from deletion of incomplete observations (White et al., 2011)[13], we apply multiple imputations (MI) to deal with missing values (Allison, 2012). We adopt fully conditional specification (FCS) implemented by chained equations algorithm because it is a non-parametric approach that is based on three main steps: imputation, analysis and pooling.[14] In the first step, plausible values are utilised to fill in the missing values by using other independent variables as predictors and iterating over the conditional densities. Several complete datasets can be generated in this step. Then, complete-data methods are applied in each separate complete dataset. Finally, Rubin's rules are used to combine the results obtained in the second step. The rule "incorporates both within-imputation variability (uncertainty

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[13] Complete-case analysis is appropriate only if the data are missing completely at random (MCAR). We run the Little's MCAR test. The chi-square statistics are 4906 for overdraft sample and 3962 for loan sample, which are highly significant. Therefore, the missing data in our sample are not MCAR patterns, and complete-case analysis will be inappropriate in such a context.
[14] This is implemented in the programming language R using the package "mice" (Buuren and Groothuis-Oudshoorn, 2011).

about the results from one imputed data set) and between-imputation variability (reflecting the uncertainty due to the missing information)" (White et al., 2011, p. 378). How many complete datasets should be generated, which is also referred to as the number of imputations, has been widely discussed (e.g. Schafer, 1999; Graham et al., 2007). In this chapter, we follow White et al. (2011)'s recommendation which is more flexible: the number of imputations should be similar to the percentage of cases that are incomplete. Approximately 40% (45%) observations for overdrafts (loans) have missing values. Therefore, 40 (45) imputed datasets are generated for overdrafts (loans). The percentages of missing values in the corresponding variables are reported in the note to Table 2.4. The independent variable of interest (application date) has 7% missing values for overdrafts and 12% missing values for loans. Credit balance has the highest percentages of missing values (24.5% for overdrafts and 25.4% for loans).[15]

To select the independent variables, we follow Wood et al. (2008) and use a backward stepwise selection approach. At first, the model with all the potential covariates is estimated. Then, the explanatory variable with the lowest significance level is dropped, and the Wald test is used to test whether the dropped covariates (except the most recently dropped) should be re-introduced into the model.[16] If the dropped variables are not re-included in the model, the model is re-estimated excluding the dropped covariates. This iterative procedure is applied until all the covariates in the model are significant at least 10% significance level. Therefore, the results reported in the next section only include significant explanatory variables.

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[15] This is likely the reason why its effect has not been examined before in previous studies (e.g. Lee and Brown, 2017; Rostamkalaei and Freel, 2017) that use the same data set.
[16] We use the function 'pool.compare' available in the R package 'mice' to implement the Wald test.

Table 2.3 List of Variables and Their Definitions

Variable	Description
Dependent variable	
Bank debt rejection	A dummy variable which equals 1 if the bank debt application was rejected (refused outright or received less credit than it requested) and 0 otherwise.
Independent variables	
Application date	Dummy variables indicating the exact year when the firm applied for the bank debt: ‘applications in 2010’, ‘applications in 2011’, ‘applications in 2012’, ‘applications in 2013’, ‘applications in 2014’, ‘applications in 2015’, ‘applications in 2016’ and ‘applications in 2017’.
Owner/Manager characteristics	
Gender	Dummy variables indicating the gender of the owner/manager: ‘male’, ‘female’ and ‘both (joint partners)’.
Legal status	Dummy variables indicating the legal status of the firm: ‘sole proprietorship’, ‘partnership’, ’limited liability partnership’ and ‘limited liability company’.
Owner Age	Dummy variables indicating the age of the owner/manager: ’18-30 years’, ’31-50 years’ and ‘>66 years’.
Financial knowledge	A dummy variable which equals 1 if the person in charge of financial management within the firm has a finance qualification or has undertaken some financial trainings and 0 otherwise.
Bank relationships and/or products	
Multiple suppliers	A dummy variable which equals 1 if the firm approached more than one bank/financial institution when the firm did its most business and 0 otherwise.
Main bank	A dummy variable which equals 1 if the firm applied to its main bank and 0 otherwise.
Use of credit card	A dummy variable which equals 1 if the firm uses credit card currently and 0 otherwise
Credit balance	Dummy variables indicating the amount that the firm usually holds in current and deposit accounts: ‘<£5,000’, ‘£5,000-9,999’, ‘£10,000-49,999’, ‘£50,000-99,999’, ‘£100,000-499,999’, ‘£500,000-999,999’ and ‘>£1m’.
Firm characteristics	
Number of employees	Dummy variables indicating the number of people working in the firm: ‘0-9’, ’10-49’ and ’50-249’.
Annual turnover	Dummy variables indicating the annual turnover of the firm: ‘<£50,000’, ‘£50,000-99,999’, ‘£100,000-499,999’, ‘£500,000-999,999’, ‘£1m-4.9m’ and ‘>£5m’.
Business age	Dummy variables indicating the number of years since the firm was established: ‘<2 years’, ‘2-5 years’, ‘6-9 years’, ’10-15 years’ and ‘>15 years’.
Standard region	Dummy variables indicating the location of the firm in the UK: ‘London’, ‘East Anglia’, ‘East Midlands’, ‘North West’, ‘North/ North East’, ‘Northern Ireland’, ‘Scotland’, ‘South East’, ‘South West’, ‘Wales’, ‘West Midlands’ and ‘Yorkshire/ Humberside’.
Industry sector	Dummy variables indicating the principal activity of the firm: ‘construction’, ‘agriculture, hunting and forestry fishing’, ‘health and social work’, ‘hotels and restaurants’, ‘manufacturing’, ‘real estate, renting and business activities’, ‘transport, storage and communication’, ‘wholesale/retail’ and ‘other community, social and personal service’
Profitability	Dummy variables indicating whether the firm made a net profit or loss: ‘loss’, ‘broken even’ and ‘profit’.
Business plan	A dummy variable which equals 1 if the firm has a formal written business plan and 0 otherwise.
Export	A dummy variable which equals 1 if the firm sells goods or services abroad and 0 otherwise.
Import	A dummy variable which equals 1 if the firm buys goods or services from abroad and 0 otherwise.
Management account	A dummy variable which equals 1 if the firm produces regular monthly or quarterly management accounts and 0 otherwise.

(continued)

Table 2.3 Continued

Variable	Description
Improvement	A dummy variable which equals 1 if the firm has significantly improved an aspect of the firm in the past 3 years and 0 otherwise.
Innovation	A dummy variable which equals 1 if the firm has developed a new product or service in the past 3 years and 0 otherwise.
D&B risk rating	Dummy variables indicating the external credit risk rating from Dun & Bradstreet of the firm: 'minimal', 'low', 'average' and 'above average'.
Application process-related	
Seeking advice	A dummy variable which equals 1 if the firm sought external advice before applying for the bank debt and 0 otherwise.
Business account	A dummy variable which equals 1 if the main current account used for the business is a business account and 0 otherwise.
Amount applied	Dummy variables indicating the amount of bank debt that the firm initially applied for: '<£5,000', '£5,000-9,999', '£10,000-49,999', '£50,000-99,999', '£100,000-499,999', '£500,000-999,999' and '>£1m'.

Note: This table reports the definitions of the dependent variable and the independent variables used in the regressions.

Table 2.3 provides the definitions of all variables used in equation (2.3)[17]. The dependent variable is the bank debt rejection, a binary variable equal to 1 if the firm was refused outright or received less credit than it requested, and zero otherwise.

One important variable is the application date for which we include eight dummy variables, (one for each year) to proxy for changes in credit market conditions as in Fraser (2012) and Armstrong et al. (2013). A higher rejection rate is expected for applications in 2016, the year of the Brexit referendum. We also include credit balance to test Hypothesis 6 and incorporate seven dummies, expecting significant coefficients with higher magnitude for higher credit balance dummies.

Following the main literature on the determinants of access to bank finance for SMEs (e.g. Cowling, Liu and Zhang, 2016; Lee and Brown, 2017) the additional independent variables included in the model can be mainly divided into four groups: owner/manager

[17] Compared to the variable list in Table 2.3, some variables are absent in Table 2.6. This is because these variables are insignificant and thus removed from the regression model after we apply the backward stepwise selection technique. It does not mean that we do not include these variables when we run regressions. Besides, the empty rows for application date in Table 2.6-2.14 also mean the dummy variables are insignificant and removed from the model.

characteristics, bank relationships and/or products, firm characteristics[18], and application process-related variables. The related descriptive statistics can be found in Table 2.4.

Table 2.4 also provides the difference in means between rejected and approved applicants for all independent variables. The t-statistics suggest that as far as overdrafts are concerned, rejected SMEs were more likely to apply in 2011-2013 and less likely in 2014-2017. Consistent with the trends shown in Table 2.2 above, results for loans are similar. Further, both in the case of overdrafts and loans, rejected firms tend to be smaller (have fewer employees and lower annual turnovers), younger, sole-traders, less creditworthy and are led by younger owners/leaders. Approved firms have a higher credit balance and tend to be more profitable and internationally traded. Their ownership is usually joint partners (males/females), who are more financially knowledgeable. They generally apply to their main banks, use a credit card, have a business account and apply for relatively higher amounts. In addition, when SMEs apply for overdrafts (not loans), rejected firms tend to be innovative and seek advice before their applications.

The correlation coefficients between all control variables are reported in Tables 2.5a and 2.5b for overdrafts and loans, respectively. In both samples, the correlation coefficient between the number of employees and the annual turnover is rather high (0.737 in the overdraft sample and 0.754 in the loan sample), both of which are proxies for firm size. These two variables are also highly correlated with the amount applied, possibly because larger firms need higher working capital (for the purpose of overdraft applications) and have larger projects to be funded (for the purpose of loan applications). Despite the high

[18] For further analysis, we will divide all firms into micro, small and medium-sized firms. To mimic the EC definition (see Table 1.1 in Chapter 1), we split the sample according to the number of employees and the annual turnover. To be consistent, we include both measures as a proxy for firm size in the regression. Fraser (2009) also uses the number of employees and the business assets simultaneously in his model. Besides, to deal with the multicollinearity concerns between these two variables, we run the VIF tests, which are smaller than 5, indicating that the correlation problem can be neglected.

Table 2.4 Descriptive Statistics and Difference in Means: Business Overdrafts and Term Loans

	Business overdrafts					Term loans				
Variables	All (N=10673)	Rejected (N=1738)	Approved (N=8935)	Difference (a-b)	t-statistic	All (N=5864)	Rejected (N=1386)	Approved (N=4478)	Difference (a-b)	t-statistic
	Mean	Mean (a)	Mean (b)			Mean	Mean (a)	Mean (b)		
Application date[b]										
Applications in 2010	0.0611	0.0691	0.0594	0.0096	1.4293	0.0683	0.0676	0.0685	-0.0009	-0.1134
Applications in 2011	0.2236	0.2547	0.2174	0.0373	3.2126***	0.2151	0.2448	0.2055	0.0394	2.8603***
Applications in 2012	0.1896	0.2571	0.1760	0.0810	7.0455***	0.1800	0.2186	0.1675	0.0511	3.8982***
Applications in 2013	0.1571	0.1952	0.1495	0.0457	4.3615***	0.1523	0.1836	0.1422	0.0415	3.3771***
Applications in 2014	0.1353	0.0979	0.1429	-0.0450	-5.4606***	0.1453	0.1216	0.1530	-0.0314	-2.8836***
Applications in 2015	0.1091	0.0589	0.1192	-0.0604	-8.9076***	0.1192	0.0787	0.1323	-0.0536	-5.7385***
Applications in 2016	0.0716	0.0420	0.0775	-0.0355	-6.1932***	0.0716	0.0548	0.0770	-0.0222	-2.8717***
Applications in 2017	0.0525	0.0252	0.0580	-0.0328	-7.0894***	0.0482	0.0302	0.0540	-0.0238	-3.9406***
Owner/Manager characteristics										
Gender										
Male	0.7941	0.8061	0.7917	0.0144	1.3810	0.7911	0.7944	0.7901	0.0043	0.3444
Female	0.1714	0.1755	0.1706	0.0049	0.4945	0.1772	0.1833	0.1753	0.0080	0.6719
Both (joint partners)	0.0346	0.0184	0.0377	-0.0193	-5.0755***	0.0317	0.0224	0.0346	-0.0122	-2.5398**
Owner Age[a]										
18-30 years	0.0245	0.0558	0.0184	0.0374	6.5086***	0.0272	0.0501	0.0201	0.0300	4.7695***
31-50 years	0.4335	0.5112	0.4183	0.0928	7.0252***	0.4598	0.5596	0.4285	0.1311	8.4988***
>50 years	0.5420	0.4331	0.5633	-0.1302	-9.9176***	0.5130	0.3903	0.5514	-0.1612	-10.5700***
Financial knowledge[a]	0.4286	0.3600	0.4420	-0.0820	-6.4244***	0.4462	0.3808	0.4666	-0.0858	-5.6584***
Legal status										
Sole proprietorship	0.1833	0.3015	0.1603	0.1412	12.0970***	0.1806	0.2973	0.1445	0.1528	11.4370***
Partnership	0.1394	0.0938	0.1483	-0.0545	-6.8636***	0.1497	0.0974	0.1659	-0.0685	-7.0527***
Limited Liability Partnership	0.0502	0.0357	0.0530	-0.0174	-3.4460***	0.0554	0.0469	0.0581	-0.0112	-1.6738*
Limited Liability Company	0.6271	0.5690	0.6384	-0.0693	-5.3656***	0.6143	0.5584	0.6315	-0.0731	-4.8193***
Bank relationships and/or products										
Multiple suppliers	0.0409	0.0397	0.0412	-0.0015	-0.2893	0.0583	0.0584	0.0583	0.0002	0.0217
Main bank	0.9813	0.9724	0.9830	-0.0106	-2.5476**	0.8852	0.8723	0.8892	-0.0169	-1.6740*
Use of credit card[a]	0.4482	0.3700	0.4634	-0.0934	-7.3401***	0.4192	0.3636	0.4364	-0.0727	-4.8804***
Credit balance[c]										
<£5,000	0.3645	0.5607	0.3230	0.2377	16.4900***	0.3374	0.4843	0.2872	0.1970	11.6230***
£5,000-9,999	0.1540	0.1696	0.1507	0.0189	1.7306*	0.1538	0.1815	0.1444	0.0371	2.8333***
£10,000-49,999	0.2304	0.1753	0.2420	-0.0667	-5.8460***	0.2245	0.1932	0.2351	-0.0420	-3.0025***
£50,000-99,999	0.0873	0.0376	0.0978	-0.0602	-9.6353***	0.0907	0.0584	0.1018	-0.0434	-4.9278***
£100,000-499,999	0.0963	0.0440	0.1074	-0.0634	-9.5253***	0.1118	0.0575	0.1303	-0.0728	-7.9660***
£500,000-999,999	0.0393	0.0071	0.0462	-0.0391	-11.4590***	0.0450	0.0153	0.0552	-0.0399	-7.3458***
>£1m	0.0282	0.0057	0.0329	-0.0273	-9.1896***	0.0368	0.0099	0.0460	-0.0361	-7.6529

(continued)

Table 2.4 Continued

Variables	Business overdrafts					Term loans				
	All (N=10673)	Rejected (N=1738)	Approved (N=8935)	Difference (a-b)	t-statistic	All (N=5864)	Rejected (N=1386)	Approved (N=4478)	Difference (a-b)	t-statistic
	Mean	Mean (a)	Mean (b)			Mean	Mean (a)	Mean (b)		
Firm characteristics										
Number of employees										
0-9	0.4442	0.6318	0.4077	0.2240	17.6590***	0.4205	0.6140	0.2826	0.2533	16.9790***
10-49	0.3909	0.2975	0.4091	-0.1116	-9.1928***	0.3883	0.3131	0.4116	-0.0984	-6.8027***
50-249	0.1649	0.0708	0.1832	-0.1124	-15.2160***	0.1912	0.0729	0.2278	-0.1549	-16.5070***
Annual turnover[b]										
<£50,000	0.1181	0.2529	0.0917	0.1612	14.4610***	0.1198	0.2405	0.0819	0.1586	12.6350***
£50,000-99,999	0.1054	0.1428	0.0981	0.0447	4.8582***	0.0964	0.1260	0.0871	0.0388	3.8214***
£100,000-499,999	0.2379	0.2680	0.2320	0.0360	3.0400***	0.2316	0.2863	0.2144	0.0719	5.1293***
£500,000-999,999	0.1422	0.1307	0.1445	-0.0138	-1.5160***	0.1353	0.1321	0.1363	-0.0043	-0.3977
£1m-4.9m	0.2892	0.1585	0.3148	-0.1563	-15.1570***	0.2995	0.1740	0.3389	-0.1649	-12.8910***
>£5m	0.1071	0.0472	0.1189	-0.0717	-11.3830***	0.1174	0.0412	0.1414	-0.1002	-13.0030***
Business age										
<2 years	0.0638	0.1893	0.0394	0.1499	15.5790***	0.0769	0.1746	0.0467	0.1279	11.9820***
2-5 years	0.1039	0.2186	0.0816	0.1371	13.2660***	0.1129	0.2092	0.0831	0.1262	10.7990***
6-9 years	0.1147	0.1381	0.1101	0.0280	3.1361***	0.1240	0.1551	0.1143	0.0408	3.7667***
10-15 years	0.1651	0.1329	0.1713	-0.0384	-4.2385***	0.1572	0.1436	0.1615	-0.0179	-1.6387
>15 years	0.5525	0.3211	0.5975	-0.2765	-22.3950***	0.5290	0.3175	0.5945	-0.2770	-13.1020***
Profitability[a]										
Loss	0.1342	0.2381	0.1143	0.1238	11.1760***	0.1296	0.2248	0.1004	0.1243	10.0010***
Broken even	0.0675	0.1074	0.0599	0.0476	5.8958***	0.0684	0.0895	0.0620	0.0275	3.1544***
Profit	0.7983	0.6545	0.8258	-0.1714	-13.7660***	0.8019	0.6858	0.8376	-0.1518	-10.8220***
Business plan	0.5378	0.5460	0.5362	0.0098	0.7523	0.5781	0.5714	0.5802	-0.0087	-0.5748
Export	0.1657	0.1387	0.1710	-0.0323	-3.5163***	0.1620	0.1335	0.1708	-0.0374	-3.4813***
Import	0.1906	0.1542	0.1976	-0.0434	-4.5095***	0.1949	0.1501	0.2088	-0.0587	-5.1707***
Management account	0.7070	0.6484	0.7184	-0.0700	-5.6400***	0.7091	0.6364	0.7316	-0.0952	-6.5556***
Improvement	0.5538	0.5587	0.5529	0.0058	0.4458	0.5694	0.5628	0.5715	-0.0087	-0.5701
Innovation	0.2570	0.2842	0.2517	0.0325	2.7669***	0.2739	0.2908	0.2686	0.0221	1.5930
D&B risk rating[b]										
Minimal	0.1681	0.0630	0.1875	-0.1245	-16.5410***	0.1706	0.0752	0.1989	-0.1238	-12.7340***
Low	0.2948	0.1969	0.3129	-0.1160	-10.2320***	0.2999	0.1900	0.3325	-0.1425	-10.6880***
Average	0.2844	0.2645	0.2881	-0.0237	-1.9245*	0.2821	0.3137	0.2728	0.0409	2.7461***
Above Average	0.2526	0.4756	0.2115	0.2642	19.5740***	0.2474	0.4212	0.1958	0.2254	14.7000***

(continued)

Table 2.4 Continued

	Business overdrafts					Term loans				
Variables	All (N=10673)	Rejected (N=1738)	Approved (N=8935)	Difference (a-b)	t-statistic	All (N=5864)	Rejected (N=1386)	Approved (N=4478)	Difference (a-b)	t-statistic
	Mean	Mean (a)	Mean (b)			Mean	Mean (a)	Mean (b)		
Application process -related										
Seeking advice[a]	0.1180	0.1697	0.1079	0.0617	6.3881***	0.2461	0.2319	0.2505	-0.0186	-1.4041
Business account[a]	0.9761	0.9476	0.9816	-0.0340	-6.1466***	0.9710	0.9465	0.9785	-0.0321	-4.9856***
Amount applied[c]										
<£5,000	0.1505	0.3202	0.1150	0.2052	16.8940***	0.0630	0.1164	0.0450	0.0714	7.4044***
£5,000-9,999	0.1057	0.1493	0.0965	0.0527	5.5710***	0.0893	0.1489	0.0692	0.0796	7.3425***
£10,000-49,999	0.3519	0.3091	0.3609	-0.0518	-4.0749***	0.2830	0.3682	0.2543	0.1138	7.4288***
£50,000-99,999	0.1293	0.0888	0.1377	-0.0489	-6.0491***	0.1212	0.0879	0.1324	-0.0445	-4.5841***
£100,000-499,999	0.1940	0.1073	0.2122	-0.1048	-11.6690***	0.2744	0.1900	0.3028	-0.1128	-8.4480***
£500,000-999,999	0.0397	0.0191	0.0440	-0.0249	-6.0343***	0.0715	0.0412	0.0818	-0.0406	-5.6677***
>£1m	0.0289	0.0062	0.0337	-0.0275	-9.7371***	0.0976	0.0475	0.1145	-0.0670	-8.4512***

Notes: This table reports the descriptive statistics of the independent variables and the difference in means between rejected firms and approved firms for overdrafts and loans separately. The definitions of all variables are provided in Table 2.3. The sample size is not identical due to the existence of missing values in some specific variables. [a]: The sample includes less than 5% missing values. [b]: The sample includes 5%-10% missing values. [c]: The sample includes more than 10% missing values. *, **, *** indicate that the differences in means between rejected firms and approved firms are significant at 10%, 5% and 1% level, respectively.

Table 2.5a Correlation Matrix: Business Overdrafts

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) Application date[a]	1.000												
(2) Gender[a]	-0.003	1.000											
(3) Legal status[a]	0.030**	-0.152***	1.000										
(4) Owner Age[a]	-0.070***	0.024*	-0.023*	1.000									
(5) Financial knowledge	-0.017	-0.056***	0.204***	-0.031**	1.000								
(6) Multiple suppliers	0.013	0.008	0.011	-0.028**	0.055***	1.000							
(7) Main bank	0.009	0.001	0.028**	-0.004	-0.019	-0.115***	1.000						
(8) Use of credit card	0.049***	-0.028**	0.128***	-0.026**	0.106***	0.055***	0.026**	1.000					
(9) Credit balance[a]	0.209***	-0.085***	0.292***	-0.083***	0.241***	0.046***	-0.000	0.122***	1.000				
(10) Number of employees[a]	-0.017	-0.085***	0.396***	-0.089***	0.344***	0.055***	-0.004	0.186***	0.451***	1.000			
(11) Annual turnover[a]	0.003	-0.129***	0.508***	-0.113***	0.334***	0.053***	0.001	0.201***	0.514***	0.737***	1.000		
(12) Business age[a]	0.061***	-0.014	0.113***	-0.276***	0.126***	0.038***	0.022*	0.139***	0.256***	0.334***	0.403***	1.000	
(13) Standard region[a]	-0.018	-0.021*	0.023*	0.008	-0.000	-0.010	-0.016	0.030**	0.004	0.006	0.024*	-0.015	1.000
(14) Industry sector[a]	0.017	0.048***	0.043***	0.019	0.079***	0.000	-0.000	-0.005	0.037***	0.091***	-0.015	-0.070***	0.073***
(15) Profitability[a]	0.095***	-0.009	0.037***	-0.021*	0.028**	0.028**	-0.000	0.059***	0.184***	0.104***	0.171***	0.167***	-0.020
(16) Business plan	-0.003	-0.022*	0.167***	0.008	0.190***	0.023*	0.001	0.084***	0.160***	0.204***	0.186***	-0.047***	0.003
(17) Export	0.009	-0.092***	0.158***	-0.074***	0.120***	0.031**	0.004	0.100***	0.140***	0.139***	0.207***	0.097***	0.032**
(18) Import	0.044***	-0.090***	0.183***	-0.045***	0.150***	0.028**	0.016	0.102***	0.170***	0.166***	0.240***	0.085***	0.028**
(19) Management account	-0.064***	-0.046***	0.300***	-0.067***	0.213***	0.039***	-0.005	0.120***	0.215***	0.350***	0.395***	0.128***	0.019
(20) Improvement	-0.048***	-0.017	0.142***	0.035***	0.096***	0.037***	0.001	0.109***	0.086***	0.128***	0.148***	-0.029**	0.026**
(21) Innovation	-0.043***	-0.033**	0.125***	0.001	0.122***	0.059***	-0.003	0.068***	0.079***	0.088***	0.113***	-0.016	0.023*
(22) D&B risk rating[a]	-0.074***	-0.027**	-0.165***	0.142***	-0.131***	-0.009	-0.019	-0.080***	-0.324***	-0.324***	-0.341***	-0.389***	0.009
(23) Seeking advice	-0.017	0.032**	0.025*	-0.003	0.023*	-0.006	-0.044***	0.030**	-0.004	0.041***	0.027**	-0.020	0.008
(24) Business account	-0.018	0.004	0.186***	-0.017	0.049***	-0.014	0.016	0.028**	0.094***	0.126***	0.181***	0.122***	0.004
(25) Amount applied[a]	-0.059***	-0.097***	0.358***	-0.162***	0.303***	0.052***	-0.002	0.166***	0.422***	0.598***	0.715***	0.436***	-0.021*

(continued)

Table 2.5a Continued

	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)
(14) Industry sector[a]	1.000											
(15) Profitability[a]	0.007	1.000										
(16) Business plan	0.097***	0.012	1.000									
(17) Export	-0.030**	0.010	0.103***	1.000								
(18) Import	-0.111***	0.022*	0.099***	0.515***	1.000							
(19) Management account	0.040***	0.046***	0.239***	0.147***	0.151***	1.000						
(20) Improvement	0.032**	0.067***	0.212***	0.145***	0.144***	0.229***	1.000					
(21) Innovation	0.025**	-0.003	0.155***	0.292***	0.272***	0.162***	0.324***	1.000				
(22) D&B risk rating[a]	-0.039***	-0.171***	-0.036***	-0.059***	-0.075***	-0.134***	-0.025*	0.005	1.000			
(23) Seeking advice	0.015	-0.025**	0.095***	0.020	-0.005	0.061***	0.059***	0.054***	0.022*	1.000		
(24) Business account	0.002	0.031**	0.058***	0.029**	0.032**	0.124***	0.048***	0.012	-0.086***	0.023*	1.000	
(25) Amount applied[a]	-0.075***	0.129***	0.148***	0.196***	0.217***	0.334***	0.101***	0.088***	-0.357***	0.048***	0.141***	1.000

Notes: This table reports the correlation coefficients between the independent variables in our overdraft sample. The definitions of all variables are provided in Table 2.3. [a]: categorical variables are constructed to calculate the correlation coefficients using the dummy variables defined in Table 2.3. *, **, *** indicate significance at 10%, 5% and 1% level, respectively.

Table 2.5b Correlation Matrix: Term Loans

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) Application date[a]	1.000												
(2) Gender[a]	0.021	1.000											
(3) Legal status[a]	0.038**	-0.129***	1.000										
(4) Owner Age[a]	0.076***	-0.046**	0.049***	1.000									
(5) Financial knowledge	-0.004	-0.071***	0.218***	0.042**	1.000								
(6) Multiple suppliers	0.011	-0.003	0.007	0.011	0.036**	1.000							
(7) Main bank	-0.022	-0.000	0.020	0.013	0.027	-0.175***	1.000						
(8) Use of credit card	0.029	-0.034*	0.121***	0.036**	0.081***	0.020	0.007	1.000					
(9) Credit balance[a]	0.204***	-0.088***	0.313***	0.102***	0.225***	0.032*	-0.022	0.082***	1.000				
(10) Number of employees[a]	-0.015	-0.061***	0.451***	0.129***	0.343***	0.032*	-0.016	0.159***	0.457***	1.000			
(11) Annual turnover[a]	-0.004	-0.129***	0.509***	0.154***	0.324***	0.044**	0.011	0.178***	0.517***	0.754***	1.000		
(12) Business age[a]	0.047***	-0.037**	0.140***	0.317***	0.095***	0.033*	0.003	0.143***	0.264***	0.353***	0.437***	1.000	
(13) Standard region[a]	0.020	-0.014	0.055***	-0.012	0.025	0.019	-0.009	-0.032*	0.001	0.002	0.021	-0.016	1.000
(14) Industry sector[a]	0.012	0.065***	0.061***	-0.009	0.082***	-0.030*	-0.001	-0.003	0.036**	0.084***	-0.021	-0.084***	0.063***
(15) Profitability[a]	0.075***	-0.014	0.080***	0.070***	0.015	0.010	0.037**	0.042**	0.214***	0.155***	0.217***	0.187***	-0.036**
(16) Business plan	-0.039**	-0.009	0.163***	-0.033*	0.162***	0.002	0.001	0.065***	0.120***	0.206***	0.166***	-0.038**	0.020
(17) Export	-0.010	-0.100***	0.149***	0.043**	0.117***	0.033*	-0.002	0.096***	0.143***	0.179***	0.224***	0.108***	0.042**
(18) Import	0.049***	-0.087***	0.146***	0.046**	0.138***	0.029	-0.009	0.109***	0.132***	0.173***	0.229***	0.112***	0.017
(19) Management account	-0.052***	-0.036**	0.320***	0.044**	0.220***	0.014	0.025	0.118***	0.216***	0.362***	0.391***	0.151***	0.005
(20) Improvement	-0.067***	-0.014	0.156***	-0.040**	0.098***	0.026	-0.021	0.113***	0.097***	0.161***	0.176***	0.009	-0.003
(21) Innovation	-0.041**	-0.048***	0.143***	-0.034*	0.133***	0.077***	-0.010	0.088***	0.086***	0.102***	0.130***	0.011	-0.023
(22) D&B risk rating[a]	-0.111***	-0.038**	-0.183***	-0.157***	-0.130***	0.013	-0.011	-0.086***	-0.350***	-0.361***	-0.365***	-0.373***	0.018
(23) Seeking advice	-0.034*	0.075***	0.040**	-0.010	0.032*	-0.014	-0.044**	0.038**	0.059***	0.073***	0.062***	0.007	-0.004
(24) Business account	-0.050***	0.003	0.221***	0.067***	0.094***	-0.025	0.051***	0.048***	0.096***	0.205***	0.214***	0.108***	0.005
(25) Amount applied[a]	-0.044**	-0.064***	0.347***	0.169***	0.267***	0.047***	-0.001	0.125***	0.462***	0.555***	0.631***	0.366***	0.024

(continued)

Table 2.5b Continued

	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)
(14) Industry sector[a]	1.000											
(15) Profitability[a]	0.002	1.000										
(16) Business plan	0.091***	-0.013	1.000									
(17) Export	-0.053***	0.038**	0.098***	1.000								
(18) Import	-0.123***	0.020	0.082***	0.507***	1.000							
(19) Management account	0.060***	0.040**	0.287***	0.152***	0.145***	1.000						
(20) Improvement	0.031*	0.066***	0.199***	0.149***	0.146***	0.262***	1.000					
(21) Innovation	-0.017	0.004	0.193***	0.277***	0.270***	0.209***	0.351***	1.000				
(22) D&B risk rating[a]	-0.039**	-0.193***	-0.049***	-0.047***	-0.069***	-0.146***	-0.056***	0.005	1.000			
(23) Seeking advice	0.018	-0.017	0.104***	0.008	0.013	0.078***	0.103***	0.080***	-0.032*	1.000		
(24) Business account	-0.006	0.034*	0.069***	0.044**	0.050***	0.155***	0.068***	0.048***	-0.120***	0.028	1.000	
(25) Amount applied[a]	0.003	0.127***	0.136***	0.169***	0.176***	0.290***	0.137***	0.099***	-0.322***	0.155***	0.151***	1.000

Notes: This table reports the correlation coefficients between the independent variables in our loan sample. The definitions of all variables are provided in Table 2.3. [a]: categorical variables are constructed to calculate the correlation coefficients using the dummy variables defined in Table 2.3. *, **, *** indicate significance at 10%, 5% and 1% level, respectively.

correlations, the variance inflation factors (VIFs) for all control variables are smaller than 5. Therefore, our regressions do not suffer from multicollinearity issues.

2.5 Empirical Results

2.5.1 Multivariate Analysis

We perform a multivariate analysis to investigate the relationship between bank debt rejections and application date. Since the variable rejection is dichotomous, multivariate regressions are estimated using a logit model. Table 2.6 reports the significant estimated coefficients after variable selection and the Wald test statistics that all coefficients (excluding the constant term) are equal to zero simultaneously.

Results from Model (1) are reported in the first two columns of Table 2.6. They suggest that for overdrafts, relative to applications in other years, applications in 2012 are more likely to be rejected. In contrast, applications in 2014-2017 are less likely to be rejected, suggesting looser lending conditions for SMEs in the most recent four years included in our analysis. This latter result is also found for loan applications for which conditions do not appear to change up to 2013 but then show significant negative signs since 2014. It is useful to recall that 2014 saw the creation of British Business Bank, a UK state-owned economic development bank, and the introduction of the so-called SME SF in the new bank regulatory framework to allow banks to offset the increase in capital requirements and to provide an adequate flow of credit and increased lending to small businesses. Although these are not the results of a formal test to directly investigate the effect of SF on the UK SMEs sector, it is interesting to see that the estimated coefficients indeed start to become negative and significant from the year it was introduced (2014).

Table 2.6 also reports the significant coefficients for Model (2) that include the control variables and results from the application of the Rubin's rule variable selection technique

Table 2.6 Bank Debt Rejection: Logit Model

	Model (1)		Model (2)	
	Overdrafts	Loans	Overdrafts	Loans
Application date				
Applications in 2011				
Applications in 2012	0.1765*** (0.0666)		0.1549* (0.0809)	
Applications in 2013			0.1700** (0.0865)	
Applications in 2014	-0.5664*** (0.0908)	-0.4332*** (0.0971)	-0.3881*** (0.1045)	-0.2718** (0.1071)
Applications in 2015	-0.8913*** (0.1119)	-0.7081*** (0.1146)	-0.7555*** (0.1263)	-0.4878*** (0.1238)
Applications in 2016	-0.7911*** (0.1323)	-0.5133*** (0.1394)	-0.4486*** (0.1527)	-0.2737* (0.1586)
Applications in 2017	-1.0138*** (0.1649)	-0.7537*** (0.1758)	-0.6902*** (0.1862)	-0.3611* (0.2008)
Owner/Manager characteristics				
Gender				
Female			-0.2309*** (0.0779)	-0.2241** (0.0899)
Both (joint partners)			-0.5451** (0.2136)	
Legal status				
Partnership			-0.2246** (0.1049)	-0.4386*** (0.1117)
Owner age				
31-50 years				0.2293*** (0.0714)
Bank relationships and/or products				
Main bank			-0.4768** (0.1872)	
Credit balance				
£5,000-9,999			-0.2949*** (0.0940)	-0.2356** (0.1121)
£10,000-49,999			-0.3880*** (0.0933)	-0.3840*** (0.1047)
£50,000-99,999			-0.6663*** (0.1553)	-0.3632** (0.1621)
£100,000-499,999			-0.5979*** (0.1541)	-0.3839** (0.1701)
£500,000-999,999			-1.2820*** (0.3244)	-0.5568* (0.2842)
>£1m			-0.8263** (0.4085)	-0.7968** (0.3335)
Firm characteristics				
Number of employees				
10-49				-0.2093** (0.0896)
50-249			-0.3217*** (0.1201)	-0.6345*** (0.1561)
Annual turnover				
£1m-4.9m			-0.2324*** (0.0862)	-0.3579*** (0.1098)
>£5m				-0.6689*** (0.1992)

(continued)

Table 2.6 Continued

	Model (1)		Model (2)	
	Overdrafts	Loans	Overdrafts	Loans
Business age				
2-5 years			-0.3281***	
			(0.1079)	
6-9 years			-0.8696***	-0.3882***
			(0.1155)	(0.1100)
10-15 years			-1.1009***	-0.6430***
			(0.1165)	(0.1106)
>15 years			-1.2222***	-0.8405***
			(0.1066)	(0.0954)
Standard region				
East Anglia			-0.5155***	-0.3187**
			(0.1364)	(0.1349)
East Midlands			-0.4986***	
			(0.1443)	
North West			-0.2784**	
			(0.1291)	
North/North East			-0.4607***	
			(0.1578)	
Northern Ireland			-0.3307**	
			(0.1571)	
Scotland			-0.2951**	-0.3269**
			(0.1295)	(0.1291)
South East			-0.2300*	
			(0.1197)	
South West			-0.3740***	
			(0.1242)	
Wales			-0.2505*	
			(0.1426)	
West Midlands			-0.3603***	
			(0.1327)	
Yorkshire/Humberside			-0.3150**	
			(0.1314)	
Industry sector				
Agriculture, hunting and forestry fishing			-0.3426***	-0.7275***
			(0.1184)	(0.1374)
Health and social work				-0.2932**
				(0.1293)
Hotels and restaurants			0.3595***	
			(0.0981)	
Manufacturing				-0.3453***
				(0.1206)
Transport, storage and communication			0.3712***	
			(0.0974)	
Profitability				
Broken even				-0.3968***
				(0.1494)
Profit			-0.4232***	-0.5652***
			(0.0678)	(0.0965)
Business plan			0.1198**	
			(0.0610)	
Innovation			0.2027***	0.2421***
			(0.0663)	(0.0776)

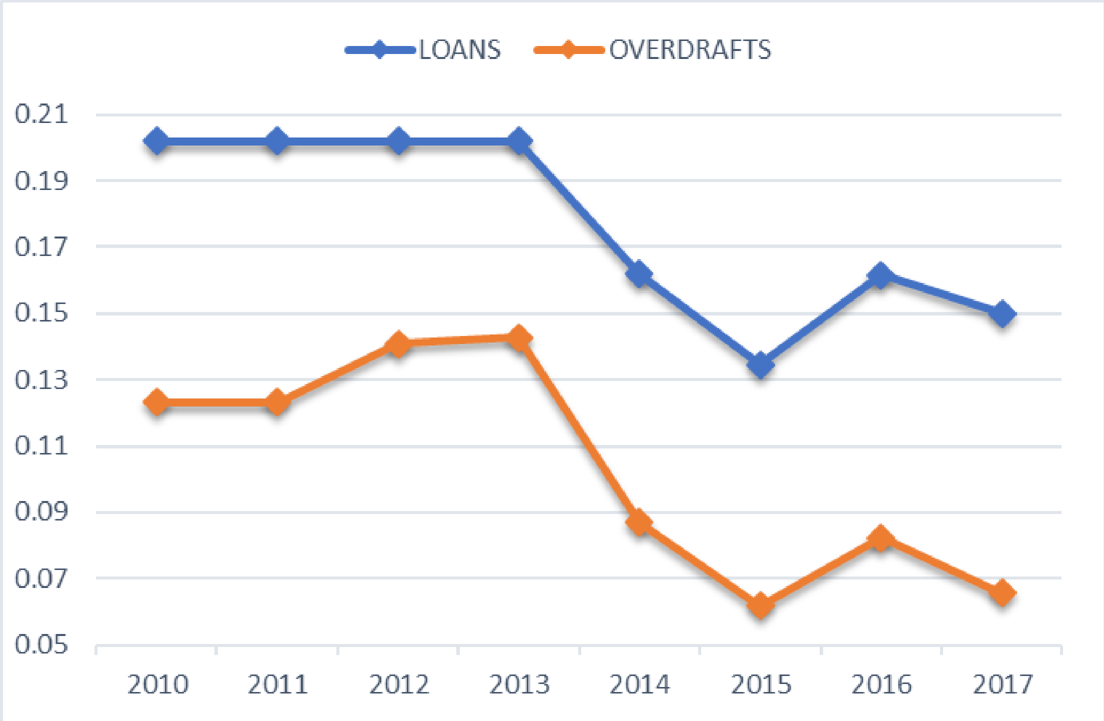
(continued)

Table 2.6 Continued

	Model (1)		Model (2)	
	Overdrafts	Loans	Overdrafts	Loans
D & B risk rating				
Low			0.5088***	
			(0.1277)	
Average			0.4797***	0.3635***
			(0.1242)	(0.0918)
Above Average			0.8521***	0.4947***
			(0.1257)	(0.1001)
Application process-related				
Seeking advice			0.6000***	
			(0.0824)	
Business account			-0.3030*	
			(0.1552)	
Amount applied				
£5,000-9,999			-0.2629***	-0.2767*
			(0.1019)	(0.1606)
£10,000-49,999			-0.4729***	-0.3168**
			(0.0889)	(0.1385)
£50,000-99,999			-0.4249***	-0.6193***
			(0.1249)	(0.1694)
£100,000-499,999			-0.4653***	-0.4246***
			(0.1263)	(0.1536)
£500,000-999,999			-0.6280***	-0.4001*
			(0.2213)	(0.2087)
>£1m			-1.2481***	-0.4376**
			(0.3492)	(0.224)
Constant	-1.4433***	-0.9722***	0.4656*	0.7067***
	(0.0374)	(0.0379)	(0.2624)	(0.1848)
No. of observations	10673	5864	10673	5864
Wald test statistics [a]	36.03***	17.61***	23.83***	20.26***
Wald test statistics (2015=2016) [b]	0.36	1.27	2.89*	1.29
Wald test statistics (2015=2016=2017) [c]	0.01	0.09	0.61	0.45
McFadden's pseudo R^2	0.0223	0.0129	0.1701	0.1600

Notes: This table only reports the significant estimated coefficients of logit regressions after variable selection. Pooled standard errors are in parentheses. The dependent variable is whether an overdraft or a loan application is rejected or not. Model 1 only includes the variable application dates. Model 2 adds other explanatory variables as listed in Table 2.3. We use a multiple imputation to treat missing values. [a]: The null hypothesis of the Wald test is that all coefficients, excluding the constant term, are equal to zero simultaneously. [b]: The null hypothesis of the Wald test is that the coefficient of 'applications in 2015' equals the coefficient of 'applications in 2016'. [C]: The null hypothesis of the Wald test is that the coefficients of 'applications in 2015', 'applications in 2016' and 'applications in 2017' are same. *, **, *** indicate significance at 10%, 5% and 1% level, respectively

Figure 2.2 Predicted Probability of Bank Debt Rejection by Sub-periods



Notes: This figure shows the predicted probability of bank debt rejections in each year from 2010 to 2017, with the blue line for loans and the orange line for overdrafts. The predicted probabilities are calculated using the estimates of Model (2) in Table 2.6.

described in Section 2.4.1. For both overdrafts and loans, after controlling for several risk characteristics, the changes in lending conditions broadly confirm the findings of Model (1). Relative to applications in 2010 and 2011, those in 2012 and 2013 are more likely to be rejected for overdrafts. In the following four years, both overdraft and loan markets show more favourable lending conditions relative to years in the wake of the financial crisis. Figure 2.2 shows the predicted probability of debt rejection for a typical applicant[19], which drops markedly in 2014 and 2015 and then climbs in 2016. As hypothesised in ***H1***, this

[19] From the first and sixth columns in Table 2.4, it is possible to identify the typical applicant for both overdrafts and loans. This is an SME which, among other characteristics, is owned/led solely by a male owner aged more than 50 years without sufficient financial knowledge. It only approaches one bank (the main bank), holds less than £5,000 in its current and deposit account and does not use a credit card. The typical applicant also has less than 10 employees and £1m-£4.9m annual turnover, established for more than 15 years, located in the South East, operating in the Construction industry, profitable, with a business plan and regular financial statements, has a low-risk level but does not have international activity (import /export) and innovation activities. It typically uses a business account to apply for credit in the range £10,000-49,000 but does not seek advice before its application.

result might have been influenced by the Brexit referendum which took place in 2016. To test whether the differences before and after Brexit are statistically significant, we run the Wald test with the results reported in the bottom of Table 2.6. For both overdrafts and loans, the differences between the rejections in 2015, 2016 and 2017 are not statistically significant. Therefore, the lending conditions do not change under the period of great uncertainty in the run-up and in the year following the Brexit referendum.[20]

A potential explanation is only a small number of firms will be affected, evidenced by merely 16% SMEs self-reported Brexit as a major obstacle in a 2016-17 survey (Brown et al., 2019). Another reason might due to the long-time spanning and the complicated procedures of Brexit, leading to an insignificant influence in a short-term. A change in lending conditions potentially comes up in the post Brexit, which is out of our sample, although, as pointed out above, data for the last available year used in this study should be interpreted with some caution.

These results only provide evidence to support part of our first hypothesis (***H1***) that rejection rates dropped over the period under study for both loans and overdrafts in conjunction with government programmes for supporting SMEs financing. Furthermore, as shown in Table 2.6, surprisingly we do not find any preliminary evidence for ***H2*** on different effects on export- vs import- oriented firms (coefficients are not reported as they are insignificant). This is consistent with the insignificance reported by Cowling, Liu and Zhang (2016) and Lee and Brown (2017) which are also devoted to UK SMEs. Hence this hypothesis is further investigated in Table 2.7.

Regarding owner/manager characteristics, applications from female-owned/led SMEs are more likely to be approved for overdrafts and loans, thus providing support to our third

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[20] For overdrafts, the difference between rejections in 2015 and 2016 are significant. However, it is only significant at 10% level, where the corresponding p-value is 0.089.

hypothesis ***H3a***. This finding is in contrast to previous studies' more classical findings that it is much more difficult for female entrepreneurs to access bank lending (Riding and Swift 1990; Coleman 2000; Bellucci et al. 2010) but conforms to the most recent empirical investigations by, for example, Cowling, Liu and Zhang (2016). This result could be interpreted in several ways. On the one hand, it could be attributed, and there are a few examples in the literature (e.g. Watson, 2002; Watson and McNaughton, 2007), to a more risk-averse attitude of female managers that will be more likely to select conservative projects or low- risk business plans. On the other hand, it could be that a larger proportion of female-run firms simply did not file a loan application as they anticipated being rejected, as recently evidenced, e.g. in Moro et al. (2017).

The legal status (partnerships) is also an important factor in reducing rejection rates, a result that contradicts both Armstrong et al. (2013) and Lee and Brown (2017). The lower rejection rate of partnerships can possibly derive from their lower default rate (Cowling and Mitchell, 2003) and from the fact that banks could have more recourse if firms with unlimited liability default thanks to the shared responsibility.

Contrary to expectations, we find that for loan applications, SMEs with middle-age owners/leaders (31-50 years old) are more likely to be rejected, in contrast to a recent study by Zhao and Jones-Evans (2017) which finds older (i.e. experienced) owners/leaders have an advantage in loan applications. In addition, we do not find evidence that financial knowledge of owners/managers proxied by the presence of relevant finance qualifications for the person in charge of the financial management of the firm provides an advantage when it comes to bank financing, inconsistent with the positive effect found by Cowling, Liu and Zhang (2016). Therefore, we cannot accept our fourth hypothesis, ***H4*** that the experience and specialisation of SMEs owners/managers can make a difference when applying for a bank loan or overdraft.

An interesting finding is the negative relationship between applying to the main bank and overdraft rejections, showing the advantage of a long-term relationship in reducing information asymmetries for overdraft applicants, but not for loan applicants. The insignificant results in our loan sample disagree with several studies (e.g. Petersen and Rajan, 2994; Kysucky and Norden, 2015) but agree with Fraser (2009)'s study whose sample is also UK SMEs. Therefore, we can only partially accept our fifth hypothesis that SMEs with a closer relationship with banks are less likely to be rejected when they apply for bank credit. This result is possibly because relative to loans, overdrafts generally have a shorter duration and smaller volumes and banks have more power on overdrafts as they can call back money at any time (Zhao and Jones-Evans, 2017). This implies that banks will be more cautious when assessing loan applications and tend to focus more on risk assessment and SMEs' ability to pay off the debt (Ofonyelu and Alimi, 2013).

Another important result refers to the variable credit balance, i.e. the funding that the SMEs hold in their current and deposit accounts. Most studies omit this variable due to missing values (e.g. Lee and Brown, 2017; Rostamkalaei and Freel, 2017). We apply a survey data multiple imputation technique (Allison, 2012) to deal with this problem and are able to check the effects of credit balance on debt rejections. As far as we are aware, no other studies have been published that determine the role of different levels of credit balance in SMEs accounts against the probability of rejection[21]. As hypothesised, our results provide support for our sixth hypothesis (***H6***) in that a higher credit balance shows a stronger significantly negative coefficient, suggesting a lower probability of rejection, for both overdrafts and loans.

[21] Studies such as Cole et al. (2004) examine the role of cash holdings in small businesses lending. Although credit balance is close to cash holdings, other studies use cash-to-asset ratio as the proxy for liquidity, whereas our variable represents a buffer that banks can use in the event of default.

On the other firm characteristics, similar determinants on bank debt rejection can be found for overdrafts and loans. Bigger (with either more employees or higher annual turnovers) and older SMEs are less likely to be rejected, revealing an expected negative effect of business size and age, consistent with the findings of Armstrong et al. (2013). The size effect appears to be stronger in loan applications, whereas an age effect seems more relevant for overdrafts. Innovative SMEs are found to be more likely to be rejected, as, e.g. in Lee et al. (2015). One possible explanation is that innovation 'is essentially a speculative process' (Freel, 2007) and most are found to fail (Mazzucato, 2013). Besides, innovative firms often rely on intangible assets to create value (Kramer et al., 2011), which are difficult for banks to evaluate, leading to high information asymmetry (Colombo and Grilli, 2007). Such reasons make banks unwilling to bear the accompanying uncertainty and reluctant to lend to innovative SMEs. External credit risk rating also plays an important role in determining debt rejection. Relative to SMEs with minimal risk, firms with any higher levels of risk rating are more likely to face rejections. The riskier the SME is, the less likely its application will be approved, in line with the findings of Fraser (2012) and Armstrong et al. (2013). However, for overdraft applications, SMEs with formal written business plans are more likely to be rejected. Lee and Brown (2017) find similar results and claim that it is possibly because their proposals are either not sufficiently robust or too ambitious, in which case equity-based finance might be a better choice.

This evidence provides support for our seventh hypothesis (***H7***) that smaller and more innovative firms are penalised when it comes to being successful in a bank loan or overdraft application. It also offers support to ***H8*** as our results also suggest that profitable SMEs are less likely to experience rejections in the case of short-term and long-term finance, thus supporting the findings of Zhao and Jones-Evans (2017).

Concerning process-related factors, SMEs using business accounts seem to be associated with considerable better access to overdrafts, maybe because banks can monitor these firms' behaviour more closely. Surprisingly and somewhat counterintuitively, seeking advice is found to have a positive effect on overdraft rejection, inconsistent with the findings of Rostamkalaei and Freel (2017) that advice is helpful to improve the bank debt availability. One possible explanation is that SMEs seeking advice before overdraft applications are risky firms which expect to fail or to encounter difficulties during the application process. Therefore, advice seekers are more likely to be rejected (Lee and Drever, 2014). Besides, in the UK, SMEs managers are increasingly citing a lack of appropriate advice as well as weak support from banks as a motive not to apply for traditional loans (Close Brothers, 2016). Finally, larger applications tend to be more likely to be approved, possibly relevant to the higher monitoring costs and thus, lower profit margins brought by the smaller amounts (Freel et al., 2012).

2.5.2 Lending Conditions for SMEs with International Trades

Although bank debt rejection rates do not differ across SMEs with and without international trades (coefficients for export and import are insignificant and thus not reported in Table 2.6), the depreciation of the GBP pound sterling since the Brexit referendum might lead to tight conditions for international traded SMEs with an asymmetric effect for importing vs exporting companies. To provide additional evidence in relation to our second hypothesis ***H2***, we re-run regressions for importing and exporting SMEs respectively by year and report the statistically significant results in Table 2.7.

The table shows that both in the case of loans but particularly for overdrafts, more import-oriented SMEs benefit from a lower probability of being rejected after 2014. The situation is different for exporting firms as our empirical results are either not statistically significant

Table 2.7 Bank Debt Rejection of Firms with International Trades: Logit Model

	Overdrafts		Loans	
	Export	Import	Export	Import
Application date				
Applications in 2011				
Applications in 2012				
Applications in 2013				
Applications in 2014	-0.4351*	-0.6901***		
	(0.2375)	(0.2225)		
Applications in 2015	-0.5943**	-1.0478***		-0.6971**
	(0.2880)	(0.2817)		(0.2999)
Applications in 2016		-0.9928***		-0.6770*
		(0.3716)		(0.3949)
Applications in 2017		-1.1084***		
		(0.4266)		
Owner/Manager characteristics				
Gender				
Female	-0.6387**			
	(0.2697)			
Both (joint partners)			1.9112***	2.6219***
			(0.6801)	(0.7297)
Legal status				
Partnership			-0.9078**	-0.9204**
			(0.4258)	(0.3707)
Limited liability company			-0.5146**	
			(0.2377)	
Financial knowledge	-0.4314***			
	(0.1540)			
Bank relationships and/or products				
Credit balance				
£10,000-49,999		-0.3841*		
		(0.2022)		
£500,000-999,999			-1.1728*	
			(0.7104)	
>£1m			-1.9737*	
			(1.0166)	
Firm characteristics				
Number of employees				
10-49				-0.4837**
				(0.2433)
50-249				-0.8302**
				(0.3504)
Annual turnover				
£1m-4.9m		-0.6682***		-0.5102**
		(0.1835)		(0.2589)
>£5m		-0.8540***	-0.7578***	-0.6896*
		(0.2696)	(0.2767)	(0.3659)
Business age				
2-5 years	-0.7355**			
	(0.3537)			
6-9 years	-1.2297***	-0.6810***	-0.7469**	-0.7890***
	(0.3562)	(0.2502)	(0.3158)	(0.2931)
10-15 years	-1.3559***	-0.9102***	-0.6704**	-0.9417***
	(0.3369)	(0.2468)	(0.2898)	(0.2918)
>15 years	-1.6074***	-1.1147***	-1.4632***	-1.0463***
	(0.3123)	(0.1993)	(0.2577)	(0.2396)

(continued)

Table 2.7 Continued

	Overdrafts		Loans	
	Export	Import	Export	Import
Standard region				
East Anglia		-0.6615**		
		(0.3176)		
East Midlands				-0.6928*
				(0.3965)
Scotland			-0.7959*	
			(0.4304)	
Wales	0.6466**			
	(0.3093)			
Industry sector				
Wholesale/retail		-0.4376**		
		(0.1833)		
Profitability				
Profit	-0.4875***	-0.5454***	-0.6182***	-0.5719***
	(0.1748)	(0.1728)	(0.2279)	(0.2118)
Innovation				0.3408**
				(0.1737)
Improvement		0.4353**	0.3880*	
		(0.1715)	(0.2153)	
D & B risk rating				
Low	0.8952***	0.7860***		0.8528**
	(0.3317)	(0.2859)		(0.3572)
Average	1.2518***	0.6207**	0.6733***	1.1820***
	(0.3275)	(0.2924)	(0.2286)	(0.3581)
Above Average	1.5171***	1.1473***	0.7172***	1.2122***
	(0.3350)	(0.2954)	(0.2479)	(0.3662)
Application process-related				
Seeking advice	0.5771***	0.6468***		
	(0.1908)	(0.1929)		
Amount applied				
£10,000-49,999		-0.4545***		
		(0.1717)		
£500,000-999,999		-0.8149*		
		(0.4787)		
>£1m	-1.3452*	-1.1210*		
	(0.6866)	(0.5784)		
Constant	-0.8844**	-0.6609*	0.0823	-0.4983
	(0.4499)	(0.3740)	(0.3908)	(0.4210)
No. of observations	1769	2034	950	1143
Wald test statistics	9.49***	9.16***	7.66***	8.36***
McFadden's pseudo R^2	0.1308	0.1647	0.1660	0.1717

Notes: This table only reports the significant estimated coefficients of logit regressions after variable selection. Pooled standard errors are in parentheses. The dependent variable is whether an overdraft or a loan application is rejected or not. The definitions of all control variables are provided in Table 2.3. The null hypothesis of the Wald test is that all coefficients, excluding the constant term, are equal to zero simultaneously. *, **, *** indicate significance at 10%, 5% and 1% level, respectively.

(and therefore not reported) or very low. In addition, exporting firms experience a lower probability of overdraft rejection in 2015, relative to 2016 and 2017. Therefore, we do not reject our second hypothesis, that with the Brexit referendum and the uncertainty that followed, exporting SMEs suffered from tighter credit conditions.

The table also shows different determinants of overdraft and loan rejections for exporting and importing firms. We only find evidence for ***H3a*** and ***H4*** when exporting firms apply for overdrafts that female-owned/led and financial knowledgeable SMEs are less likely to be rejected, but no strong evidence for H5 and H6 that relationship lending and credit balance play a key role. Despite these differences, in every case, SMEs with higher-level external risk ratings are more likely to be rejected and older and profitable firms are favoured by banks, thereby lending some support to ***H7*** and ***H8***.

2.5.3 How Much do SMEs Size and Age Matter?

Our evidence presented above adds to the extant literature by providing additional support that in the UK market, size and age do matter when it comes to applying for traditional bank debt, as smaller and younger SMEs are more likely to be rejected for both overdrafts and loans. Given the costs of not channelling funds to small young firms and start-ups for the economy, we carried out an additional test to check the extent to which size and age matter by testing our seventh hypothesis using different subsamples.

First, we focus on size and split the full sample into three clusters using the number of employees and the annual turnover. Following the European Commission[22], we define

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[22] For the number of employees, limits in EC definition are 10 (between micro and small firms) and 50 (between small and medium-sized firms). Our data can match the limit perfectly. For annual turnovers, limits in EC definition is €2 million, approximately £1.7 million (between micro and small firms) and €10 million, approximately £8 million (between small and medium-sized firms). The most similar band in our data is £1-1.9 million and £5-£9.9 million. Therefore, we define micro, small and medium-sized firms in the way described above. Where there are missing values in annual turnover (see Table 2.4), the definition is made only according to the number of employees.

firms with 0-9 employees and less than £2 million annual turnovers as 'micro'; firms with 10-49 employees and £2-10 million annual turnovers as 'small'; and firms with 50-249 employees and £10-25 million annual turnovers as 'medium-sized'. We re-run the regressions in each sub-sample and report the significant results after variable selection in Table 2.8. The table reveals significant results of application date only for micro firms. In all other cases, lending conditions for both overdrafts and loans do not change at all since all coefficients for application date are insignificant. Micro firms appear to have benefited the most, possibly from the introduction of recent government programmes to stimulate bank lending to small businesses, particularly with regard to overdraft applications after 2014.

For micro firms, those owned/led by females are less likely to be rejected for both overdrafts and loans, thus supporting ***H3a***. In contrast, those with younger (i.e. less experienced) owners/managers face a higher probability of loan rejection (***H4***). A closer bank relationship helps micro firms access to overdrafts and small firms access to loans (***H5***) while a higher credit balance lowers the overdraft rejection rates for small firms and loan rejection rates for micro firms (***H6***). Except medium-sized firms, banks tend to issue credit to older firms as we hypothesise in ***H7***. In addition, both in the case of overdraft and loan applications, innovative micro firms are more likely to be rejected (part of ***H7***) whereas profitable micro firms are more likely to be approved (***H8***).

Further, we follow Criscuolo et al. (2014) and Ayyagari et al. (2011) and split the sample into start-ups (firms aged less than 2 years), 'young' (firms aged between 2-5 years) and 'mature firms' (more than 5 years). Start-ups are widely recognised as drivers of job creation and also play a crucial role in intensifying competition and driving innovation and opportunities, therefore whether start-ups are credit rationed is a key concern for the economy. Since mature firms account for more than 80% of the full sample, we further split

Table 2.8 Bank Debt Rejection by Firm Size: Logit Model

	Overdrafts			Loans		
	Micro	Small	Medium	Micro	Small	Medium
Application date						
Applications in 2011						
Applications in 2012				0.2556*		
				(0.1309)		
Applications in 2013				0.3994***		
				(0.1342)		
Applications in 2014	-0.5353***					
	(0.1289)					
Applications in 2015	-0.8891***					
	(0.1490)					
Applications in 2016	-0.5506***					
	(0.1830)					
Applications in 2017	-1.0332***					
	(0.2404)					
Owner/Manager characteristics						
Gender						
Female	-0.3244***			-0.2782**		
	(0.1011)			(0.1214)		
Both (joint partners)	-0.5413**	1.5019*				
	(0.2749)	(0.7958)				
Legal status						
Partnership	-0.3721***	-1.0571*		-0.5936***		
	(0.1357)	(0.6125)		(0.1517)		
Owner age						
18-30 years				0.4180*		
				(0.2270)		
31-50 years				0.3303***		
				(0.1038)		
Bank relationships and/or products						
Main bank	-0.7571***				-1.1335***	
	(0.2445)				(0.3584)	
Credit balance						
£5,000-9,999	-0.2625**			-0.2985**		
	(0.1120)			(0.1305)		
£10,000-49,999	-0.3545***	-0.6717*		-0.4918***		
	(0.1280)	(0.3534)		(0.1409)		
£50,000-99,999		-0.7643**		-0.7092**		
		(0.3865)		(0.3166)		
£100,000-499,999		-0.7326*		-1.0091**		
		(0.3800)		(0.4262)		
£500,000-999,999		-1.5168**				
		(0.7500)				
Firm characteristics						
Business age						
2-5 years	-0.2550**					1.4255**
	(0.1208)					(0.6983)
6-9 years	-0.7025***	-1.1468***		-0.3460**	-1.4517**	
	(0.1326)	(0.4184)		(0.1429)	(0.6452)	
10-15 years	-1.1066***	-1.4151***		-0.5707***	-1.1757***	
	(0.1398)	(0.3935)		(0.1519)	(0.4319)	
>15 years	-0.1795***	-1.2327***		-0.8296***		
	(0.1251)	(0.3312)		(0.1298)		

(continued)

Table 2.8 Continued

	Overdrafts			Loans		
	Micro	Small	Medium	Micro	Small	Medium
Standard region						
East Anglia		-1.0033**		-0.3397*		
		(0.4630)		(0.1893)		
East Midlands		-1.3392**			-1.8219*	
		(0.6147)			(1.0409)	
Scotland				-0.4750***		
				(0.1809)		
South West				-0.3610**		
				(0.1572)		
Wales		-2.2392**		0.4067**		
		(1.0482)		(0.1877)		
West Midlands		-0.8523*				
		(0.4699)				
Industry sector						
Agriculture, hunting and forestry fishing	-0.5895***			-0.9976***		
	(0.1432)			(0.1700)		
Health and social work				-0.4436**		
				(0.1963)		
Hotels and restaurants	0.4221***					
	(0.1391)					
Manufacturing				-0.3093*		
				(0.1786)		
Transport, storage and communication	0.4875***	0.6885**				
	(0.1287)	(0.3168)				
Other community, social and personal service		0.7446**		-0.5301***	1.0435***	
		(0.3499)		(0.1678)	(0.3964)	
Profitability						
Profit	-0.4363***			-0.4511***		
	(0.0876)			(0.1128)		
Business plan	0.1315*					
	(0.0796)					
Innovation	0.2072**			0.3380***		
	(0.0912)			(0.1119)		
Import		-0.4754*				
		(0.2572)				
D & B risk rating						
Low	0.6146***		1.1748**			
	(0.2116)		(0.5852)			
Average	0.5764***		1.1148*	0.3567**	0.5643*	
	(0.2008)		(0.6062)	(0.1486)	(0.3116)	
Above Average	0.9037***	1.0568***	1.7362***	0.5335***	1.0167***	
	(0.1962)	(0.2533)	(0.6368)	(0.1445)	(0.3532)	
Application process-related						
Seeking advice	0.3188***	0.8133***				
	(0.1207)	(0.2647)				
Business account	-0.3407**					-2.5241*
	(0.1631)					(1.4294)
Amount applied						
£5,000-9,999	-0.2671**					
	(0.1098)					
£10,000-49,999	-0.4860***				-1.4518**	
	(0.0971)				(0.5978)	
£50,000-99,999	-0.4077**				-2.1135***	
	(0.1892)				(0.6895)	
£100,000-499,999					-1.0582**	
					(0.5184)	
£500,000-999,999					-1.4266**	
					(0.6465)	
>£1m			-1.4242**		-1.7755***	
			(0.7210)		(0.6687)	

(continued)

Table 2.8 Continued

	Overdrafts			Loans		
	Micro	Small	Medium	Micro	Small	Medium
Constant	0.4512	-0.6982*	-3.4504***	0.0783	0.1549	-2.5241***
	(0.3335)	(0.3624)	(0.5139)	(0.1991)	(0.5756)	(0.2079)
No. of observations	4679	1073	541	2423	594	351
Wald test statistics	21.52***	4.52***	3.03**	13.12***	3.46***	3.49**
McFadden’s pseudo R^2	0.1621	0.1459	0.0675	0.1551	0.1213	0.0286

Notes: This table only reports the significant estimated coefficients of logit regressions after variable selection. Pooled standard errors are in parentheses. The dependent variable is whether an overdraft or a loan application is rejected or not. Firms with 0-9 employees and less than £2m annual turnover are defined as micro firms. Firms with 10-49 employees and £2m-10m annual turnover are defined as small firms. Firms with 50-249 employees and £10m-25m annual turnover are defined as medium-sized firms. Firms with missing turnover are defined according to the number of employees only. The definitions of all control variables are provided in Table 2.3. The null hypothesis of the Wald test is that all coefficients, excluding the constant term, are equal to zero simultaneously. *, **, *** indicate significance at 10%, 5% and 1% level, respectively.

them into two subsamples: 'firms aged 6-9 years' and 'firms aged more than 10 years'. We re-run the regressions in each sub-sample, with the significant results for overdrafts reported in Table 2.9 and loans in Table 2.10.

We find that both start-ups and mature firms appear to benefit from significantly improved conditions from 2014 (relative to 2013) thanks to a lower probability of rejection for overdrafts and loans while conditions do not appear to have changed symmetrically for young firms. In order to explore which group benefits most, we calculate the marginal effects of application dates. For start-ups (mature firms), relative to applications in 2013, applications in 2014 are 21.33% (5.26%) and 12.76% (4.48%) less likely to be rejected for overdrafts and loans. Therefore, start-ups have substantially stronger marginal effects relative to other firms. Another noticeable finding is that changes in the loan market are remarkably different for firms aged 6-9 years over the years under investigation, but the differences disappear for more mature firms.

The common determinant in each group is profitability, where profitable firms are less likely to be rejected, providing evidence for ***H8***. As for owner/manager characteristics, female-owned/led firms are less likely to be rejected when start-ups and firms aged more than 10 years apply for overdrafts and firms aged 6-9 years apply for loans (***H3a***). We also find a negative relationship between owner/manager age (a proxy for experience) and loan rejection among start-ups and firms aged 6-9 years (H4). For both overdrafts and loans, mature firms with closer relationships with banks are less likely to be rejected (***H5***) while innovative mature firms are more likely to be rejected (part of ***H7***). Besides, a significant role of credit balance is found for young and mature firms when they apply for overdrafts (***H6***).

Table 2.9 Bank Overdraft Rejection by Firm Age: Logit Model

	Start up (<2 years)	Young (2-5 years)	Mature (>5 years)	*-of which* (6-9 years)	(>10 years)
Application date					
Applications in 2011			-0.1720*		
			(0.0878)		
Applications in 2012					
Applications in 2013					
Applications in 2014	-0.8812***		-0.6154***	-1.1110***	-0.4333***
	(0.2626)		(0.1191)	(0.3106)	(0.1255)
Applications in 2015	-1.3111***		-1.0274***	-0.5163*	-1.0411***
	(0.3207)		(0.1549)	(0.3042)	(0.1777)
Applications in 2016	-0.8514**		-0.8156***	-0.8357**	-0.7246***
	(0.4104)		(0.1732)	(0.3611)	(0.1942)
Applications in 2017	-0.9100**		-0.9232***	-1.1603**	-0.7810***
	(0.4627)		(0.2135)	(0.5370)	(0.2300)
Owner/Manager characteristics					
Gender					
Female	-0.3642*				-0.1997*
	(0.2038)				(0.1124)
Both (joint partners)		-1.2141**			-0.6319**
		(0.5674)			(0.2497)
Legal status					
Partnership	-0.8404***		-0.2801**	-0.4426*	
	(0.3176)		(0.1119)	(0.2658)	
Owner age					
31-50 years		0.2433*			
		(0.1405)			
Bank relationships and/or products					
Main bank			-0.5456**	-1.1037**	-0.4266*
			(0.2203)	(0.4677)	(0.2567)
Use of credit card				-0.5107***	
				(0.1622)	
Credit balance					
£5,000-9,999	-0.5031**	-0.3814**	-0.2615**		
	(0.2415)	(0.1836)	(0.1019)		
£10,000-49,999		-0.5614***	-0.4611***		-0.3506***
		(0.1989)	(0.1614)		(0.1177)
£50,000-99,999		-1.1685**	-0.3664**		-0.5679***
		(0.4862)	(0.1577)		(0.1800)
£100,000-499,999		-1.3492**	-0.9675***		-0.4327***
		(0.6404)	(0.3298)		(0.1673)
£500,000-999,999					-0.9702***
					(0.3385)
>£1m					-0.8361*
					(0.4494)
Firm characteristics					
Number of employees					
10-49			-0.1790*	-0.3416*	-0.1938*
			(0.0935)	(0.1843)	(0.1020)
50-249			-0.5460***	-1.5793***	-0.4535***
			(0.1438)	(0.4895)	(0.1565)
Annual turnover					
£1m-4.9m			-0.1677*	-0.7559***	
			(0.0979)	(0.2667)	
>£5m		-1.0897*			
		(0.6344)			

(continued)

Table 2.9 Continued

	Start up (<2 years)	Young (2-5 years)	Mature (>5 years)	*-of which* (6-9 years)	(>10 years)
Standard region					
East Anglia			-0.3027**		-0.4344***
			(0.1372)		(0.1620)
East Midlands			-0.2643*		-0.3902**
			(0.1460)		(0.1702)
North/North East					-0.3315*
					(0.1915)
West Midlands					-0.2600*
					(0.1458)
Industry sector					
Agriculture, hunting and forestry fishing	-0.6549*		-0.3994***		-0.5497***
	(0.3619)		(0.1371)		(0.1519)
Health and social work	-0.6026**				
	(0.2957)				
Hotels and restaurants		0.4443**	0.4329***		0.4366***
		(0.2025)	(0.1210)		(0.1412)
Transport, storage and communication		0.7236***	0.3291***		0.3075**
		(0.2207)	(0.1198)		(0.1337)
Profitability					
Broken even			-0.3849**		-0.3636**
			(0.1539)		(0.1697)
Profit	-0.4374**	-0.3154**	-0.6113***	-0.3490**	-0.6573***
	(0.1810)	(0.1527)	(0.0925)	(0.1768)	(0.1053)
Business plan	0.3708**				
	(0.1734)				
Innovation			0.3790***		0.3754***
			(0.0778)		(0.0882)
Improvement				0.3066*	
				(0.1595)	
D & B risk rating					
Low			0.5569***		0.5763***
			(0.1351)		(0.1435)
Average			0.5536***		0.4977***
			(0.1348)		(0.1462)
Above Average	0.7136***	0.3849***	0.9500***	0.3831**	0.9207***
	(0.1901)	(0.1451)	(0.1381)	(0.1704)	(0.1498)
Application process-related					
Seeking advice		0.7363***	0.6416***	0.5568**	0.6742***
		(0.2030)	(0.0960)	(0.2172)	(0.1079)
Business account			-0.4756**		-0.5615**
			(0.2119)		(0.2442)
Amount applied					
£5,000-9,999	-0.5005**		-0.3361**		
	(0.2221)		(0.1403)		
£10,000-49,999		-0.2888*	-0.6113***	-0.3707**	-0.4388***
		(0.1533)	(0.1183)	(0.1644)	(0.1164)
£50,000-99,999			-0.5028***		-0.3423**
			(0.1487)		(0.1476)
£100,000-499,999			-0.5379***		-0.3881***
			(0.1514)		(0.1494)
£500,000-999,999			-0.6790***		-0.4059*
			(0.2409)		(0.2418)
>£1m			-1.3132***		-0.9798***
			(0.3573)		(0.3623)
Constant	0.2447	-0.5991***	-0.5833**	0.4696	-0.8731***
	(0.2382)	(0.2057)	(0.2826)	(0.5057)	(0.3112)
No. of observations	681	1109	8883	1224	7659
Wald test statistics	6.54***	5.65***	15.95***	6.41***	11.55***
McFadden's pseudo R^2	0.1180	0.0681	0.1032	0.1053	0.0982

Notes: This table only reports the significant estimated coefficients of logit regressions after variable selection. Pooled standard errors are in parentheses. The dependent variable is whether an overdraft application is rejected or not. The definitions of all control variables are provided in Table 2.3. The null hypothesis of the Wald test is that all coefficients, excluding the constant term, are equal to zero simultaneously. *, **, *** indicate significance at 10%, 5% and 1% level, respectively.

Table 2.10 Bank Loan Rejection by Firm Age: Logit Model

	Start up (<2 years)	Young (2-5 years)	Mature (>5 years)	*-of which* (6-9 years)	(>10 years)
Application date					
Applications in 2011				0.8611***	
				(0.3075)	
Applications in 2012	0.8309***			1.1421***	
	(0.2892)			(0.3286)	
Applications in 2013	0.5135*			1.1326***	
	(0.3049)			(0.3298)	
Applications in 2014			-0.3765***	0.9079***	-0.5189***
			(0.1234)	(0.3358)	(0.1459)
Applications in 2015		-0.7346**	-0.5887***		-0.4675***
		(0.3297)	(0.1482)		(0.1606)
Applications in 2016			-0.5075***	1.1910***	-0.6691***
			(0.1807)	(0.4268)	(0.2140)
Applications in 2017			-0.6937***		-0.6564**
			(0.2339)		(0.2675)
Owner/Manager characteristics					
Gender					
Female				-0.3996*	
				(0.2310)	
Legal status					
Partnership			-0.7696***	-0.8744**	-0.7163***
			(0.1454)	(0.3469)	(0.1633)
Limited liability company	0.4470**		-0.2607**	-0.6419***	-0.2171*
	(0.2207)		(0.1016)	(0.2175)	(0.1157)
Owner age					
18-30 years	0.8037**			1.3895***	
	(0.3876)			(0.5359)	
31-50 years	0.7280***		0.2706***	0.3512*	0.2479***
	(0.2459)		(0.0823)	(0.1946)	(0.0940)
Bank relationships and/or products					
Multiple suppliers		1.0767***			
		(0.3845)			
Main bank			-0.2561**		-0.2344*
			(0.1183)		(0.1356)
Credit balance					
£5,000-9,999		-0.4618**			
		(0.2289)			
£10,000-49,999		-0.7045***			
		(0.2377)			
Firm characteristics					
Number of employees					
10-49	-0.6750**		-0.2288**		-0.3355***
	(0.3322)		(0.1107)		(0.1197)
50-249			-0.8229***		-1.0844***
			(0.1725)		(0.1908)
Annual turnover					
£50,000-99,999			-0.2474*		-0.2957*
			(0.1460)		(0.1770)
£500,000-999,999			-0.2800**	-0.4359*	
			(0.1352)	(0.2621)	
£1m-4.9m		-0.5172*	-0.5942***	-1.0894***	-0.3486***
		(0.2913)	(0.1289)	(0.2660)	(0.1257)
>£5m		-1.0900*	-0.8669***	-1.5055**	-0.5146**
		(0.5997)	(0.2068)	(0.6678)	(0.2080)

(continued)

Table 2.10 Continued

	Start up (<2 years)	Young (2-5 years)	Mature (>5 years)	*-of which* (6-9 years)	(>10 years)
Standard region					
East Anglia			-0.4433***		-0.4043**
			(0.1617)		(0.1815)
East Midlands			-0.3376**		-0.3923**
			(0.1716)		(0.1977)
North West	-1.1497***				
	(0.3484)				
North/North East				0.6459**	
				(0.2980)	
Scotland	-1.1494***		-0.3014**		-0.3102*
	(0.4060)		(0.1533)		(0.1759)
West Midlands				0.6018*	
				(0.3150)	
Yorkshire/Humberside				0.9274***	
				(0.3153)	
Industry sector					
Agriculture, hunting and forestry fishing		-0.9752**	-0.8608***	-0.8298**	-0.8505***
		(0.4103)	(0.1594)	(0.3990)	(0.1777)
Health and social work	-0.6656*				
	(0.3554)				
Hotels and restaurants	0.8198**				
	(0.3322)				
Manufacturing		-0.6865**	-0.3230**	-0.8643**	
		(0.3192)	(0.1375)	(0.3552)	
Transport, storage and communication	1.0310***				
	(0.3441)				
Profitability					
Broken even			-0.5023***	-1.2383***	-0.3928*
			(0.1912)	(0.4535)	(0.2144)
Profit	-0.5668**	-0.5178**	-0.6061***	-0.8677***	-0.6418***
	(0.2305)	(0.2026)	(0.1156)	(0.2792)	(0.1298)
Innovation		0.4459**	0.1888**	0.4066*	
		(0.1892)	(0.0922)	(0.2113)	
D & B risk rating					
Low			0.2445*		0.2718*
			(0.1466)		(0.1596)
Average			0.6048***		0.5985***
			(0.1441)		(0.1590)
Above Average			0.8207***		0.8724***
			(0.1512)		(0.1667)
Application process-related					
Seeking advice	-0.5056*				
	(0.2614)				
Amount applied					
£50,000-99,999		-0.7960**			
		(0.3368)			
£100,000-499,999	-0.6984*				
	(0.3668)				
>£1m		-1.2306**		-1.0061*	
		(0.5779)		(0.5720)	
Constant	-0.1847	0.5925***	-0.1742	-0.4028	-0.3200
	(0.2945)	(0.1931)	(0.2187)	(0.3782)	(0.2453)
No. of observations	451	662	4751	727	4024
Wald test statistics	4.32***	5.19***	15.90***	4.11***	13.34***
McFadden's pseudo R^2	0.1321	0.0920	0.1114	0.1487	0.1040

Notes: This table only reports the significant estimated coefficients of logit regressions after variable selection. Pooled standard errors are in parentheses. The dependent variable is whether a loan application is rejected or not. The definitions of all control variables are provided in Table 2.3. The null hypothesis of the Wald test is that all coefficients, excluding the constant term, are equal to zero simultaneously. *, **, *** indicate significance at 10%, 5% and 1% level, respectively.

2.6 Robustness Checks

As discussed in Section 2.4, data for applications in 2010 and 2017 are not complete. To check whether this has any influence on our results, we exclude applications in 2010 and 2017 and then re-run all models. Results are reported in Table 2.11 and are broadly confirmed. The only differences worth noting are that i) in the case of loans, applications in 2016 become insignificant, indicating tighter loan conditions during Brexit; and ii) SMEs with multiple finance suppliers are found to be positively related to loan rejections.

We also test whether our results are robust to the definition of the dependent variable: bank debt rejection. Our definition (see Table 2.3) includes two situations: when the SME is refused outright or when the SME receives less credit than it requested. Considering that receiving less credit than it requested only represents a ‘partial rejection’ (or ‘partial Approval’), we create another ordinal dependent variable, which equals 0 when the application was approved, 1 when it received less credit than it requested and 2 when the applicant was turned down. An ordered logit model is employed to perform regressions, with the independent variables staying the same as those listed in Table 2.3. The results for independent variables reported in Table 2.12 are very similar, showing the robustness of our results to the definition of bank debt rejection. Besides, the cut-off points between ‘partial rejection’ and ‘total rejection’ (i.e. cut-off point (1/2) in Table 2.12) are highly insignificant for both overdrafts and loans, suggesting no need for separation.

Finally, we perform the robustness check concerning sample selection issues. By definition, bank debt rejection can only be observed if the firm actually applies for bank finance. Since the application decisions are not random, there might be sample selection bias if firms which do not apply are omitted from the analysis (Cowling, Liu and Zhang, 2016). We employ the probit model with sample selection (Van de Ven and Van Pragg 1981), an extended Heckman model using maximum likelihood estimation, to test the possibility of selection bias in our sample. The dependent variable in the outcome equation is whether the application is rejected and the dependent variable in the selection equation is whether a firm applies for bank debt. The variable 'improvement', a dummy which equals 1 if the firm has significantly improved an aspect of the firm in the past three years and 0 otherwise, is used as the selection criterion for both overdraft and loan sample. This variable has been found significant in the selection equation (that is, related to the application decision making) but insignificant in the outcome equation (that is, unrelated to the bank decision making). The results are reported in Tables 2.13 and 2.14 for overdrafts and loans, respectively.

First, since the variable selection technique is difficult to be implemented in a simultaneous equation structure, we include all available control variables in Model (1) in each table. Then keeping the variables in the selection equation unchanged, we only include the selected significant variables (same as the significant variables in Table 2.6) in the outcome equation. In both tables (Table 2.13 and 2.14), the results are shown in Model (2). The correlation coefficients between the two equations in every model are insignificant, indicating there is no selection bias in our overdraft and loan sample.

Table 2.11 Robustness Check: Excluding Observations in 2010 and 2017

	Overdrafts	Loans
Application date		
Applications in 2011		
Applications in 2012	0.1726**	
	(0.0855)	
Applications in 2013	0.1726*	
	(0.0910)	
Applications in 2014	-0.3846***	-0.2632**
	(0.1085)	(0.1095)
Applications in 2015	-0.7518***	-0.4568***
	(0.1291)	(0.1285)
Applications in 2016	-0.4774***	
	(0.1525)	
Owner/Manager characteristics		
Gender		
Female	-0.2475***	-0.1737*
	(0.0842)	(0.1004)
Both (joint partners)	-0.4843**	
	(0.2273)	
Legal status		
Partnership	-0.2304**	-0.5650***
	(0.1132)	(0.1304)
Owner age		
31-50 years		0.1904**
		(0.0798)
Bank relationships and/or products		
Multiple suppliers		0.3731**
		(0.1629)
Use of credit card	-0.1439**	
	(0.0656)	
Credit balance		
£5,000-9,999	-0.2621***	-0.4282***
	(0.1003)	(0.1206)
£10,000-49,999	-0.4075***	-0.4794***
	(0.0978)	(0.1160)
£50,000-99,999	-0.6185***	-0.6035***
	(0.1664)	(0.1888)
£100,000-499,999	-0.5457***	-0.5530***
	(0.1687)	(0.1778)
£500,000-999,999	-1.5837***	-0.6742**
	(0.4565)	(0.3080)
>£1m		-1.1206***
		(0.3751)
Firm characteristics		
Number of employees		
10-49		-0.1894*
		(0.1009)
50-249	-0.3914***	-0.5587***
	(0.1294)	(0.1697)
Annual turnover		
£1m-4.9m	-0.2020**	-0.4479***
	(0.0943)	(0.1217)
>£5m		-0.6853***
		(0.2092)

(continued)

Table 2.11 Continued

	Overdrafts	Loans
Business age		
2-5 years	-0.3352*** (0.1165)	
6-9 years	-0.8811*** (0.1239)	-0.3167*** (0.1218)
10-15 years	-1.1275*** (0.1269)	-0.6205*** (0.1219)
>15 years	-1.2834*** (0.1157)	-0.8565*** (0.1065)
Standard region		
East Anglia	-0.2160* (0.1173)	-0.3158** (0.1521)
Scotland		-0.3613** (0.1449)
Industry sector		
Agriculture, hunting and forestry fishing	-0.3612*** (0.1266)	-0.7799*** (0.1576)
Health and social work		-0.4035*** (0.1442)
Hotels and restaurants	0.3335*** (0.1062)	
Manufacturing		-0.5453*** (0.1401)
Transport, storage and communication	0.3484*** (0.1069)	
Wholesale/retail	-0.2205** (0.1066)	-0.2712** (0.1303)
Other community, social and personal service		-0.2710** (0.1325)
Profitability		
Broken even		-0.3591** (0.1673)
Profit	-0.4222*** (0.0727)	-0.5660*** (0.1083)
Business plan	0.1401** (0.0657)	
Innovation	0.1819** (0.0716)	0.2420*** (0.0929)
Improvement		0.1415* (0.0850)
D & B risk rating		
Low	0.4957*** (0.1365)	
Average	0.4579*** (0.1328)	0.3302*** (0.1038)
Above Average	0.8357*** (0.1348)	0.5643*** (0.1112)
Application process-related		
Seeking advice	0.6461*** (0.0879)	
Business account	-0.3652** (0.1691)	

(continued)

Table 2.11 Continued

	Overdrafts	Loans
Amount applied		
£5,000-9,999	-0.2396**	-0.2557*
	(0.1108)	(0.1367)
£10,000-49,999	-0.4322***	
	(0.0957)	
£50,000-99,999	-0.3945***	
	(0.1349)	
£100,000-499,999	-0.4832***	
	(0.1391)	
£500,000-999,999	-0.6327***	
	(0.2397)	
>£1m	-1.2581***	
	(0.3660)	
Constant	-0.1848	0.4834**
	(0.1860)	(0.1686)
No. of observations	8828	4530
Wald test statistics [a]	17.55***	11.98***
Wald test statistics (2015=2016) [b]	2.41	1.61
McFadden's pseudo R^2	0.1733	0.1694

Notes: This table only reports the significant estimated coefficients of logit regressions after variable selection. Pooled standard errors are in parentheses. The dependent variable is whether an overdraft or a loan application is rejected or not. The definitions of all control variables are provided in Table 2.3. [a]: The null hypothesis of the Wald test is that all coefficients, excluding the constant term, are equal to zero simultaneously. [b]: The null hypothesis of the Wald test is that the coefficient of 'applications in 2015' equals the coefficient of 'applications in 2016'. *, **, *** indicate significance at 10%, 5% and 1% level, respectively.

Table 2.12 Robustness Check: Ordered Logit Model

	Overdrafts	Loans
Application date		
Applications in 2011		
Applications in 2012	0.1553*	
	(0.0795)	
Applications in 2013	0.1761**	
	(0.0851)	
Applications in 2014	-0.3942***	-0.2788***
	(0.1039)	(0.1059)
Applications in 2015	-0.7621***	-0.5015***
	(0.1258)	(0.1225)
Applications in 2016	-0.4451***	-0.2860*
	(0.1513)	(0.1561)
Applications in 2017	-0.6735***	-0.3401*
	(0.1851)	(0.2001)
Owner/Manager characteristics		
Gender		
Female	-0.2646***	-0.2306***
	(0.0771)	(0.0884)
Both (joint partners)	-0.5911***	
	(0.2126)	
Legal status		
Partnership	-0.2328**	-0.4551***
	(0.1043)	(0.1103)
Owner age		
31-50 years		0.2063***
		(0.0703)
Bank relationships and/or products		
Main bank	-0.5111***	
	(0.1840)	
Use of credit card	-0.1363**	
	(0.0597)	
Credit balance		
£5,000-9,999	-0.3065***	-0.2442**
	(0.0924)	(0.1096)
£10,000-49,999	-0.3902***	-0.4078***
	(0.0921)	(0.1041)
£50,000-99,999	-0.6386***	-0.3517**
	(0.1548)	(0.1618)
£100,000-499,999	-0.5458***	-0.3927**
	(0.1532)	(0.1685)
£500,000-999,999	-1.2396***	-0.6012**
	(0.3245)	(0.2827)
>£1m	-0.7919*	-0.8280**
	(0.4088)	(0.3344)
Firm characteristics		
Number of employees		
10-49		-0.2388***
		(0.0885)
50-249	-0.3330***	-0.6498***
	(0.1194)	(0.1554)
Annual turnover		
£1m-4.9m	-0.2269***	-0.3530***
	(0.0857)	(0.1093)
>£5m		-0.6790***
		(0.1988)

(continued)

Table 2.12 Continued

	Overdrafts	Loans
Business age		
2-5 years	-0.3580*** (0.1048)	
6-9 years	-0.9400*** (0.1130)	-0.4210*** (0.1074)
10-15 years	-1.1820*** (0.1145)	-0.6286*** (0.1089)
>15 years	-1.2989*** (0.1045)	-0.8445*** (0.0936)
Standard region		
East Anglia	-0.2426** (0.1088)	-0.3465*** (0.1342)
East Midlands	-0.2031* (0.1181)	
Scotland		-0.3292** (0.1286)
South West		-0.1863* (0.1089)
Industry sector		
Agriculture, hunting and forestry fishing	-0.3763*** (0.1168)	-0.7549*** (0.1375)
Health and social work		-0.3426*** (0.1288)
Hotels and restaurants	0.3469*** (0.0955)	
Manufacturing		-0.3841*** (0.1200)
Transport, storage and communication	0.4034*** (0.0954)	
Other community, social and personal service		-0.2097* (0.1139)
Profitability		
Broken even		-0.3609** (0.1452)
Profit	-0.4346*** (0.0666)	-0.5542*** (0.0937)
Business plan	0.1228** (0.0603)	
Innovation	0.2207*** (0.0654)	0.2541*** (0.0763)
D & B risk rating		
Low	0.5004*** (0.1275)	
Average	0.4699*** (0.1242)	0.3517*** (0.0909)
Above Average	0.8501*** (0.1254)	0.5019*** (0.0994)
Application process-related		
Seeking advice	0.5470*** (0.0808)	
Business account	-0.2867* (0.1504)	

(continued)

Table 2.12 Continued

	Overdrafts	Loans
Amount applied		
£5,000-9,999	-0.3176***	
	(0.0998)	
£10,000-49,999	-0.5353***	-0.1948*
	(0.0875)	(0.1006)
£50,000-99,999	-0.5068***	-0.5238***
	(0.1231)	(0.1394)
£100,000-499,999	-0.5572***	-0.3605***
	(0.1248)	(0.1206)
£500,000-999,999	-0.7139***	-0.3241*
	(0.2191)	(0.1861)
>£1m	-1.3179***	-0.3408*
	(0.3476)	(0.1999)
Cut-off point (0/1)	-0.4328*	-0.6967***
	(0.2476)	(0.1566)
Cut-off point (1/2)	0.1939	-0.2500
	(0.2475)	(0.1562)
No. of observations	10673	5864
Wald test statistics	20.72***	12.31***

Notes: This table only reports the significant estimated coefficients of ordered logit regressions after variable selection. Pooled standard errors are in parentheses. The ordinal dependent variable equals 0 when an overdraft or a loan application is approved, 1 when an overdraft or a loan applicant receives less credit than it requests and 2 when an overdraft or a loan application is turned down outright. The definitions of all control variables are provided in Table 2.3. The null hypothesis of the Wald test is that all coefficients, excluding the constant term, are equal to zero simultaneously. *, **, *** indicate significance at 10%, 5% and 1% level, respectively.

Table 2.13 Robustness Check: Probit Model with Sample Selection for Overdrafts

	Model (1)		Model (2)	
	Rejection	Application	Rejection	Application
Application date				
Applications in 2011	-0.0128			
	(0.0712)			
Applications in 2012	0.0796		0.0901**	
	(0.0718)		(0.0447)	
Applications in 2013	0.0683		0.0772	
	(0.0738)		(0.0477)	
Applications in 2014	-0.2087***		-0.1988***	
	(0.0778)		(0.0548)	
Applications in 2015	-0.4010***		-0.3902***	
	(0.0872)		(0.0652)	
Applications in 2016	-0.2753***		-0.2708***	
	(0.0987)		(0.0797)	
Applications in 2017	-0.3969***		-0.3938***	
	(0.1047)		(0.0886)	
Owner/Manager characteristics				
Gender				
Female	-0.1106**	0.0209	-0.1233***	0.0208
	(0.0434)	(0.0143)	(0.0429)	(0.0143)
Both (joint partners)	-0.2694**	-0.0772**	-0.2944***	-0.0772**
	(0.1136)	(0.0338)	(0.1104)	(0.0338)
Legal status				
Partnership	-0.1564*	0.2836***	-0.0999*	0.2837***
	(0.0869)	(0.0220)	(0.0570)	(0.0220)
Limited liability partnership	-0.0938	0.1883***		0.1887***
	(0.0967)	(0.0290)		(0.0290)
Limited liability company	-0.0211	0.0122		0.0123
	(0.0484)	(0.0171)		(0.0171)
Owner age				
18-30 years	0.0489	-0.1108***		-0.1110***
	(0.0961)	(0.0331)		(0.0331)
31-50 years	-0.0060	-0.0263**		-0.0262**
	(0.0363)	(0.0116)		(0.0116)
Financial knowledge	0.0100	-0.0476***		-0.0476***
	(0.0369)	(0.0117)		(0.0117)
Bank relationships and/or products				
Multiple suppliers	0.0223	0.2987***		0.2981***
	(0.1059)	(0.0303)		(0.0303)
Main bank	-0.2320**		-0.2480**	
	(0.1071)		(0.1064)	
Use of credit card	-0.0947	0.3686***		0.3688***
	(0.0880)	(0.0113)		(0.0113)
Credit balance				
£5,000-9,999	-0.0901	-0.2395***	-0.1353***	-0.2396***
	(0.0753)	(0.0209)	(0.0514)	(0.0209)
£10,000-49,999	-0.1435	-0.3238***	-0.2069***	-0.3239***
	(0.0897)	(0.0178)	(0.0478)	(0.0178)
£50,000-99,999	-0.2496*	-0.4241***	-0.3343***	-0.4242***
	(0.1314)	(0.0252)	(0.0848)	(0.0252)
£100,000-499,999	-0.1699	-0.4960***	-0.2713***	-0.4961***
	(0.1438)	(0.0269)	(0.0869)	(0.0269)
£500,000-999,999	-0.2560	-0.6101***	-0.3828***	-0.6103***
	(0.1841)	(0.0350)	(0.1203)	(0.0350)
>£1m	-0.2516	-0.6559***	-0.3880**	-0.6562***
	(0.2240)	(0.0432)	(0.1623)	(0.0431)

(continued)

Table 2.13 Continued

	Model (1)		Model (2)	
	Rejection	Application	Rejection	Application
Firm characteristics				
Number of employees				
10-49	-0.0613	0.0065		0.0070
	(0.0477)	(0.0162)		(0.0162)
50-249	-0.1831**	-0.0597***	-0.1762***	-0.0595***
	(0.0793)	(0.0230)	(0.0593)	(0.0230)
Annual turnover				
£50,000-99,999	-0.1448	0.2897***		0.2904***
	(0.0895)	(0.0215)		(0.0215)
£100,000-499,999	-0.1074	0.5233***		0.5234***
	(0.1317)	(0.0220)		(0.0220)
£500,000-999,999	-0.1041	0.6022***		0.6022***
	(0.1568)	(0.0258)		(0.0258)
£1m-4.9m	-0.2439	0.6446***	-0.1081**	0.6447***
	(0.1644)	(0.0270)	(0.0469)	(0.0270)
>£5m	-0.2240	0.7268***		0.7274***
	(0.1963)	(0.0354)		(0.0353)
Business age				
2-5 years	-0.2035***	-0.0046	-0.2026***	-0.0047
	(0.0651)	(0.0249)	(0.0652)	(0.0249)
6-9 years	-0.5241***	0.0454*	-0.5219***	0.0452*
	(0.0689)	(0.0255)	(0.0689)	(0.0255)
10-15 years	-0.6432***	0.0659***	-0.6435***	0.0658***
	(0.0690)	(0.0249)	(0.0687)	(0.0249)
>15 years	-0.7150***	0.0941***	-0.7088***	0.0940***
	(0.0647)	(0.0235)	(0.0642)	(0.0235)
Standard region				
East Anglia	-0.2986***	0.0881***	-0.2797***	0.0882***
	(0.0760)	(0.0245)	(0.0754)	(0.0245)
East Midlands	-0.3006***	0.1267***	-0.2710***	0.1268***
	(0.0814)	(0.0256)	(0.0795)	(0.0256)
North West	-0.1715**	0.0958***	-0.1486**	0.0959***
	(0.0732)	(0.0243)	(0.0719)	(0.0243)
North/North East	-0.2732***	0.1412***	-0.2409***	0.1413***
	(0.0897)	(0.0283)	(0.0871)	(0.0283)
Northern Ireland	-0.1944**	0.0890***	-0.1782**	0.0890***
	(0.0881)	(0.0288)	(0.0870)	(0.0288)
Scotland	-0.1905**	0.2280***	-0.1394*	0.2281***
	(0.0847)	(0.0240)	(0.0717)	(0.0240)
South East	-0.1401**	0.0694***	-0.1185*	0.0694***
	(0.0676)	(0.0225)	(0.0667)	(0.0225)
South West	-0.2218***	0.1966***	-0.1758**	0.1967***
	(0.0783)	(0.0234)	(0.0696)	(0.0234)
Wales	-0.1647**	0.1041***	-0.1403*	0.1041***
	(0.0823)	(0.0273)	(0.0801)	(0.0273)
West Midlands	-0.2198***	0.0935***	-0.2003***	0.0936***
	(0.0749)	(0.0244)	(0.0737)	(0.0244)
Yorkshire/Humberside	-0.1778**	0.1162***	-0.1552**	0.1163***
	(0.0753)	(0.0242)	(0.0726)	(0.0242)

(continued)

Table 2.13 Continued

	Model (1)		Model (2)	
	Rejection	Application	Rejection	Application
Industry sector				
Agriculture, hunting and forestry fishing	-0.3067***	0.2123***	-0.1632***	0.2132***
	(0.0826)	(0.0228)	(0.0628)	(0.0228)
Health and social work	-0.0800	-0.1488***		-0.1480***
	(0.0819)	(0.0242)		(0.0243)
Hotels and restaurants	0.1459**	-0.1296***	0.2068***	-0.1289***
	(0.0689)	(0.0230)	(0.0555)	(0.0230)
Manufacturing	-0.0857	-0.1069***		-0.1061***
	(0.0699)	(0.0217)		(0.0217)
Real estate, renting and business activities	-0.0790	-0.0710***		-0.0704***
	(0.0577)	(0.0182)		(0.0182)
Transport, storage and communication	0.1248*	-0.0851***	0.1958***	-0.0844***
	(0.0643)	(0.0217)	(0.0547)	(0.0217)
Wholesale/retail	-0.1355**	-0.0404*		-0.0395*
	(0.0634)	(0.0207)		(0.0207)
Other community, social and personal service	-0.1419**	-0.0421**		-0.0411*
	(0.0653)	(0.0211)		(0.0211)
Profitability				
Broken even	-0.0619	-0.2895***		-0.2885***
	(0.0949)	(0.0248)		(0.0248)
Profit	-0.2415***	-0.1904***	-0.2355***	-0.1900***
	(0.0644)	(0.0174)	(0.0374)	(0.0174)
Business plan	0.0544	0.0672***	0.0621*	0.0671***
	(0.0402)	(0.0115)	(0.0339)	(0.0115)
Export	0.0166	0.0103		0.0101
	(0.0534)	(0.0181)		(0.0181)
Import	0.0288	0.0211		0.0209
	(0.0518)	(0.0171)		(0.0171)
Management account	-0.0036	0.0586***		0.0585***
	(0.0429)	(0.0127)		(0.0127)
Improvement		0.1627***		0.1623***
		(0.0117)		(0.0117)
Innovation	0.1086***	0.0070	0.1173***	0.0072
	(0.0417)	(0.0138)	(0.0368)	(0.0138)
D & B risk rating				
Low	0.1989***	0.0746***	0.2180***	0.0747***
	(0.0669)	(0.0179)	(0.0628)	(0.0179)
Average	0.1882***	0.1287***	0.2250***	0.1289***
	(0.0706)	(0.0197)	(0.0612)	(0.0197)
Above Average	0.3734***	0.1698***	0.4314***	0.1701***
	(0.0819)	(0.0217)	(0.0634)	(0.0217)
Application process-related				
Seeking advice	0.3318***		0.3315***	
	(0.0477)		(0.0464)	
Business account	-0.1419		-0.1678*	
	(0.0919)		(0.0907)	

(continued)

Table 2.13 Continued

	Model (1)		Model (2)	
	Rejection	Application	Rejection	Application
Amount applied				
£5,000-9,999	-0.1306**		-0.1396**	
	(0.0613)		(0.0608)	
£10,000-49,999	-0.2473***		-0.2535***	
	(0.0575)		(0.0538)	
£50,000-99,999	-0.2161***		-0.2285***	
	(0.0813)		(0.0763)	
£100,000-499,999	-0.2318***		-0.2584***	
	(0.0757)		(0.0707)	
£500,000-999,999	-0.2956**		-0.3443***	
	(0.1239)		(0.1183)	
>£1m	-0.5366***		-0.5833***	
	(0.1626)		(0.1601)	
Constant	0.4254	-1.4785***	0.1411	-1.4789***
	(0.5296)	(0.0396)	(0.2248)	(0.0397)
Correlation coefficient (ρ)	-0.1436		0.0742	
No. of observations	129918		129918	

Notes: This table reports the maximum likelihood estimated coefficients of probit models with sample selection. Pooled standard errors are in parentheses. The dependent variable in the outcome equation is whether an overdraft application is rejected or not and the dependent variable in the selection equation is whether a firm applies for an overdraft. The outcome equation in Model (1) includes all explanatory variables as listed in Table 2.3 whereas the outcome equation in Model (2) only includes the selected significant explanatory variables shown in the third column of Table 2.6. The selection equations in both Model (1) and (2) include explanatory variables available to all firms, i.e. except application date, main bank and application process-related variables. *, **, *** indicate significance at 10%, 5% and 1% level, respectively.

Table 2.14 Robustness Check: Probit Model with Sample Selection for Loans

	Model (1)		Model (2)	
	Rejection	Application	Rejection	Application
Application date				
Applications in 2011	0.0427			
	(0.0814)			
Applications in 2012	0.0875			
	(0.0820)			
Applications in 2013	0.0681			
	(0.0856)			
Applications in 2014	-0.1059		-0.1654***	
	(0.0868)		(0.0598)	
Applications in 2015	-0.1609*		-0.2400***	
	(0.0928)		(0.0671)	
Applications in 2016	-0.1322		-0.2148**	
	(0.1010)		(0.0856)	
Applications in 2017	-0.2091*		-0.2860***	
	(0.1197)		(0.1034)	
Owner/Manager characteristics				
Gender				
Female	-0.1066**	0.0091	-0.1249**	0.0091
	(0.0493)	(0.0170)	(0.0521)	(0.0170)
Both (joint partners)	0.1054	-0.1715***		-0.1715***
	(0.1219)	(0.0407)		(0.0407)
Legal status				
Partnership	-0.3602***	0.2842***	-0.2438***	0.2843***
	(0.0786)	(0.0256)	(0.0669)	(0.0256)
Limited liability partnership	-0.1235	0.1904***		0.1907***
	(0.0990)	(0.0337)		(0.0337)
Limited liability company	-0.0068	-0.0258		-0.0256
	(0.0557)	(0.0206)		(0.0206)
Owner age				
18-30 years	0.1102	-0.0533		-0.0538
	(0.1055)	(0.0397)		(0.0397)
31-50 years	0.1031**	0.0249*	0.1261***	0.0249*
	(0.0441)	(0.0136)	(0.0417)	(0.0136)
Financial knowledge	0.0295	-0.0287**		-0.0286**
	(0.0392)	(0.0139)		(0.0139)
Bank relationships and/or products				
Multiple suppliers	-0.1045	0.4641***		0.4637***
	(0.1364)	(0.0321)		(0.0321)
Main bank	-0.0655			
	(0.0554)			
Use of credit card	-0.1381**	0.2467***		0.2468***
	(0.0641)	(0.0136)		(0.0136)
Credit balance				
£5,000-9,999	-0.0208	-0.1521***	-0.1032	-0.1520***
	(0.0721)	(0.0239)	(0.0632)	(0.0239)
£10,000-49,999	-0.0648	-0.2240***	-0.1908***	-0.2240***
	(0.0912)	(0.0214)	(0.0635)	(0.0214)
£50,000-99,999	-0.0429	-0.2823***	-0.1912**	-0.2822***
	(0.1205)	(0.0282)	(0.0928)	(0.0282)
£100,000-499,999	-0.0676	-0.3007***	-0.2144**	-0.3006***
	(0.1325)	(0.0280)	(0.0968)	(0.0280)
£500,000-999,999	-0.0351	-0.4073***	-0.2408	-0.4072***
	(0.1940)	(0.0387)	(0.1661)	(0.0387)
>£1m	-0.0824	-0.4039***	-0.2893**	-0.4040***
	(0.1845)	(0.0399)	(0.1456)	(0.0399)

(continued)

Table 2.14 Continued

	Model (1)		Model (2)	
	Rejection	Application	Rejection	Application
Firm characteristics				
Number of employees				
10-49	-0.1124**	0.0364*	-0.1233**	0.0365*
	(0.0530)	(0.0195)	(0.0541)	(0.0195)
50-249	-0.3186***	0.0302	-0.3690***	0.0304
	(0.0899)	(0.0275)	(0.0880)	(0.0275)
Annual turnover				
£50,000-99,999	-0.1913**	0.2181***		0.2184***
	(0.0852)	(0.0280)		(0.0280)
£100,000-499,999	-0.2059*	0.4215***		0.4216***
	(0.1154)	(0.0255)		(0.0254)
£500,000-999,999	-0.2821**	0.4839***		0.4840***
	(0.1336)	(0.0317)		(0.0317)
£1m-4.9m	-0.4672***	0.5495***	-0.1928***	0.5494***
	(0.1311)	(0.0330)	(0.0617)	(0.0330)
>£5m	-0.6336***	0.6211***	-0.3359***	0.6209***
	(0.1551)	(0.0423)	(0.1057)	(0.0423)
Business age				
2-5 years	-0.0443	-0.0571**		-0.0568**
	(0.0766)	(0.0287)		(0.0288)
6-9 years	-0.2410***	-0.0171	-0.2441***	-0.0172
	(0.0853)	(0.0294)	(0.0663)	(0.0294)
10-15 years	-0.3518***	-0.0681**	-0.3961***	-0.0683**
	(0.1021)	(0.0290)	(0.0652)	(0.0290)
>15 years	-0.4341***	-0.0527*	-0.4951***	-0.0528*
	(0.1028)	(0.0271)	(0.0564)	(0.0271)
Standard region				
East Anglia	-0.3153***	0.0163	-0.1945**	0.0169
	(0.0926)	(0.0291)	(0.0762)	(0.0291)
East Midlands	-0.2273**	0.0244		0.0253
	(0.0924)	(0.0309)		(0.0310)
North West	-0.2354***	0.0513*		0.0522*
	(0.0819)	(0.0285)		(0.0286)
North/North East	-0.1501	-0.0047		-0.0039
	(0.1015)	(0.0349)		(0.0349)
Northern Ireland	-0.1902**	0.0747**		0.0752**
	(0.0929)	(0.0333)		(0.0333)
Scotland	-0.3471***	0.0813***	-0.1861**	0.0819***
	(0.0858)	(0.0289)	(0.0722)	(0.0290)
South East	-0.1503**	0.0141		0.0148
	(0.0760)	(0.0266)		(0.0267)
South West	-0.2819***	0.1412***		0.1422***
	(0.0757)	(0.0275)		(0.0276)
Wales	-0.0939	0.0657**		0.0660**
	(0.0877)	(0.0319)		(0.0319)
West Midlands	-0.1412*	0.0712**		0.0717**
	(0.0790)	(0.0284)		(0.0285)
Yorkshire/Humberside	-0.1812**	0.0734**		0.0740**
	(0.0795)	(0.0286)		(0.0286)

(continued)

Table 2.14 Continued

	Model (1)		Model (2)	
	Rejection	Application	Rejection	Application
Industry sector				
Agriculture, hunting and forestry fishing	-0.5834***	0.3796***	-0.3907***	0.3797***
	(0.0872)	(0.0275)	(0.0781)	(0.0275)
Health and social work	-0.2990***	0.1300***	-0.1591**	0.1303***
	(0.0808)	(0.0280)	(0.0732)	(0.0280)
Hotels and restaurants	-0.1124	0.1843***		0.1844***
	(0.0824)	(0.0267)		(0.0267)
Manufacturing	-0.2745***	0.0666**	-0.1956***	0.0667**
	(0.0785)	(0.0267)	(0.0679)	(0.0267)
Real estate, renting and business activities	-0.1295*	0.0198		0.0202
	(0.0679)	(0.0233)		(0.0233)
Transport, storage and communication	-0.1299*	0.0971***		0.0974***
	(0.0751)	(0.0266)		(0.0266)
Wholesale/retail	-0.1380*	0.0847***		0.0848***
	(0.0725)	(0.0258)		(0.0258)
Other community, social and personal service	-0.2003***	0.0890***		0.0896***
	(0.0738)	(0.0264)		(0.0264)
Profitability				
Broken even	-0.1114	-0.2224***	-0.2301**	-0.2223***
	(0.1135)	(0.0292)	(0.0910)	(0.0292)
Profit	-0.2215***	-0.1410***	-0.3309***	-0.1409***
	(0.0821)	(0.0207)	(0.0574)	(0.0207)
Business plan	-0.0037	0.1135***		0.1133***
	(0.0515)	(0.0137)		(0.0137)
Export	0.0849	-0.0358*		-0.0358*
	(0.0601)	(0.0216)		(0.0216)
Import	-0.0944*	0.0308		0.0309
	(0.0565)	(0.0201)		(0.0201)
Management account	-0.0485	0.0237		0.0238
	(0.0443)	(0.0153)		(0.0153)
Improvement		0.1423***		0.1422***
		(0.0141)		(0.0141)
Innovation	0.0905*	0.0299*	0.1359***	0.0300*
	(0.0544)	(0.0163)	(0.0462)	(0.0163)
D & B risk rating				
Low	0.0513	0.0936***		0.0934***
	(0.0714)	(0.0208)		(0.0208)
Average	0.1814**	0.1296***	0.2073***	0.1295***
	(0.0878)	(0.0222)	(0.0510)	(0.0222)
Above Average	0.2177**	0.1547***	0.2787***	0.1545***
	(0.0992)	(0.0239)	(0.0557)	(0.0239)
Application process-related				
Seeking advice	0.0051			
	(0.0430)			
Business account	-0.0907			
	(0.0990)			

(continued)

Table 2.14 Continued

	Model (1)		Model (2)	
	Rejection	Application	Rejection	Application
Amount applied				
£5,000-9,999	-0.1672*		-0.1838*	
	(0.0911)		(0.0985)	
£10,000-49,999	-0.1615**		-0.2055**	
	(0.0805)		(0.0851)	
£50,000-99,999	-0.3018***		-0.3610***	
	(0.1045)		(0.1060)	
£100,000-499,999	-0.2407***		-0.2938***	
	(0.0892)		(0.0907)	
£500,000-999,999	-0.2011*		-0.2479**	
	(0.1165)		(0.1250)	
>£1m	-0.2044*		-0.2633**	
	(0.1168)		(0.1239)	
Constant	0.9746*	-1.7912***	0.3550	-1.7915***
	(0.5813)	(0.0468)	(0.2333)	(0.0468)
Correlation coefficient (ρ)	-0.4807		0.0321	
No. of observations	130100		130100	

Notes: This table reports the maximum likelihood estimated coefficients of probit models with sample selection. Pooled standard errors are in parentheses. The dependent variable in the outcome equation is whether a loan application is rejected or not and the dependent variable in the selection equation is whether a firm applies for a loan. The outcome equation in Model (1) includes all explanatory variables as listed in Table 2.3 whereas the outcome equation in Model (2) only includes the selected significant explanatory variables shown in the fourth column of Table 2.6. The selection equations in both Model (1) and (2) include explanatory variables available to all firms, i.e. except application date, main bank and application process-related variables. *, **, *** indicate significance at 10%, 5% and 1% level, respectively.

2.7 Conclusions

This chapter explores the determinants of bank loan and overdraft rejections and makes an assessment of bank lending conditions for UK SMEs over 2010-17. As far as we are aware, little research is devoted to studying bank lending conditions for SMEs in the aftermath of the global financial crisis and no study covers a relatively long time period after 2010 and incorporates the years before, during and in the immediate aftermath of the Brexit referendum, which brought further uncertainty and risk to the credit market.

Using the UK SMEs Finance Monitor data over 2010-2017, it examines the changes in bank financing and focus on the determinants of bank debt rejections. It uses logit regression models and applies multiple imputations to cope with the missing values in our survey data. In the aftermath of the global financial crisis, overdrafts and term loans show slightly different trends, although the factors affecting rejections are similar. The evidence suggests that rejection rates first reduced for both facilities since 2014, possibly as a result of government programmes supporting SME financing, and then stayed unchanged in the run-up to the Brexit referendum and its immediate aftermath, although the overdraft market became tighter for exporting firms.

It presents fresh evidence that partnerships with female owners and higher initial credit balance are more likely to be approved. Younger, smaller and more innovative SMEs with lower application amount are more likely to be rejected. Finally, start-ups (<2 years) and micro firms (less than 10 employees and turnover <£2m) appear to experience significantly improved lending conditions after 2014, particularly for overdrafts while the loan market is still tight.

From a practical perspective, the analysis on the changes in bank lending conditions provides useful insights about the current situation in the bank credit market in relation to UK SMEs. The finding that micro firms may have benefited particularly is a positive development overall, but there seems some concern about bigger SMEs that may be in vital need of financing. One would also recommend paying particular attention and considering the case of exporting SMEs as they will need to find fewer barriers to access to bank finance during the depreciation period of sterling brought about by the recent Brexit developments, especially the short-term financing to maintain daily operations.

Additional government programmes to encourage female ownership of small businesses is recommended as the results suggest that SMEs led by women have significantly lower rejection rates compared to their male counterparts. Equally, a more structural use of the SME SF recommended by the European Commission to support lending expansion would also be desirable. However, to date, there is still insufficient evidence to assess whether this temporary measure has been successful in providing additional stimulus for lending to SMEs. Future research should provide more evidence on the impact of this as well as other measures on UK SMEs and build a counterfactual vs large firms that did not benefit from them.

Chapter 3 To Borrow or Not to Borrow? Government Initiatives and Discouraged Borrowers

3.1 Introduction

It is widely accepted that small and medium-sized enterprises (SMEs) bring job opportunities and innovations to the economy and their development can foster local economic growth. However, relative to large firms, access to external finance is often more difficult for SMEs (Berger and Udell, 1998), mainly due to the lack of adequate collateral and information transparency (Armstrong et al., 2013), which imposes larger growth obstacles (Beck and Demirguc-Kunt, 2006). Hence, credit rationing among SMEs has raised much concern among researchers (e.g. Berger and Udell, 1992; Cowling et al., 2012). This is especially so after the global financial crisis, which led to a deterioration of lending conditions and was followed by lower approval rates and higher application costs for SMEs (Fraser, 2012).

To relieve the credit pressure that UK SMEs faced in the aftermath of the financial crisis, the government proposed a number of initiatives to boost bank lending to SMEs (Calabrese et al., 2017). One of the initiatives is the Enterprise Finance Guarantee Scheme (EFGS), the successor of the Small Firms Loan Guarantee Scheme (SFLGS). EFGS [23] was established in 2009 to help small businesses get better access to finance (e.g. bank finance including overdrafts and term loans, asset finance and invoice finance) and create a more diversified lending market. Since October 2013, the operation of the scheme has been overseen by the British Business Bank on behalf of the Department for Business, Innovation and Skills (DBIS).

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[23] See more details at the official website: https://www.british-business-bank.co.uk/ourpartners/supporting-business-loans-enterprise-finance-guarantee/about-efg/

Figure 3.1 Quarterly Breakdown of Enterprise Finance Guarantee Lending During 2009Q1-2017Q3

Notes: This figure shows the number and the value of loans offered under the Enterprise Finance Guarantee Scheme in each quarter from 2009Q1 to 2017Q3, with the blue line for the number and the red line for the value. The data are accessed from British Business Bank (2017), Enterprise Finance Guarantee quarterly statistics.

EFGS is aimed at small businesses that have sound business plans to grow but are rejected by lenders because they do not have sufficient collateral or financial track record to meet the security requirements. An up to 75% guarantee provided by EFGS to lenders can change lenders' decisions from rejections to approvals. Despite the involvement of the government in the lending process, the decision to issue credit is still fully made by the lenders. That is to say, SMEs eligible for the scheme must meet the lending criteria of the lenders except for the requirement on collateral and/or track record.

The EFGS-supported debt instruments can range from £1,000 to £1.2m. As for the term, overdrafts and invoice finance are up to 3 years while term loans and asset finance higher (lower) than £600,000 are up to 5 (10) years. By the end of October in 2017, it had already offered more than 28,300 loans to the value of more than £3 billion with a spike in 2009, as illustrated by Figure 3.1.

While there are considerable concerns about the supply-side of credit rationing, Levenson and Willard (2000) point to the importance of the demand-side debt gap and call attention to incorporating discouraged borrowers (see Figure 1.2 in Chapter 1) in the 'true' credit constraints. They estimate that 4.22% of US small businesses, almost twice the percentage of refused firms, were discouraged from borrowing in 1988-1989. Discouraged borrowers account for 0.51% of small businesses in Canada (Chandler, 2010), 2.65-8.13% in UK (Freel et al., 2012; Cowling, Liu, Minniti and Zhang, 2016), 10.05% in Italy (Mac an Bhaird et al., 2016), 20.53% in China (Chakravarty and Xiang, 2013), 23.93% in Germany (Mac an Bhaird et al., 2016) and 44.36% in Pakistan (Chakravarty and Xiang, 2013). Inspired by the findings of Levenson and Willard (2000), Kon and Storey (2003) construct a theoretical model to explain the rationale underlying discouraged borrowers. They posit that the scale of discouragement is determined by the screening errors of banks, the application costs (covering financial, in-kind and psychic costs) and the difference between the interest rates charged by the banks and other financing alternatives. Based on their model, there has been scant empirical research on discouraged borrowers in either developed (e.g. Han et al., 2009; Fraser, 2014) or developing countries (Chakravarty and Xiang, 2013; Leon, 2015).

In this chapter, we aim to empirically examine the relationship between EFGS, financial literacy and bank debt discouragement. We treat business overdrafts and term loans separately, as overdrafts are short-term, usually renewed annually while loans are medium-term, typically lasting for 1-5 years. Moreover, overdrafts tend to be more readily available for SMEs while banks conduct monitoring in term loan agreements. Another reason relates to the different determinants of rejections for overdrafts and loans (Armstrong et al., 2013). Since the probability of rejection will straightforwardly influence psychic application costs, one of the important factors determining the scale of discouragement (Kon and Storey, 2003), the determinants of overdraft discouragement might differ from those of loans.

This chapter relates to three strands of the literature. First, previous studies which evaluate the effectiveness of UK government initiatives observe its benefits on the alleviation of SME credit constraints (Cowling, 2010), the improvement in SME post-loan performance (Cowling and Siepel, 2013), and the growth of the UK economy (Allinson et al., 2013). As far as we know, only Fraser (2014) analyses its effect (via awareness) on 'latent' demand and concludes that, using awareness of government initiatives, one is unable to distinguish discouraged borrowers from applicants, possibly because only two-years of data are available for his study. We use a richer data set providing four years of data for overdrafts and five years of data for loans[24] to check whether raising the awareness of EFGS could reduce firms' application costs, especially their psychic costs, and lower the discouragement levels.

Second, this chapter also offers novel insights into studies on financial literacy. Its effects on SMEs capital structure (Delić et al., 2016), loan repayment capability (Mutegi et al., 2015) and firm performance (Eniola and Entebang, 2016) have already been explored. Financial literacy is found to have no bearing on discouragement for UK SMEs (Rostamkalaei, 2017). We provide some insights that financial literacy can have opposite effects on good and bad borrowers, perhaps explaining the insignificance found by Rostamkalaei (2017). As far as we know, this has not been previously investigated.

In addition, the extant literature on discouragement predominantly investigates the scale and the determinants of discouraged borrowers and whether discouragement is an efficient self-rationing mechanism before application. Only a small number of researchers addresses the 'how' question: how to bring discouraged borrowers, or good discouraged borrowers, back to borrowing? Han et al. (2009) demonstrate that, in the US market, a longer-term

[24] The data set we use in this chapter provides data on overdraft discouragement since 2012Q4 and loan discouragement since 2011Q3. Therefore, we can access one more year of data for loans. See more descriptions of the data set in Section 3.5.1.

relationship with banks could encourage good borrowers and discourage bad borrowers, bringing back the creditworthy borrowers. However, the relationship length is shown to have no effect on discouragement in the UK market (Fraser, 2009). A recent study by Fraser (2014) puts forward several recommendations for encouraging more UK SMEs to apply, mainly on the basis of his in-depth interviews with discouraged businesses. For example, banks are recommended to take actions to raise the awareness of the appeal process, in which refused SMEs can have their applications reassessed and banks may change the initial decisions from rejections to approvals. To fill in this gap, we offer a contribution by performing empirical analysis to check if raising the awareness of EFGS and improving financial literacy could play such a role in the UK bank credit market.

We use firm-level survey data drawn from the UK SME Finance Monitor during 2011-2015 and employ a trivariate probit model with sample selection (Cappellari and Jenkins 2004, 2006) to deal with the potential endogeneity problems and selection bias. Our main findings are that financially literate SMEs are more likely to be aware of EFGS and aware SMEs are less likely to be discouraged. We also find some similar determinants of bank debt discouragement. For both overdrafts and loans, younger and riskier SMEs with older owners and past business improvement are more likely to be discouraged, while profitable businesses receiving proactive approaches from banks are more likely to apply. An in-depth analysis by low- versus high-risk businesses indicates that raising awareness of government initiatives could bring all borrowers back to the overdraft market, but only high-risk borrowers back to the loan market. As high risk-high growth businesses (i.e. innovative SMEs) are often informationally opaque for credit suppliers and seek other financing sources (e.g. peer-to-peer lending), raising awareness might encourage them to take out loans, creating more financing opportunities for these potentially high-growth firms. Further, our results also imply that improving financial literacy could reduce loan discouragement among low-risk borrowers and increase loan discouragement among high-risk borrowers, thus making discouragement an efficient self-rationing mechanism before loan applications.

The rest of this chapter is organised as follows. Section 3.2 provides a review of the theoretical background and empirical evidence of discouragement. Section 3.3 sets out our research hypotheses. Sections 3.4 explains the methodology. Section 3.5 describes the data and the variables employed in the regression models. It also presents some trends in the data and descriptive statistics. The empirical results are discussed in Sections 3.6. Finally, Section 3.7 concludes and provides a discussion of the main related policy issues.

3.2 Literature Review

3.2.1 Theoretical Background on Small Businesses' Discouragement

The Kon and Storey (2003) seminal theoretical study extends the general adverse selection model and develops a framework for understanding the existence of discouragement. Specifically, they define a discouraged borrower as a good (creditworthy) borrower who does not apply for a bank loan for fear of rejection. The intuition behind their model is that a good firm will apply for a bank loan only if the net expected return of this application exceeds the expected return of non-application. Based on a few assumptions, it turns out that the investment return needs to be higher than the "effective borrowing cost". This is the sum of the interest payment charged by the bank, the opportunity cost and the effective application cost. To be clear, the effective application cost depends on the fixed application cost, covering financial, in-kind and psychic costs, and misclassification probability (i.e. the probability that the bank perceives this good/creditworthy firm as a bad/uncreditworthy firm). Therefore, discouragement appears when the effective borrowing cost is too high and/or cannot be compensated for by the investment opportunity. In this sense, the extent of the discouragement is determined by banks' screening errors, the application costs and the difference between the interest rates charged by the banks and other financing alternatives.

Information asymmetry lies at the heart of the theory (Cowling, Liu, Minniti and Zhang, 2016) since it impacts on both screening errors and application costs. Considering the worst case of imperfect information, banks have no information about firms, which means they will make decisions randomly and issue loans by lottery. Therefore, firms will put little effort into preparing their applications, resulting in a lower level of borrowing cost and leading to a relatively small scale of discouragement. When banks have some information, they will use this to develop their screening techniques and require firms to provide better data, increasing firms' application costs and further enhancing the discouragement scale. However, under perfect information, good firms are informed that their applications will not be rejected and thus no discouragement would exist. "Discouragement is therefore at a maximum where there is some, but not perfect, information" (Kon and Storey, 2003, p.47). In addition, if the application cost becomes zero, firms would be able to apply for loans repeatedly at no cost, regardless of the screening error. In this case, both application cost and screening error will have no impact on discouragement. It only depends on the spread of different interest rates charged by financial institutions.

3.2.2 Empirical Studies

Although Kon and Storey (2003) provide a solid theoretical foundation for research on discouraged small businesses, the problem encountered in empirical studies is good borrowers cannot be distinguished from bad borrowers because of the counter-factual "creditworthiness" that their application would be approved had they applied. Due to this limitation, almost all empirical studies extend the definition of discouraged borrowers to firms that need bank credit but choose not to apply because they fear their application would be rejected, irrespective of their creditworthiness. In general, the empirical literature tries to answer the following three questions. (1) What is the scale and trend of discouragement among small businesses? (2) What factors could be the determinants of discouragement? (3) Is discouragement a self-rationing mechanism before application? (Or are discouraged firms riskier than refused firms?)

Levenson and Willard (2000) were the first to highlight the importance of discouragement in research on credit rationing. 4.22% of US small businesses are estimated to be discouraged in 1988-1989, almost twice the number of refused firms. The predominance of discouraged small businesses in the US still prevails in 1990-1993, 1995-1998 and 2000-2003 (Cole and Sokolyk 2016). A similar ratio of discouraged small businesses over refused businesses is also found in the 2005 UK market and is even more prevalent for SMEs in knowledge-intensive services (Freel et al. 2012). These findings point to the suggestions that policy interventions should pay attention to the latent demand for bank debt and make an effort to bring discouraged firms back to bank lending markets. Despite the evidence that the discouragement level among UK SMEs is quite low in stable economic periods, Cowling, Liu, Minniti and Zhang (2016) discover it grew during the most recent financial crisis, especially at the beginning of the crisis. A recent study of Rostamkalaei (2017) shows an inverted U-shape for the discouragement rate in the wake of the crisis, where a significant decline occurs in 2013, revealing that the fall of discouragement level lags behind improvements in bank lending credit since 2010. Hence, her findings reveal a slower recovery of perceptions among SME entrepreneurs than the recovery of the UK economy.

Several factors having potential effects on discouragement have been investigated, such as firm and entrepreneur characteristics as well as bank relationships. In general, there has been little consensus in the empirical literature regarding what a discouraged borrower should look like. For example, some studies focusing on US small businesses (Han et al. 2009; Cole and Sokolyk 2016) find that businesses with an older owner/manager are less likely to be discouraged whereas other studies focusing on UK SMEs (Freel et al. 2012; Rostamkalaei 2017) find no significant effect. Mixed empirical results can often be found in studies using data in different countries and different time periods. We observe that a typical discouraged borrowing firm is likely to be smaller[25] (e.g. see Chakravarty and Xiang 2013), less profitable (e.g. see Mac an Bhaird et al. 2016), have a poorer credit history (e.g. see Fraser 2009), be owned by entrepreneurs from a minority ethnic group[26] (e.g. see Blanchflower et al. 2003) and rely on a lower personal wealth (e.g. see Chakravarty and Yilmazer 2009). Lee and Brown (2017) also argue that innovative UK SMEs are more likely to be discouraged, especially those innovative SMEs located in 'peripheral' areas.[27] However, no effect of innovation is found in the research of Cowling, Liu, Minniti and Zhang (2016) and Rostamkalaei (2017) which also focus on UK SMEs.

Bank relationships are expected to mitigate the information asymmetry and further reduce the screening errors, leading to a lower level of discouragement.[28] However, the empirical evidence on this is also mixed. A firm self-reported better relationship has been shown to lower the discouragement level (Freel et al. 2012; Cowling, Liu, Minniti and Zhang 2016) whereas relationship duration has been shown to have no bearing at all (Fraser 2009;

[25] From a theoretical perspective, smaller firms are faced with higher application costs and thus are more likely to be discouraged. This hypothesis has been supported by most empirical studies, with the exception of Fraser (2009) and Lee and Brown (2017) in which no significant effect could be observed.

[26] Minority ethnic owners/managers potentially suffer an additional psychic application cost caused by perceived ethnic discrimination in the bank credit market and thus are more likely to be discouraged. It has been proven in the US market (Blanchflower et al., 2003) and the UK market (Fraser, 2009). However, the perception of ethnic discrimination is shown to be true in the US but should be misperceptions in the UK since after controlling other risk characteristics, minority ethnic owned SMEs are not more likely to be rejected when they apply for bank debts (i.e. no discrimination).

[27] The peripheral areas are measured by multimodal accessibility index and mainly located in South West England, Northern Scotland, the Islands and North Wales.

[28] Due to the fast development of lending techniques based on hard information (e.g. credit scoring model), the information required to submit for applications is quite standardised now. Therefore, when banking relationships reduce the information asymmetry between banks and borrowers, the resulting decline of screening error is believed to outweigh the resulting increase in application costs.

Chakravarty and Xiang 2013). Charavarty and Yilmazer (2009) develop a multi-stage model for the loan granting process and explore the possible different roles of relationships at different stages. They find multiple credit sources (i.e. less concentrated relationships) have a positive effect on firm application decisions but have a negative effect on credit availability. However, they have no impact on the interest rate charged by banks after banks decide to grant loans. Evidence of the significant role of concentrated relationships for discouragement is found in some US studies (Han et al., 2009; Cole and Sokolyk, 2016) but disappears when Fraser (2009) includes financial delinquencies as explanatory variables. It is also found to be insignificant in more recent UK investigations (Fraser, 2014; Rostamkalaei, 2017).

Since good borrowers cannot be distinguished from bad borrowers, whether the discouraged small businesses are creditworthy becomes an important issue. If they are riskier than refused firms, they would be rejected had they applied. In this case, it is rational for discouraged firms not to apply and discouragement acts as an efficient self-rationing mechanism before application. However, if discouraged borrowers are much less risky than refused firms, or even more reliable than approved firms, their applications would be successful had they applied. Given the prevalence of discouragement, many firms are credit constrained, and actions should be taken by the government to mitigate the 'latent' constraints faced by discouraged borrowers, which would promote the growth and expansion of these firms and further stimulate the development of the whole economy.

Han et al. (2009) firstly investigate this issue and use the Dun and Bradstreet credit score as a proxy for creditworthiness. They illustrate the efficiency of the self-rationing mechanism in the US market, especially in a more concentrated market. They also point out that a longer relationship could improve the efficiency of discouragement since it prompts good borrowers to be more encouraged and bad borrowers more discouraged.

Using the same dataset, Cole and Sokolyk (2016) estimate that between 21% and 55% of discouraged small businesses would not be rejected had they applied. The Cowling, Liu, Minniti and Zhang (2016) study employs firm size and growth performance as proxies for riskiness and validates this in the UK market. 55.6% of discouraged SMEs are estimated to be able to access bank credit successfully if they had applied. However, the research of Charkravarty and Xiang (2013) reports a less efficient self-rationing mechanism in developing countries. They use the 2002-2003 data for small businesses in 10 emerging economies spanning 4 continents, where adverse selection issues are believed to be more severe than in developed countries. Good borrowers are also found to be more likely to be discouraged, especially in those relatively underdeveloped countries.

In summary, based on the Kon and Storey (2003) theoretical model, the empirical studies on discouraged borrowers mainly evaluate their prevalence and trend, explore their typical characteristics and examine whether they should be discouraged or not. Among UK SMEs, the number of discouraged borrowers is almost double the number of refused firms (Freel et al., 2012) and more than half of them would not be rejected if they applied for bank debt (Cowling, Liu, Minniti and Zhang, 2016). These findings point to the need for more investigations on how to bring these discouraged borrowers back to borrowing, which is still underexplored.

3.3 Hypothesis Development

In this section, we set out several hypotheses on the relationship between discouragement, financial literacy and EFGS awareness. Financial literate SMEs refer to the firms with owners or managers who are able to "manage and strategise financial knowledge" (Eniola and Entebang, 2016). These firms have better access to new knowledge and are better informed on business financial management (Lusardi and Mitchell, 2014; Sabri et al., 2015). They also tend to navigate the financial markets more frequently (Beal and Delpachitra, 2003) and collect financial information and notice opportunities in a timely fashion (Hussain et al., 2018). Relative to SMEs with no (or poor) financial literacy, they have better ability to analyse, interpret and evaluate the new information (Agarwalla et al., 2015). This leads to our first hypothesis:

> ***H1:*** *Financially literate SMEs are more likely to be aware of the Enterprise Finance Guarantee Scheme.*

The UK EFGS can provide an up to 75% guarantee to banks. Hence, SMEs do not have to provide all the collateral by themselves, reducing their financial costs. Moreover, informed SMEs do not have to endure the psychic cost brought by the perceptions that the bank will require collateral they are not able to afford or provide. As explained in the Kon and Storey (2003) model, reduced fixed application costs (financial and psychic costs here) decrease effective application costs and further result in lower discouragement levels. Therefore, SMEs aware of EFGS are believed to have lower application costs and less likely to be discouraged borrowers. Considering these, we propose our second hypothesis:

> ***H2:*** *SMEs aware of the Enterprise Finance Guarantee Scheme are less likely to be discouraged from applying for bank debt (both overdrafts and loans).*

A higher financial literacy level can drive firms to keep detailed financial records (Kidwell and Turrisi, 2004) and offer required documents in a timely fashion during their bank debt application process (Van Auken and Carraher, 2013). Thus, they are less likely to be rejected and have lower psychic costs before application. Meantime, the reduced information asymmetry by tracked financial records can also reduce misclassification probability. Moreover, financially literate SMEs are more involved in the financial markets (Lusardi and Michell, 2006), have more diversified financing sources (Marcolin and Abraham, 2006) and tend to use various financial products (Hastings et al., 2013). The perception that they can seek funding from other sources if their bank debt applications are rejected also lowers their psychic costs. Additionally, financially literate SMEs have been trained on how to deal with financial information (Eniola and Entebang, 2016), which makes them better at handling application forms and have lower application costs. Given the above discussions, financial literacy can have a negative effect on discouragement.

However, the effect of financial literacy on discouraged borrowers might differ among low- and high-risk SMEs. This is because financially literate SMEs can make more precise evaluations of their risk profiles and more accurate evaluations of their business plans (Hussain et al., 2018; Ye and Kulathunga, 2019). In this sense, for low- (high-) risk borrowers, a higher level of financial literacy will encourage (discourage) them to apply since they know the likelihood of rejection is relatively low (high) if they applied. It indicates a negative (positive) effect of financial literacy on discouragement for low- (high-) risk borrowers. Hence, the last hypothesis can be formulated as follows:

> ***H3:*** *Low- (high-) risk SMEs with financial literacy are less (more) likely to be discouraged from borrowing.*

3.4 Methodology

This chapter seeks to explore the relationship between EFGS awareness, financial literacy and discouragement. Two problems have to be taken into account when we construct the econometric model. First, when testing ***H2***, EFGS awareness might be an endogenous variable for discouragement. This is because there might be a correlation between unobservable factors underlying these two variables, such as the talent of owners/managers. The idea is that less talented owners/managers might have fewer resources and be less likely to be aware of government initiatives, but more likely to suffer unpleasant credit outcomes and thus be unwilling to apply for bank debt. Second, there is a potential sample selection bias when modelling discouragement. By definition, whether an SME is discouraged from borrowing can only be observed if it has a demand for bank lending (see Figure 1.2 in Chapter 1). In this case, a single model (only considering firms with demand) could lead to inconsistent estimated coefficients and misleading inferences (Cappellari and Jenkins, 2006).

In order to examine the three hypotheses discussed above, we utilise three dependent variables: awareness (A), demand (D) and discouragement (K). A equals one if the firm is aware of EFGS and zero otherwise. D equals one if the firm has a demand for bank debt and zero otherwise. K equals one if the firm has a demand but does not apply for bank debt for fear of rejection and zero otherwise. Since these three dependent variables are all dichotomous variables following a Bernoulli distribution, we employ the trivariate probit model with sample selection (Cappellari and Jenkins 2004, 2006) to deal with the potential problems. More specifically, we construct the following equations for each observation:

$$A^* = X'\beta + a, where\ A = I(A^* > 0) \tag{3.1}$$

$$D^* = Y'\delta + d, where\ D = I(D^* > 0) \tag{3.2}$$

$$K^* = Z'\theta + k, where\ K = I(K^* > 0)\ if\ D = 1 \tag{3.3}$$

$$and\ is\ missing\ if\ D = 0$$

where the variables with asterisks represent the latent variables and $I(.)$ is the indicator function equal to 1 if the argument in the bracket is true and 0 otherwise. X, $Y$and Z denote covariate vectors, β, δ and θ denote the unknown parameter vectors to be estimated and a, d and k are error terms. We assume that the error term $(a, d, k) \sim N_3(0, V)$, where V is a symmetric matrix with $\rho_{rs} = \rho_{sr}$ for $r, s \in \{a, d, k\}$ and $r \neq s$, and $\rho_{rr} = 1$, for all r. The statistical significance of ρ_{ak} indicates the existence of an endogeneity problem of awareness and the statistical significance of ρ_{dk} indicates the existence of sample selection bias in the data. Another assumption is the error term is orthogonal to the independent variables in each equation.

We employ maximum likelihood estimation to obtain the estimated coefficients in the model. The likelihood contribution for each observation differs in two scenarios. When D=0 and K is missing (the firm has no demand for bank debt), its likelihood contribution is:

$$\Pr(D = 0;\ A = 0) = \Phi_2\left(-Y^{'}\ \delta, -X^{'}\ \beta, \rho_{ad}\right) \tag{3.4}$$

$$\Pr(D = 0;\ A = 1) = \Phi_2\left(-Y^{'}\ \delta, X^{'}\ \beta, -\ \rho_{ad}\right) \tag{3.5}$$

where $\Phi_2(.)$ denotes the c.d.f. of a standard bivariate normal distribution. When D=1 and K is not missing (the firm has a demand for bank debt), its likelihood contribution is

$$\Pr(D = 1;\ A = 0;\ K = 0) = \Phi_3\left(Y^{'}\delta, -X^{'}\beta, -Z^{'}\theta, -\rho_{ad}, \rho_{ak}, -\rho_{dk}\right) \quad (3.6)$$

$$\Pr(D = 1;\ A = 0;\ K = 1) = \Phi_3\left(Y^{'}\delta, -X^{'}\beta, Z^{'}\theta, -\rho_{ad}, -\rho_{ak}, \rho_{dk}\right) \quad (3.7)$$

$$\Pr(D = 1;\ A = 1;\ K = 0) = \Phi_3\left(Y^{'}\delta, X^{'}\beta, -Z^{'}\theta, \rho_{ad}, -\rho_{ak}, -\rho_{dk}\right) \quad (3.8)$$

$$\Pr(D = 1;\ A = 1;\ K = 1) = \Phi_3\left(Y^{'}\delta, X^{'}\beta, Z^{'}\theta, \rho_{ad}, \rho_{ak}, \rho_{dk}\right) \quad (3.9)$$

where $\Phi_3(.)$ denotes the c.d.f. of a standard trivariate normal distribution. If a set of sign variables are defined in the way $\kappa_T = 2T - 1$ for $T \in \{A, D, K\}$, the likelihood contribution for each observation with $D = 0$ can be written as:

$$L_2 = \Phi_2\left(\kappa_D Y^{'}\delta, \kappa_A X^{'}\beta, \kappa_A \kappa_D \rho_{ad}\right) \quad (3.10)$$

and the likelihood contribution for each observation with $D = 1$ can be written as:

$$L_3 = \Phi_3\left(\kappa_D Y^{'}\delta, \kappa_A X^{'}\beta, \kappa_K Z^{'}\theta, \kappa_A \kappa_D \rho_{ad}, \kappa_A \kappa_K \rho_{ak}, \kappa_D \kappa_K \rho_{dk}\right) \quad (3.11)$$

Therefore, the log-likelihood contribution for each observation is

$$lnL = (1 - D)lnL_2 + DlnL_3 \quad (3.12)$$

The estimation is implemented by the Stata ‘cmp’ command written by Roodman (2011). For identification purposes, we have to find at least one covariate significant in equation (3.1) and (3.2), but insignificant in equation (3.3). That is to say, the covariate used as exclusion criterion is required to have an effect on EFGS awareness and bank debt demand but no effect on discouragement.

3.5 Data and Variable Description

3.5.1 Dataset

The dataset used in this chapter is drawn from the Small and Medium-Sized Enterprise Finance Monitor (SMEFM) accessed from the UK Data Archive (BDRC Continental, 2018), the same data source as in Chapter 2. As discouraged borrowers are defined as the firms which have a demand for bank debt but do not apply for fear of rejection (Han et al., 2009; Freel et al., 2012), the probability of rejection has a direct effect on the psychic application cost and will potentially determine the probability of discouragement. Hence, any factors affecting the probability of rejection may have a bearing on discouragement. The determinants of overdraft rejections are significantly different from those of loans for UK SMEs in the Armstrong et al. (2013) and Lee and Brown (2017) studies. This suggests the possibility that the determinants of overdraft discouragement may also differ from those of loans. In this sense, we consider both business overdrafts and term loans and analyse them separately, where overdraft (loan) discouraged borrowers are defined as the firms which need overdrafts (loans) but choose not to apply because they think their applications would be rejected.

The information on discouragement was collected from 2012 Q4 for overdrafts and 2011 Q3 for loans. From the survey carried out in 2016 Q1, the questions relevant to discouragement were combined for overdrafts and loans, which previously were asked separately. Since we cannot identify overdraft and loan discouraged borrowers accurately since 2016, we only use the data till 2015 Q4. Hence, 13 waves data are used for overdrafts and 18 waves for loans. Around 5,000 SMEs are interviewed in each wave. In total, there are 65,137 observations for overdrafts and 90,257 observations for loans. Excluding observations with missing values of discouragement and/or demand, our final overdraft sample includes 56,641 observations and our loan sample 85,862.

As depicted in Figure 1.2 in Chapter 1, first, we identify firms with demand (seekers) and without demand (non-seekers) in each sample. Then among debt seekers, we identify firms applying for bank debt (applicants) and discouraged from applying (discouraged borrowers). Overall, 6,275 (6,219) are overdraft (loan) seekers and 50,366 (79,643) are non-seekers. Among the overdraft (loan) seekers, 5,739 (5,365) are applicants and 536 (854) are discouraged borrowers, accounting for 0.9% (1.0%) in the whole overdraft (loan) sample. The ratio in the loan sample (1.0%) is lower than the ratios estimated in the previous studies: 2.65% by Cowling, Liu, Minniti and Zhang (2016) using survey data in 2008-2010 and 8.1% by Freel et al. (2012) using survey data in 2005. One possible reason is that the government has launched several initiatives to stimulate bank lending to SMEs in the most recent years (Calabrese et al., 2017), which reduced the discouragement level sharply. In addition, in our loan sample, the ratio of discouraged borrowers over refused firms (0.76=854/1131) is much higher than the ratio in the Cowling, Liu, Minniti and Zhang (2016) study (0.38=82/218), emphasising the importance of considering discouragement when assessing the 'true' extent of credit rationing among UK SMEs in recent years.

3.5.2 Trends in the Data

The discouragement rate is defined as the proportion of discouraged borrowers to debt seekers. Table 3.1 displays the trends of discouragement rates during 2011-2015 for both business overdrafts and term loans. Since the data for overdraft discouragement was first collected in 2012, the discouragement rate in 2011 can only be observed for term loans. Some 8.54% (13.73%) firms are discouraged from applying for overdrafts (loans) even if they have a demand.

The rate is significantly higher for loans relative to overdrafts in every year, possibly because of the higher costs of loan applications (higher margins, higher arrangement fees

Table 3.1 Business Overdrafts and Term Loans Discouragement Rates by Sub-Periods During 2011-2015

Survey year	Overdraft Discouraged Borrowers (%)	Loan Discouraged Borrowers (%)	Difference (%)	t-statistics
All	8.54	13.73	-5.19	-9.2557***
2011		11.51		
2012	11.41	17.95	-6.53	-3.5981***
2013	10.38	16.82	-6.44	-5.5141***
2014	7.89	11.05	-3.16	-3.0172***
2015	5.82	9.19	-3.37	-3.4182***

Notes: This table reports the discouragement rates in each year from 2011 to 2015. Percentages are calculated out of SMEs which have a demand for overdrafts/loans. The data used for business overdrafts cover 2012Q4-2015Q4 while the data used for term loans cover 2011Q3-2015Q4. Therefore, the discouragement rate in 2011 can only be observed for term loans. *** indicates that the difference between overdraft and loan discouragement rate is significant at 1% significance level.

and higher incidence of collateral requirement) (Armstrong et al., 2013). As for trends, fewer and fewer borrowers are discouraged from applying for overdrafts in 2012-2015, and the discouragement rate in 2015 is almost half of that in 2012. For term loans, it goes up at the beginning, stays at a high level at 2013 and then a downward trend can be observed in the following years, consistent with the inverted U-shape found by Rostamkalaei (2017). This may be attributable to the introduction of the capital reduction factor (SME Supporting Factor) in 2014, which was launched to facilitate banks to increase credit to SMEs. This may reduce the psychic application cost and further reduce the discouragement level.

The proxy for financial literacy used is whether the financial manager has a finance qualification or has undertaken some financial training. A general relationship between EFGS awareness, financial literacy and discouragement are illustrated in Table 3.2, Table 3.3 and Table 3.4. Almost 33% of financially literate SMEs are aware of EFGS, 11.5% higher than the percentage among SMEs with no financial literacy. This indicates that financially literate SMEs are more likely to be aware of EFGS, providing preliminary support to ***H1***. As for discouragement rate, 6.61% (10.54%) SMEs aware of EFGS are

Table 3.2 Awareness of Enterprise Finance Guarantee Scheme by Financial Literacy

	Awareness (%)
All[a]	25.93
Financial literacy	32.67
No financial literacy	21.17
Difference	11.50
t-statistic	37.6235***

Notes: This table reports the difference of awareness rates between SMEs with and without financial literacy. Percentages are calculated out of SMEs which have no missing values for financial literacy during 2011Q3-2015Q4. [a]: If we include firms which have missing values for financial literacy, the percentage of SMEs aware of EFGS will become 25.68%. *** indicates that the difference in EFGS awareness between SMEs with and without financial literacy is significant at 1% significance level.

Table 3.3 Business Overdrafts and Term Loans Discouragement Rates by Awareness of Enterprise Finance Guarantee Scheme (EFGS)

	Overdrafts Discouraged Borrowers (%)	Loans Discouraged Borrowers (%)
All	8.54	13.75[a]
Aware of EFGS	6.61	10.54
Unaware of EFGS	9.41	15.31
Difference	-2.80	-4.77
t-statistic	-3.6851***	5.1204***

Notes: This table reports the difference of discouragement rates between SMEs aware and unaware of EFGS. Percentages are calculated out of SMEs which have a demand for overdrafts/loans with no missing values for EFGS awareness. The data used for business overdrafts cover 2012Q4-2015Q4 while the data used for term loans cover 2011Q3-2015Q4. [a]: If we include firms which have missing values for EFGS awareness, the discouragement rate will become 13.73%, as shown in Table 3.1. *** indicates that the difference in discouragement rate between SMEs aware and unaware of EFGS is significant at 1% significance level.

Table 3.4 Business Overdrafts and Term Loans Discouragement Rates by Financial Literacy

	Overdraft Discouraged Borrowers (%)	Loan Discouraged Borrowers (%)
Panel A: All SMEs	8.56[a]	13.81[a]
Financial literacy	6.03	10.40
No financial literacy	10.36	16.48
Difference	-4.32	-6.07
t-statistic	-5.9875***	-6.8551***
Panel B: Low-risk SMEs (minimal, low and average risk)	4.89	8.71
Financial literacy	3.04	6.06
No financial literacy	6.45	11.17
Difference	-3.41	-5.11
t-statistic	-5.0246***	-5.7120***
Panel C: High-risk SMEs (above average risk)	14.90	24.50
Financial literacy	13.26	22.31
No financial literacy	15.75	25.76
Difference	-2.49	-3.45
t-statistic	-1.3235	-1.5709

Notes: This table reports the difference of discouragement rates between SMEs with and without financial literacy. Panel A shows the difference in all SMEs while Panel B and C show the difference in low-risk and high-risk SMEs respectively. Percentages are calculated out of SMEs which have a demand for overdrafts/loans with no missing values for financial literacy. The data used for business overdrafts cover 2012Q4-2015Q4 while the data used for term loans cover 2011Q3-2015Q4. [a]: If we include firms which have missing values for financial literacy, the discouragement rate will become 8.54% for overdrafts and 13.73% for loans, as shown in Table 3.1. *** indicates that the difference in discouragement rate between SMEs with and without financial literacy is significant at 1% significance level.

discouraged from applying for overdrafts (loans), around 3% (5%) lower than the discouragement rate for SMEs unaware of EFGS. EFGS awareness shows a potential positive effect on reducing discouragement level (***H2***), which seems to be stronger for term loans. This could be explained by the design of EFGS in which the targeted SMEs are those without sufficient collateral. After the financial crisis, banks are more likely to impose collateral requirements on loans, relative to overdrafts, to offset losses in the event of default (Armstrong et al., 2013). Loan-seekers suffer higher application costs (related to collateral) and therefore, EFGS awareness has a stronger effect on reducing loan discouragement.

A similar result is also found for financial literacy where 6.03% (10.40%) of financially literate SMEs are overdraft (loan) discouraged borrowers, around 4% (6%) lower than the ratio for SMEs with no financial literacy. However, for both overdrafts and loans, the difference in discouragement rate between SMEs with and without financial literacy is only significant among low-risk borrowers (minimal, low and average risk rating from Dun & Bradstreet), providing some evidence to support ***H3a***.

3.5.3 Control Variables

Table 3.5 provides the definitions of all control variables included in equations (3.1), (3.2) and (3.3). Inspired by Han et al. (2009) and in order to test ***H3***, we use the Dun & Bradstreet external credit risk rating to identify low-risk (creditworthy) and high-risk (uncreditworthy) borrowers. Following the main literature on the determinants of SMEs' discouragement (e.g. Freel et al., 2012; Cowling, Liu, Minniti and Zhang, 2016), the control variables can be broadly separated into four groups: firm characteristics, owner/manager characteristics, bank relationships and/or products, and time indicators.

Table 3.5 List of Variables and Their Definitions

Variable	Description
Dependent variables	
Discouragement	A dummy variable which equals 1 if the firm has a demand but does not apply for bank debt for fear of rejection and 0 otherwise.
Demand	A dummy variable which equals 1 if the firm has a demand for bank debt and 0 otherwise
Awareness	A dummy variable which equals 1 if the firm is aware of Enterprise Finance Guarantee Scheme and 0 otherwise
Independent variables	
Financial literacy	A dummy variable which equals 1 if the person in charge of financial management within the firm has a finance qualification or has undertaken some financial trainings and 0 otherwise.
D&B risk rating	Dummy variables indicating the external credit risk rating from Dun & Bradstreet of the firm: ‘minimal’, ‘low’, ‘average’ and ‘above average’.
Firm characteristics	
Number of employees	Dummy variables indicating the number of people working in the firm: ‘0’, ‘1-9’, ’10-49’ and ’50-249’.
Business age	Dummy variables indicating the number of years since the firm was established: ‘<2 years’, ‘2-5 years’, ‘6-9 years’, ’10-15 years’ and ‘>15 years’.
Standard region	Dummy variables indicating the location of the firm in the UK: ‘Scotland’, ‘East Anglia’, ‘East Midlands’, ‘North West’, ‘North/North East’, ‘Northern Ireland’, ‘London’, ‘South East’, ‘South West’, ‘Wales’, ‘West Midlands’ and ‘Yorkshire/Humberside’.
Industry sector	Dummy variables indicating the principal activity of the firm: ‘agriculture, hunting and forestry fishing’, ‘construction’, ‘health and social work’, ‘hotels and restaurants’, ‘manufacturing’, ‘real estate, renting and business activities’, ‘transport, storage and communication’, ‘wholesale/retail’ and ‘other community, social and personal service’
Legal status	Dummy variables indicating the legal status of the firm: ‘sole proprietorship’, ‘partnership’, ’limited liability partnership (LLP)’ and ‘limited liability company (LLC)’.
Profitability	Dummy variables indicating whether the firm made a net profit or loss: ‘loss’, ‘broken even’ and ‘profit’.
Growth orientation	Dummy variables indicating the plan for business turnover over the next year: ‘grow substantially’, ‘grow moderately’, ‘stay the same size’, ‘become smaller’ and ‘exit’
Business plan	A dummy variable which equals 1 if the firm has a formal written business plan and 0 otherwise.
Export	A dummy variable which equals 1 if the firm sells goods or services abroad and 0 otherwise.
Import	A dummy variable which equals 1 if the firm buys goods or services from abroad and 0 otherwise.
Management account	A dummy variable which equals 1 if the firm produces regular monthly or quarterly management accounts and 0 otherwise.
Business Improvement	A dummy variable which equals 1 if the firm has significantly improved an aspect of the firm in the past 3 years and 0 otherwise.
Innovation	A dummy variable which equals 1 if the firm has developed a new product or service in the past 3 years and 0 otherwise.
Business account	A dummy variable which equals 1 if the main current account used for the business is a business account and 0 otherwise.
Owner/Manager characteristics	
Gender	Dummy variables indicating the gender of the owner//manager: ‘male’, ‘female’ and ‘both (joint partners)’.
Owner Age	Dummy variables indicating the age of the owner/manager: ’18-30 years’, ’31-50 years’, ’51-65 years’ and ‘>66 years’.

(continued)

Table 3.5 Continued

Variable	Description
Bank relationships and/or products	
Multiple suppliers	A dummy variable which equals 1 if the firm approached more than one bank or financial institution when the firm did its most business and 0 otherwise.
Use of credit card	A dummy variable which equals 1 if the firm uses credit card currently and 0 otherwise.
Credit card application	Dummy variables indicating the experience of credit card application in the previous 12 months: 'not applied', 'unsuccessful' and 'successful'.
Proactive approach	A dummy variable which equals 1 if the firm was approached proactively by the main bank or another bank to indicate that the bank would be willing to lend to the firm, if the firm wanted to borrow in the previous 3 months and 0 otherwise
Time indicators	
Wave[a]	Dummy variables indicating the survey wave: 'wave 2', 'wave 3', 'wave 4', 'wave 5', 'wave 6', 'wave 7', 'wave 8', 'wave 9', 'wave 10', 'wave 11', 'wave 12', 'wave 13', 'wave 14', 'wave 15', 'wave 16', 'wave 17', 'wave 18' and 'wave 19'.

Notes: This table reports the definitions of the dependent variables and the independent variables used in the regressions. [a]: Since the information of overdraft discouragement was first collected in wave 7, 'wave 2', 'wave 3', 'wave 4', 'wave 5' and 'wave 6' are not included in the model for overdrafts.

Firm characteristics consist of demography, profitability, growth orientation, business activities and type of account. Demographic information includes size, age, region, industry and legal status. We use the number of employees as the proxy for firm size (Freel et al., 2012; Cowling, Liu, Minniti and Zhang, 2016). Profitability is defined as whether the firm made a net profit or loss in the last year, and growth orientation is defined as whether the firm plans to expand or shrink its turnover over the next year. Business activities include information about the presence of a business plan, internationalisation (import and export activities), management competency, business improvement and innovation. Similar to the Cole and Sokolyk (2016) study that employs a variable indicating whether a firm uses personal or business credit card, we control for whether the main current account used for the business is a business or personal account.

Owner/Manager characteristics include gender and age. Since Watson (2002) and Watson and McNaughton (2007) reveal a more risk-averse attitude for females towards selecting conservative projects or low-risk business plans, we employ gender to examine whether females are more likely to be discouraged from applying for bank debt, including male, female and joint partners. Owner age includes four dummy variables, partially representing the experience (Rostamkalaei, 2017) and venture ambition (Vos et al., 2007) of owners/managers.

As for the intensity of bank relationship measures related to information asymmetry, we use the number of finance providers as the proxy for financial concentration (Fraser, 2009; Chakravarty and Yilmazer, 2009). Following Petersen and Rajan (2002) and Han et al. (2009), we include the extent of credit card usage to test whether it will enhance transparency. In addition, we analyse whether the success or failure of credit card applications will impact the discouragement rate of bank debt. And in line with Fraser (2014), the role of proactive approaches from banks is also investigated. Finally, we add the survey wave as time controls as in Rostamkalaei (2017) that finds a significant relationship between time and the probability of discouragement.

3.5.4 Descriptive Statistics

Tables 3.6a and 3.6b report the descriptive statistics of the explanatory variables for overdrafts and loans, respectively. The statistics for all firms are shown in the first column, then non-seekers and seekers separately, as well as the differences in means and their corresponding t-test statistics. We also present the statistics for applicants and discouraged borrowers in a similar way to that for non-seekers and seekers.

The difference in means between seekers and non-seekers reveals that debt seekers tend to be bigger, riskier, more profitable, innovative, internationally active and led by females for both overdrafts and loans. They also tend to use business accounts, use credit cards and apply for credit cards in the previous year. Non-seekers are usually sole-traded and led by joint partners (males/females). They are more financially concentrated and have an unchanging plan for the next year’s turnover. However, overdraft seekers (not loan seekers)

Table 3.6a Descriptive Statistics and Difference in Means: Business Overdrafts

Variable	**All** (N=56641) Mean	**No Demand** (N=50366) Mean (a)	**Demand** (N=6275) Mean (b)	Difference (a-b)	t-statistic	**Applicants** (N=5739) Mean (c)	**Discouraged Borrowers** (N=536) Mean (d)	Difference (c-d)	t-statistic
Financial literacy[a]	0.4228	0.4238	0.4148	0.0090	1.3475	0.4262	0.2922	0.1340	5.9875***
D&B risk rating[a]									
Minimal	0.1878	0.1923	0.1522	0.0401	7.3304***	0.1614	0.0430	0.1184	6.6795***
Low	0.2721	0.2705	0.2850	-0.0145	-2.3263**	0.2984	0.1244	0.1739	7.8224***
Average	0.2670	0.2654	0.2797	-0.0143	-2.3126**	0.2797	0.2805	-0.0009	-0.0390
Above Average	0.2731	0.2718	0.2831	-0.0112	-1.8034*	0.2606	0.5520	-0.2914	-13.2629***
Firm characteristics									
Number of employees									
0	0.2049	0.2161	0.1149	0.1012	18.7867***	0.0965	0.3116	-0.2150	-15.1955***
1-9	0.3222	0.3162	0.3697	-0.0535	-8.5567***	0.3631	0.4403	-0.0772	-3.5424***
10-49	0.3178	0.3108	0.3739	-0.0631	-10.1289***	0.3908	0.1922	0.1987	9.1505***
50-249	0.1552	0.1569	0.1415	0.0154	3.1726***	0.1495	0.0560	0.0935	5.9573***
Business age									
<2 years	0.1043	0.1069	0.0838	0.0230	5.6304***	0.0653	0.2817	-0.2164	-17.7113***
2-5 years	0.1344	0.1365	0.1171	0.0194	4.2473***	0.1039	0.2593	-0.1555	-10.8021***
6-9 years	0.1190	0.1205	0.1073	0.0043	3.0472***	0.1084	0.0951	0.0132	0.9467
10-15 years	0.1614	0.1620	0.1565	0.0055	1.1248	0.1607	0.1119	0.0487	2.9703***
>15 years	0.4809	0.4741	0.5353	-0.0612	-9.1518***	0.5618	0.2519	0.3099	13.9675***
Legal status									
Sole proprietorship	0.2797	0.2895	0.2010	0.0886	14.7699***	0.1783	0.4440	-0.2658	-14.9416***
Partnership	0.0889	0.0823	0.1422	-0.0599	-15.7481***	0.1478	0.0821	0.0657	4.1689***
LLP	0.0468	0.0459	0.0540	-0.0081	-2.8793***	0.0563	0.0299	0.0264	2.5896***
LLC	0.5846	0.5823	0.6029	-0.0206	-3.1184***	0.6177	0.4440	0.1737	7.8964***
Profitability[a]									
Loss	0.0931	0.0862	0.1462	-0.0600	-15.0475***	0.1332	0.2871	-0.1539	-9.4357***
Broken even	0.0995	0.1025	0.0764	0.0261	6.3590***	0.0697	0.1485	-0.0788	-6.4018***
Profit	0.8074	0.8113	0.7774	0.0338	6.2429***	0.7971	0.5644	0.2327	12.1768***
Growth orientation									
Grow substantially	0.1072	0.1044	0.1300	-0.0256	-6.1929***	0.1241	0.1940	-0.0700	-4.6128***
Grow moderately	0.4369	0.4312	0.4824	-0.0512	-7.7158***	0.4875	0.4272	0.0603	2.6730***
Stay the same size	0.4005	0.4107	0.3187	0.0919	14.0384***	0.3210	0.2948	0.0262	1.2442
Become smaller	0.0240	0.0235	0.0280	-0.0046	-2.2258***	0.0284	0.0243	0.0041	0.5562
Exit	0.0314	0.0303	0.0408	-0.0105	-4.5030***	0.0390	0.0597	-0.0207	-2.3141**

(continued)

Table 3.6a Continued

Variable	All (N=56641)	No Demand (N=50366)	Demand (N=6275)	Difference (a-b)	t-statistic	Applicants (N=5739)	Discouraged Borrowers (N=536)	Difference (c-d)	t-statistic
	Mean	Mean (a)	Mean (b)			Mean (c)	Mean (d)		
Business plan	0.4724	0.4661	0.5227	-0.0566	-8.4682***	0.5299	0.4459	0.0839	3.7265***
Export	0.1502	0.1476	0.1712	-0.0235	-4.9172***	0.1741	0.1399	0.0341	2.0076**
Import	0.1683	0.1641	0.2022	-0.0382	-7.6210***	0.2075	0.1455	0.0620	3.4205***
Management account	0.6236	0.6152	0.6908	-0.0757	-11.6789***	0.7031	0.5597	0.1434	6.8941***
Improvement	0.4373	0.4240	0.5439	-0.1199	-18.1114***	0.5482	0.4981	0.0500	2.2252**
Innovation	0.2149	0.2101	0.2534	-0.0433	-7.8796***	0.2511	0.2780	-0.0269	-1.3691
Business account[a]	0.9336	0.9297	0.9644	-0.0347	-10.4090***	0.9745	0.8563	0.1182	14.3521***
Owner/Manager characteristics									
Gender									
Male	0.7897	0.7891	0.7939	-0.0048	-0.8799	0.7932	0.8022	-0.0091	-0.4964
Female	0.1864	0.1881	0.1732	0.0149	2.8496***	0.1727	0.1791	-0.0064	-0.3759
Both (joint partners)	0.0239	0.0228	0.0328	-0.0100	4 9199***	0.0342	0.0187	0.0155	1.9257*
Owner Age[a]									
18-30 years	0.0414	0.0431	0.0286	0.0145	5.3433***	0.0256	0.0608	-0.0353	-4.6441***
31-50 years	0.4567	0.4597	0.4325	0.0273	4.0343***	0.4224	0.5399	-0.1176	-5.2138***
51-65 years	0.4159	0.4126	0.4413	-0.0287	-4.2856***	0.4517	0.3308	0.1209	5.3503***
>66 years	0.0860	0.0846	0.0976	-0.0131	-3.4313***	0.1004	0.0684	0.0319	2.3586**
Bank relationships and/or products									
Multiple suppliers	0.0179	0.0151	0.0405	-0.0254	-14.3101***	0.0411	0.0336	0.0075	0.8470
Use of credit card[a]	0.2494	0.2271	0.4282	-0.2011	-35.0905***	0.4476	0.2201	0.2275	10.2626***
Credit card application									
Not applied	0.9500	0.9574	0.8907	0.0668	22.9933***	0.8890	0.9086	-0.0196	-1.3891
Unsuccessful	0.0044	0.0036	0.0102	-0.0066	-7.4468***	0.0099	0.0131	-0.0031	-0.6891
Successful	0.0456	0.0389	0.0991	-0.0602	-21.6393***	0.1011	0.0784	0.0227	1.6824*
Proactive approach	0.1614	0.1554	0.2094	-0.0540	-10.9715***	0.2225	0.0690	0.1535	8.3974***

Notes: This table reports the descriptive statistics of the independent variables in our overdraft sample. It also reports the difference in means between firms with and without demand and the difference in means between applicants and discouraged borrowers. The definitions of all variables are provided in Table 3.5. The data were collected from 2012Q4 to 2015Q4. [a]: The sample size is not identical due to the existence of missing values. *, **, *** indicate that the differences in means are significant at 10%, 5% and 1% level, respectively.

Table 3.6b Descriptive Statistics and Difference in Means: Term Loans

Variable	All (N=85862) Mean	No Demand (N=79643) Mean (a)	Demand (N=6219) Mean (b)	Difference (a-b)	t-statistic	Applicants (N=5365) Mean (c)	Discouraged Borrowers (N=854) Mean (d)	Difference (c-d)	t-statistic
Financial literacy[a]	0.4137	0.4118	0.4389	-0.0271	-4.1462***	0.4562	0.3306	0.1257	6.8551***
D&B risk rating[a]									
Minimal	0.1821	0.1847	0.1492	0.0356	6.6974***	0.1655	0.0423	0.1232	8.9145***
Low	0.2592	0.2583	0.2710	-0.0127	-2.1081**	0.2894	0.1508	0.1386	8.0266***
Average	0.2777	0.2770	0.2861	-0.0090	-1.4653	0.2885	0.2698	0.0187	1.0598
Above Average	0.2810	0.2800	0.2938	-0.0138	-2.2344**	0.2566	0.5370	-0.2805	-16.1194***
Firm characteristics									
Number of employees									
0	0.2019	0.2085	0.1179	0.0906	17.1718***	0.0919	0.2810	-0.1891	-16.2533***
1-9	0.3267	0.3251	0.3467	-0.0216	-3.4948***	0.3327	0.4344	-0.1017	-5.8159***
10-49	0.3191	0.3155	0.3650	-0.0495	-8.0647***	0.3849	0.2400	0.1449	8.2096***
50-249	0.1523	0.1509	0.1704	-0.0195	-4.1320***	0.1905	0.0445	0.1460	10.6323***
Business age									
<2 years	0.0988	0.0988	0.0997	-0 .0009	-0.2332	0.0792	0.2283	-0.1491	-13.7106***
2-5 years	0.1402	0.1406	0.1351	0.0055	1.2021	0.1159	0.2553	-0.1393	-11.1734***
6-9 years	0.1236	0.1238	0.1211	0.0027	0.6252	0.1187	0.1358	-0.0171	-1.4227
10-15 years	0.1606	0.1608	0.1585	0.0022	0.4568	0.1637	0.1265	0.0372	2.7649***
>15 years	0.4768	0.4761	0.4856	-0.0095	-1.4441	0.5225	0.2541	0.2684	14.8273***
Legal status									
Sole proprietorship	0.2841	0.2893	0.2187	0.0706	11.8937***	0.1868	0.4192	-0.2324	-15.5546***
Partnership	0.0950	0.0913	0.1421	-0.0509	-13.1902***	0.1527	0.0761	0.0765	5.9657***
LLP	0.0415	0.0407	0.0524	-0.0118	-4.4798***	0.0559	0.0304	0.0255	3.1042***
LLC	0.5794	0.5788	0.5868	-0.0079	-1.2220	0.6047	0.4742	0.1304	7.2179***
Profitability[a]									
Loss	0.1058	0.1013	0.1624	-0.0611	-14.7057***	0.1358	0.3321	-0.1963	-14.2456***
Broken even	0.1024	0.1045	0.0766	0.0279	6.7994***	0.0677	0.1336	-0.0659	-6.5425***
Profit	0.7918	0.7943	0.7610	0.0332	6.0528***	0.7966	0.5343	0.2622	16.5491***
Growth orientation									
Grow substantially	0.0968	0.0928	0.1487	-0.0560	-14.3896***	0.1467	0.1616	-0.0149	-1.1366
Grow moderately	0.4361	0.4322	0.4867	-0.0545	-8.3569***	0.4939	0.4415	0.0525	2.8519***
Stay the same size	0.4078	0.4172	0.2869	0.1304	20.1991***	0.2906	0.2635	0.0271	1.6276
Become smaller	0.0278	0.0273	0.0336	-0.0063	-2.9048***	0.0317	0.0457	-0.0140	-2.1061**
Exit	0.0314	0.0305	0.0441	-0.0136	-5.9188***	0.0371	0.0878	-0.0507	-6.7328***

(continued)

Table 3.6b Continued

Variable	All (N=85862) Mean	No Demand (N=79643) Mean (a)	Demand (N=6219) Mean (b)	Difference (a-b)	t-statistic	Applicants (N=5365) Mean (c)	Discouraged Borrowers (N=854) Mean (d)	Difference (c-d)	t-statistic
Business plan	0.4705	0.4627	0.5712	-0.1085	-16.5324***	0.5836	0.4930	0.0906	4.9792***
Export	0.1451	0.1443	0.1561	-0.0119	-2.5558**	0.1635	0.1101	0.0534	3.9973***
Import	0.1595	0.1578	0.1815	-0.0237	-4.9186***	0.1883	0.1393	0.0489	3.4470***
Management account	0.6277	0.6231	0.6866	-0.0635	-9.9766***	0.7012	0.5948	0.1064	6.2422***
Improvement	0.4462	0.4368	0.5671	-0.1304	-19.9633***	0.5732	0.5293	0.0439	2.4048**
Innovation	0.2180	0.2134	0.2782	-0.0648	-11.9339***	0.2768	0.2869	-0.0101	-0.6112
Business account[a]	0.9340	0.9325	0.9538	-0.0213	-6.5212***	0.9673	0.8687	0.0986	12.9136***
Owner/Manager characteristics									
Gender									
Male	0.7862	0.7857	0.7935	-0.0079	-1.4598	0.7961	0.7775	0.0186	1.2451
Female	0.1869	0.1878	0.1758	0.0120	2.3450**	0.1715	0.2026	-0.0311	-2.2180**
Both (joint partners)	0.0269	0.0266	0.0307	-0.0042	-1.9527*	0.0324	0.0199	0.0125	1.9708**
Owner Age[a]									
18-30 years	0.0409	0.0414	0.0344	0.0070	2.6618***	0.0302	0.0609	-0.0307	-4.5300***
31-50 years	0.4593	0.4577	0.4803	-0.0227	-3.4094***	0.4703	0.5430	-0.0727	-3.9132***
51-65 years	0.4149	0.4155	0.4077	0.0078	1.1819	0.4162	0.3544	0.0618	3.3839***
>66 years	0.0848	0.0854	0.0776	0.0079	2.1149**	0.0833	0.0418	0.0415	4.1774***
Bank relationships and/or products									
Multiple suppliers	0.0202	0.0174	0.0564	-0.0390	-21.1140***	0.0583	0.0445	0.0138	1.6285
Use of credit card[a]	0.2670	0.2564	0.4026	-0.1463	-25.2063***	0.4190	0.2998	0.1192	6.6218***
Credit card application									
Not applied	0.9500	0.9558	0.8757	0.0801	28.0486***	0.8703	0.9098	-0.0396	-3.2574***
Unsuccessful	0.0040	0.0032	0.0143	-0.0111	-13.4401***	0.0136	0.0187	-0.0051	-1.1720
Successful	0.0460	0.0410	0.1100	-0.0690	-25.0988***	0.1161	0.0714	0.0447	3.8815***
Proactive approach	0.1667	0.1615	0.2327	-0.0712	-14.5212***	0.2570	0.0796	0.1774	11.5155***

Notes: This table reports the descriptive statistics of the independent variables in our loan sample. It also reports the difference in means between firms with and without demand and the difference in means between applicants and discouraged borrowers. The definitions of all variables are provided in Table 3.5. The data were collected from 2011Q3 to 2015Q4. [a]: The sample size is not identical due to the existence of missing values. *, **, *** indicate that the differences in means are significant at 10%, 5% and 1% level, respectively.

tend to be older and led by younger owners/leaders, whereas loan seekers (not overdraft seekers) tend to be more financially literate.

As for applicants and discouraged borrowers among debt seekers, the comparisons demonstrate that on average, discouraged borrowers (for both overdrafts and loans) are smaller, younger, sole-traded, led by younger owners/leaders and riskier (potential bad borrowers) whereas applicants are more financially literate and internationally active. The applicants also tend to make profits in the previous year, use business accounts, use credit cards and receive proactive approaches from banks.

Despite the above similarities, there are also some differences between the characteristics of overdraft and loan discouraged borrowers. The most striking difference is found in their growth plans. Overdraft discouraged borrowers usually decide to make a significant change (grow substantially or exit) in the following year while loan discouraged borrowers usually intend to shrink their business turnover. In addition, loan discouraged borrowers (not overdraft discouraged borrowers) tend to be led by females and not apply for credit cards in the last year.

The correlation coefficients between all control variables are reported in Tables 3.7a and 3.7b for overdrafts and loans, respectively. In both samples, most correlation coefficients are less than 0.5. To ensure that the level of multicollinearity is not a concern, we also compute the variance inflation factors (VIFs) for explanatory variables and all values are lower than 5. Therefore, our regression models do not suffer from multicollinearity issues.

Table 3.7a Correlation Matrix: Business Overdrafts

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) Financial literacy	1.000											
(2) D&B risk rating[a]	-0.163***	1.000										
(3) Number of employees[a]	0.333***	-0.420***	1.000									
(4) Business age[a]	0.132***	-0.425***	0.396***	1.000								
(5) Standard region[a]	0.028***	-0.007	0.005	-0.008*	1.000							
(6) Industry sector[a]	0.065***	-0.029***	0.058***	-0.064***	0.068***	1.000						
(7) Legal status[a]	0.233***	-0.299***	0.569***	0.235***	0.023***	0.052***	1.000					
(8) Profitability[a]	0.029***	-0.136***	0.106***	0.130***	-0.012**	-0.016***	0.080***	1.000				
(9) Growth orientation[a]	0.059***	0.017***	0.040***	-0.053***	0.013***	0.009**	0.046***	-0.035***	1.000			
(10) Business plan	0.215***	-0.102***	0.289***	0.025***	-0.001	0.094***	0.228***	0.016***	0.058***	1.000		
(11) Export	0.140***	-0.120***	0.191***	0.110***	0.047***	-0.039***	0.188***	0.025***	0.080***	0.116***	1.000	
(12) Import	0.126***	-0.107***	0.202***	0.108***	0.033***	-0.092***	0.186***	0.029***	0.075***	0.112***	0.550***	1.000
(13) Management account	0.223***	-0.173***	0.366***	0.149***	0.003	0.046***	0.314***	0.046***	0.059***	0.296***	0.155***	0.156***
(14) Business Improvement	0.138***	-0.065***	0.198***	0.045***	0.013***	0.020***	0.172***	0.055***	0.125***	0.211***	0.172***	0.185***
(15) Innovation	0.140***	-0.056***	0.169***	0.039***	0.019***	0.012**	0.157***	0.010**	0.101***	0.180***	0.285***	0.278***
(16) Business account	0.095***	-0.171***	0.276***	0.175***	-0.008	0.000	0.317***	0.076***	0.018***	0.121***	0.070***	0.065***
(17) Gender[a]	-0.043***	0.015***	-0.073***	-0.064***	-0.016***	0.084***	-0.138***	-0.030***	-0.016***	-0.026***	-0.075***	-0.070***
(18) Owner Age[a]	0.032***	-0.189***	0.112***	0.338***	-0.012**	-0.041***	0.051***	0.011**	0.011**	-0.028***	0.057***	0.042***
(19) Multiple suppliers	0.024***	-0.017***	0.033***	0.023***	0.012**	0.013***	0.028***	0.008*	0.024***	0.016***	0.037***	0.042***
(20) Use of credit card	0.128***	-0.118***	0.240***	0.160***	0.010**	-0.016***	0.189***	0.031***	0.046***	0.114***	0.118***	0.121***
(21) Credit card application[a]	-0.040***	0.014***	-0.057***	-0.007	-0.004	0.003	-0.031***	0.006	-0.033***	-0.035***	-0.054***	-0.059***
(22) Proactive approach	0.042***	-0.056***	0.069***	0.061***	-0.011**	-0.030***	0.044***	0.051***	0.039***	0.043***	0.074***	0.078***
(23) Wave[a]	-0.005	-0.072***	0.001	0.052***	0.006	-0.003	0.010**	0.083***	-0.027***	0.012**	0.008*	0.025***

(continued)

Table 3.7a Continued

	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)
(13) Management account	1.000										
(14) Business Improvement	0.256***	1.000									
(15) Innovation	0.198***	0.394***	1.000								
(16) Business account	0.167***	0.076***	0.057***	1.000							
(17) Gender[a]	-0.045***	-0.033***	-0.039***	-0.031***	1.000						
(18) Owner Age[a]	0.029***	-0.023***	-0.012**	0.054***	-0.046***	1.000					
(19) Multiple suppliers	0.028***	0.032***	0.041***	-0.003	-0.007	0.021***	1.000				
(20) Use of credit card	0.180***	0.143***	0.108***	0.079***	-0.057***	0.041***	0.047***	1.000			
(21) Credit card application[a]	-0.028***	-0.046***	-0.050***	-0.009*	0.005	0.010**	-0.034***	-0.174***	1.000		
(22) Proactive approach	0.054***	0.097***	0.069***	0.020***	-0.014***	0.030***	0.022***	0.039***	-0.046***	1.000	
(23) Wave[a]	-0.024***	-0.021***	-0.023***	-0.011**	0.005	0.042***	0.006	-0.031***	0.002	0.012**	1.000

Notes: This table reports the correlation coefficients between the independent variables in our overdraft sample. The definitions of all variables are provided in Table 3.5. [a]: categorical variables are constructed to calculate the correlation coefficients using the dummy variables defined in Table 3.5. *, **, *** indicate significance at 10%, 5% and 1% level, respectively.

Table 3.7b Correlation Matrix: Term Loans

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) Financial literacy	1.000											
(2) D&B risk rating[a]	-0.157***	1.000										
(3) Number of employees[a]	0.334***	-0.412***	1.000									
(4) Business age[a]	0.131***	-0.427***	0.404***	1.000								
(5) Standard region[a]	0.027***	-0.008**	0.003	-0.005	1.000							
(6) Industry sector[a]	0.070***	-0.042***	0.065***	-0.060***	0.060***	1.000						
(7) Legal status[a]	0.238***	-0.295***	0.572***	0.241***	0.021***	0.051***	1.000					
(8) Profitability[a]	0.030***	-0.146***	0.109***	0.136***	-0.013***	-0.009**	0.079***	1.000				
(9) Growth orientation[a]	0.055***	0.024***	0.034***	-0.059***	0.011***	0.018***	0.042***	-0.035***	1.000			
(10) Business plan	0.218***	-0.095***	0.284***	0.016***	0.003	0.098***	0.224***	0.014***	0.064***	1.000		
(11) Export	0.144***	-0.121***	0.198***	0.117***	0.049***	-0.052***	0.195***	0.038***	0.077***	0.119***	1.000	
(12) Import	0.133***	-0.109***	0.204***	0.113***	0.031***	-0.101***	0.187***	0.036***	0.069***	0.111***	0.559***	1.000
(13) Management account	0.227***	-0.174***	0.380***	0.156***	0.005	0.049***	0.325***	0.046***	0.056***	0.293***	0.158***	0.155***
(14) Business Improvement	0.134***	-0.072***	0.203***	0.049***	0.011***	0.026***	0.175***	0.068***	0.121***	0.216***	0.176***	0.176***
(15) Innovation	0.141***	-0.058***	0.167***	0.038***	0.022***	0.008**	0.159***	0.017***	0.100***	0.181***	0.287***	0.270***
(16) Business account	0.093***	-0.169***	0.278***	0.185***	-0.007*	0.001	0.313***	0.076***	0.018***	0.119***	0.071***	0.066***
(17) Gender[a]	-0.047***	0.012***	-0.070***	-0.057***	-0.012***	0.088***	-0.137***	-0.028***	-0.015***	-0.020***	-0.078***	-0.072***
(18) Owner Age[a]	0.037***	-0.194***	0.127***	0.351***	-0.014***	-0.034***	0.066***	0.016***	0.002	-0.025***	0.061***	0.046***
(19) Multiple suppliers	0.030***	-0.018***	0.043***	0.032***	0.009**	0.009**	0.029***	0.007*	0.023***	0.019***	0.033***	0.036***
(20) Use of credit card	0.116***	-0.114***	0.228***	0.157***	0.008**	-0.014***	0.179***	0.034***	0.041***	0.104***	0.116***	0.117***
(21) Credit card application[a]	-0.038***	0.010**	-0.058***	-0.000	-0.004	0.001	-0.033***	0.007*	-0.032***	-0.039***	-0.051***	-0.059***
(22) Proactive approach	0.048***	-0.061***	0.079***	0.066***	-0.008**	-0.027***	0.055***	0.058***	0.037***	0.048***	0.075***	0.079***
(23) Wave[a]	0.008**	-0.064***	-0.005	0.052***	-0.002	0.001	0.016***	0.093***	-0.008**	0.003	0.021***	0.049***

(continued)

Table 3.7b Continued

	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)
(13) Management account	1.000										
(14) Business Improvement	0.254***	1.000									
(15) Innovation	0.196***	0.382***	1.000								
(16) Business account	0.168***	0.079***	0.056***	1.000							
(17) Gender[a]	-0.049***	-0.030***	-0.034***	-0.031***	1.000						
(18) Owner Age[a]	0.040***	-0.019***	-0.008**	0.062***	-0.046***	1.000					
(19) Multiple suppliers	0.026***	0.036***	0.038***	0.003	-0.009**	0.021***	1.000				
(20) Use of credit card	0.172***	0.139***	0.108***	0.086***	-0.048***	0.046***	0.048***	1.000			
(21) Credit card application[a]	-0.032***	-0.046***	-0.052***	-0.010***	0.007*	0.013***	-0.024***	-0.167***	1.000		
(22) Proactive approach	0.058***	0.091***	0.072***	0.030***	-0.017***	0.028***	0.020***	0.041***	-0.039***	1.000	
(23) Wave[a]	-0.024***	-0.030***	-0.020***	-0.001	-0.009**	0.042***	-0.012***	-0.032***	-0.006	-0.006	1.000

Notes: This table reports the correlation coefficients between the independent variables in our loan sample. The definitions of all variables are provided in Table 3.5. [a]: categorical variables are constructed to calculate the correlation coefficients using the dummy variables defined in Table 3.5. *, **, *** indicate significance at 10%, 5% and 1% level, respectively.

3.6 Econometric Results

In this section, we will discuss the results derived from a multivariate analysis (details are provided in Section 3.4) to explore the relationship between EFGS awareness, financial literacy and discouragement among UK SMEs. Explanatory variables include those listed in Table 3.5. For identification purposes, Business plan, which is found to be relevant for awareness and demand but irrelevant to discouragement, is used as the selection criterion for both overdrafts and loans.

Table 3.8 reports the maximum likelihood coefficient estimates and the Wald test statistics that all coefficients (excluding the constant term) are equal to zero simultaneously. The correlation coefficients between the error terms in equation (3.1), (3.2) and (3.3) are all significant, indicating an endogeneity problem and sample selection bias. Therefore, modelling the three dependent variables separately is inappropriate and potentially would yield misleading empirical inferences. Hence, we employ a trivariate probit model with sample selection to overcome these issues.

The coefficient estimates of equation (3.1) are presented in the second and fifth columns in Table 3.8 for the overdraft and loan sample, respectively. The coefficients for financial literacy are both positive and significant at the 1% level, suggesting a positive effect on EFGS awareness. This supports our ***H1*** that financially literate SMEs are more likely to be aware of EFGS. Our results for both overdraft and loan discouragement (the first and fourth column in Table 3.8) reveal a significantly negative sign for awareness of EFGS, providing strong evidence in support of ***H2***. These findings suggest the effectiveness of government initiatives in alleviating the ‘latent’ credit constraints. However, the loan finding is inconsistent with the finding of Fraser (2014) that uses 2011-2013 data to find an insignificant effect of EFGS awareness on loan discouragement. One possible explanation for the difference is that the data he uses covers a much shorter period.

Table 3.8 The Results of Trivariate Probit Model with Sample Selection

	Overdrafts			**Loans**		
	Discouragement	**Awareness**	Demand	**Discouragement**	**Awareness**	Demand
Financial literacy	**-0.1211****	**0.1643*****	-0.1015***	**0.0289**	**0.1869*****	-0.0420**
	(0.0570)	(0.0142)	(0.0179)	(0.0375)	(0.0115)	(0.0163)
Awareness of EFGS	**-0.5872****			**-1.1078*****		
	(0.2531)			(0.2476)		
D & B risk rating						
Low	0.2296**	-0.0014	0.1706***	0.2576***	0.0194	0.1573***
	(0.1009)	(0.0199)	(0.0255)	(0.0704)	(0.0162)	(0.0236)
Average	0.3921***	0.0105	0.2414***	0.3177***	0.0206	0.1992***
	(0.0957)	(0.0208)	(0.0264)	(0.0791)	(0.0167)	(0.0241)
Above Average	0.4498***	-0.0005	0.3337***	0.4305***	0.0176	0.2645***
	(0.1002)	(0.0231)	(0.0289)	(0.0833)	(0.0187)	(0.0267)
Firm characteristics						
Number of employees						
1-9	-0.0132	0.0022	0.2713***	0.0382	-0.0127	0.2317***
	(0.1096)	(0.0232)	(0.0299)	(0.0592)	(0.0187)	(0.0279)
10-49	-0.1216	-0.0139	0.2756***	-0.0046	-0.0165	0.3120***
	(0.1290)	(0.0267)	(0.0348)	(0.1072)	(0.0216)	(0.0325)
50-249	-0.1609	0.0526*	0.1137***	-0.1388	0.0366	0.3018***
	(0.1300)	(0.0309)	(0.0407)	(0.1880)	(0.0251)	(0.0372)
Business age						
2-5 years	-0.1620**	-0.0423	-0.0167	-0.0591	-0.0215	-0.0611*
	(0.0799)	(0.0292)	(0.0369)	(0.0628)	(0.0239)	(0.0327)
6-9 years	-0.4036***	-0.0222	0.0140	-0.1709***	0.0178	-0.0226
	(0.1231)	(0.0306)	(0.0385)	(0.0585)	(0.0251)	(0.0346)
10-15 years	-0.4241***	-0.0078	0.0674*	-0.2478***	0.0183	-0.0428
	(0.1374)	(0.0296)	(0.0373)	(0.0594)	(0.0245)	(0.0345)
>15 years	-0.4223***	-0.0018	0.1278***	-0.2546**	0.0406*	-0.0148
	(0.1312)	(0.0280)	(0.0352)	(0.1084)	(0.0233)	(0.0326)
Standard region						
East Anglia	0.0137	0.0479	-0.1468***	0.0030	0.0671***	-0.0426
	(0.1130)	(0.0316)	(0.0381)	(0.0991)	(0.0255)	(0.0361)
East Midlands	-0.0574	-0.0012	-0.1392***	0.0183	0.0120	-0.0521
	(0.1263)	(0.0337)	(0.0406)	(0.1460)	(0.0271)	(0.0382)
North West	0.0567	0.0178	-0.1637***	-0.0401	-0.0230	0.0027
	(0.1169)	(0.0317)	(0.0380)	(0.0767)	(0.0257)	(0.0356)
North/North East	-0.0170	0.0265	-0.0770*	-0.0712	0.0133	-0.0496
	(0.1319)	(0.0372)	(0.0439)	(0.1703)	(0.0302)	(0.0426)
Northern Ireland	-0.0192	-0.0536	-0.0530	0.1683**	-0.0843***	0.1044***
	(0.1331)	(0.0385)	(0.0444)	(0.0716)	(0.0306)	(0.0402)
London	0.1079	-0.1008***	-0.2312***	-0.0245	-0.0812***	-0.0542
	(0.1138)	(0.0302)	(0.0362)	(0.0652)	(0.0244)	(0.0341)
South East	-0.0045	-0.0050	-0.1695***	-0.0544	0.0009	-0.0499
	(0.1136)	(0.0298)	(0.0355)	(0.1028)	(0.0241)	(0.0336)
South West	0.1834	0.0316	-0.0554	0.0281	0.0203	0.0802**
	(0.1130)	(0.0317)	(0.0370)	(0.1396)	(0.0257)	(0.0347)
Wales	0.0589	-0.0307	-0.1287***	-0.0409	-0.0251	0.0021
	(0.1180)	(0.0354)	(0.0419)	(0.1723)	(0.0286)	(0.0392)
West Midlands	-0.1784	0.0187	-0.1592***	-0.0453	0.0201	-0.0250
	(0.1202)	(0.0318)	(0.0381)	(0.0976)	(0.0256)	(0.0356)
Yorkshire /Humberside	0.1143	0.0270	-0.1345***	0.0081	0.0137	0.0200
	(0.1157)	(0.0316)	(0.0377)	(0.1111)	(0.0255)	(0.0352)

(continued)

Table 3.8 Continued

	Overdrafts			Loans		
	Discouragement	**Awareness**	Demand	**Discouragement**	**Awareness**	Demand
Industry sector						
Construction	0.0230	-0.0084	-0.2176***	0.0164	-0.0154	-0.3575***
	(0.1207)	(0.0318)	(0.0351)	(0.0815)	(0.0251)	(0.0331)
Health and social work	-0.1296	0.0553	-0.4258***	0.0494	0.0410	-0.2097***
	(0.1594)	(0.0350)	(0.0423)	(0.1399)	(0.0279)	(0.0368)
Hotels and restaurants	0.2492	-0.0136	-0.3180***	0.0828	-0.0220	-0.1300***
	(0.1580)	(0.0355)	(0.0399)	(0.0747)	(0.0285)	(0.0353)
Manufacturing	0.0788	0.0385	-0.3706***	-0.0136	0.0605**	-0.3005***
	(0.1536)	(0.0342)	(0.0395)	(0.0802)	(0.0271)	(0.0361)
Real estate renting / business activities	0.0989	0.1448***	-0.3748***	0.0964	0.1499***	-0.3301***
	(0.1462)	(0.0311)	(0.0357)	(0.0788)	(0.0245)	(0.0323)
Transport, storage and communication	0.1739	0.0318	-0.3084***	0.1272	0.0077	-0.2386***
	(0.1470)	(0.0349)	(0.0403)	(0.0817)	(0.0279)	(0.0363)
Wholesale/retail	-0.1022	0.0484	-0.3232***	-0.0225	0.0209	-0.2514***
	(0.1258)	(0.0340)	(0.0387)	(0.0865)	(0.0270)	(0.0346)
Other community, social/ personal service	0.1312	0.0738**	-0.3000***	0.0370	0.0418	-0.2782***
	(0.1377)	(0.0339)	(0.0386)	(0.1052)	(0.0269)	(0.0357)
Legal status						
Partnership	-0.0541	0.0262	0.3303***	-0.0592	0.0485**	0.2238***
	(0.1127)	(0.0309)	(0.0349)	(0.1430)	(0.0245)	(0.0311)
LLP	-0.1742	0.0219	0.1905***	-0.0620	0.0430	0.1590***
	(0.1413)	(0.0362)	(0.0430)	(0.1600)	(0.0304)	(0.0408)
LLC	-0.1241*	0.0695***	0.0587**	-0.0093	0.1063***	-0.0152
	(0.0703)	(0.0212)	(0.0266)	(0.1005)	(0.0171)	(0.0247)
Profitability						
Broken even	-0.3126***	-0.1633***	-0.3455***	-0.3517***	-0.1485***	-0.3150***
	(0.0946)	(0.0317)	(0.0371)	(0.0592)	(0.0245)	(0.0327)
Profit	-0.4424***	0.0307	-0.3116***	-0.4098***	0.0388**	-0.2577***
	(0.0587)	(0.0234)	(0.0261)	(0.0688)	(0.0179)	(0.0225)
Growth Orientation						
Grow substantially	0.2125***	0.0823***	0.2186***	0.2487***	0.0887***	0.3309***
	(0.0736)	(0.0239)	(0.0289)	(0.0843)	(0.0199)	(0.0270)
Grow moderately	0.0224	0.0410***	0.1382***	0.1176**	0.0452***	0.1624***
	(0.0541)	(0.0152)	(0.0191)	(0.0486)	(0.0124)	(0.0177)
Become smaller	0.0954	0.0165	0.2075***	0.2439	0.0309	0.2609***
	(0.1359)	(0.0448)	(0.0527)	(0.2066)	(0.0335)	(0.0440)
Exit	0.1573	0.0152	0.2914***	0.3520***	0.0482	0.3495***
	(0.1093)	(0.0400)	(0.0452)	(0.0984)	(0.0320)	(0.0408)
Business plan		0.1477***	0.0422**		0.1579***	0.1136***
		(0.0143)	(0.0175)		(0.0124)	(0.0178)
Export	0.1022	0.0681***	-0.0345	-0.0610	0.0716***	-0.0858***
	(0.0779)	(0.0218)	(0.0272)	(0.0561)	(0.0180)	(0.0261)
Import	0.0256	0.0595***	0.0413	0.0283	0.0478***	-0.0024
	(0.0703)	(0.0210)	(0.0255)	(0.0536)	(0.0174)	(0.0244)
Management account	0.0319	0.1554***	0.0602***	0.0974	0.1462***	-0.0186
	(0.0554)	(0.0158)	(0.0194)	(0.0646)	(0.0128)	(0.0180)
Improvement	0.1456***	0.0811***	0.1573***	0.1771***	0.1088***	0.1350***
	(0.0538)	(0.0149)	(0.0183)	(0.0440)	(0.0119)	(0.0166)
Innovation	0.1171*	0.0861***	-0.0222	0.1297	0.0631***	0.0164
	(0.0606)	(0.0173)	(0.0215)	(0.0818)	(0.0139)	(0.0191)
Business account	-0.2500*	-0.0453	0.1709***	-0.2630*	-0.0575**	0.0285
	(0.1358)	(0.0313)	(0.0428)	(0.1443)	(0.0252)	(0.0369)

(continued)

Table 3.8 Continued

	Overdrafts			Loans		
	Discouragement	**Awareness**	Demand	**Discouragement**	**Awareness**	Demand
Owner/Manager characteristics						
Gender						
Female	-0.0592	-0.0569***	-0.0123	-0.0502	-0.0625***	-0.0479**
	(0.0602)	(0.0179)	(0.0220)	(0.0420)	(0.0144)	(0.0200)
Both (joint partners)	-0.1251	-0.0210	-0.1095**	-0.0423	-0.0461	-0.2108***
	(0.1609)	(0.0487)	(0.0548)	(0.1737)	(0.0374)	(0.0488)
Owner Age						
18-30 years	-0.2650*	-0.3751***	-0.2498***	-0.2986**	-0.3653***	-0.0584
	(0.1386)	(0.0435)	(0.0552)	(0.1219)	(0.0357)	(0.0500)
31-50 years	-0.0809	-0.2269***	-0.0991***	-0.0663	-0.2018***	0.0818***
	(0.0894)	(0.0249)	(0.0305)	(0.0923)	(0.0202)	(0.0298)
51-65 years	-0.0788	-0.1062***	-0.0354	0.0062	-0.0855***	0.0505*
	(0.0881)	(0.0242)	(0.0296)	(0.0867)	(0.0196)	(0.0292)
Bank relationships and/or products						
Multiple suppliers	0.1341	0.1406***	0.4351***	0.2881*	0.1004***	0.5372***
	(0.1493)	(0.0455)	(0.0494)	(0.1484)	(0.0348)	(0.0393)
Use of credit card	-0.0094	0.0900***	0.4341***	0.1431***	0.0595***	0.2495***
	(0.1036)	(0.0155)	(0.0182)	(0.0359)	(0.0123)	(0.0165)
Credit card application						
Unsuccessful	-0.0027	-0.0432	0.1987**	0.3430*	-0.0352	0.3722***
	(0.2385)	(0.1018)	(0.0989)	(0.1981)	(0.0868)	(0.0852)
Not applied	-0.1170	0.0701**	-0.3618***	-0.0560	0.0497**	-0.4125***
	(0.0877)	(0.0311)	(0.0323)	(0.0775)	(0.0248)	(0.0285)
Proactive approach	-0.2101**	0.2171***	0.1299***	-0.1250**	0.2025***	0.1651***
	(0.0900)	(0.0169)	(0.0205)	(0.0561)	(0.0135)	(0.0182)
Constant	-1.2144***	-0.8692***	-1.0168***	-1.4355***	-0.9815***	-1.2686***
	(0.4066)	(0.0698)	(0.0828)	(0.3159)	(0.0574)	(0.0757)
Wave	Yes	Yes	Yes	Yes	Yes	Yes
Correlation coefficient ($\rho_{awaredem}$)		0.0708***			0.0656***	
Correlation coefficient ($\rho_{awaredis}$)		**0.3812****			**0.6948*****	
Correlation coefficient (ρ_{demdis})		**0.7170***			**0.7482*****	
No. of observations		44820			68340	
Wald Chi-square test		5225.33***			7464.16***	

Notes: This table reports the estimated coefficients of a trivariate probit model with sample selection for business overdrafts and term loans. Standard errors are reported in parentheses. The dependent variables used in the model are whether a firm does not apply for fear of rejection even if it has a demand for overdrafts/loans, whether the firm is aware of the Enterprise Guarantee Finance Scheme and whether the firm has a demand for overdrafts/loans. The definitions of all control variables are provided in Table 3.5. The null hypothesis of the Wald test is that all coefficients, excluding the constant term, are equal to zero simultaneously. The data used for business overdrafts cover 2012Q4-2015Q4 while the data used for term loans cover 2011Q3-2015Q4. *, **, *** indicate significance at 10%, 5% and 1% level, respectively.

Similar Determinants for Overdraft and Loan Discouragement

Similar determinants for discouragement are found to be significant for overdrafts and loans. Riskier firms are more likely to be discouraged although they have higher demand, indicating that discouragement acts as an efficient self-rationing mechanism for UK small businesses, consistent with the findings in several US studies (Han et al., 2009; Chakravarty and Yilmazer, 2009). It also implies market imperfection, in the sense that good borrowers will always apply in a perfect market (Han et al., 2009).

Firm characteristics

Similar to Fraser (2009), older firms are found to be less likely to be discouraged while firm size (proxied by number of employees) fails to distinguish discouraged borrowers from applicants. This points to the potential dominance of an age effect instead of a size effect. It is at variance with most studies (e.g. Fraser, 2014; Mac an Bhaird et al., 2016) where bigger and older firms are deemed to be safer and have lower application costs (Cowling, Liu, Minniti and Zhang, 2016) and both firm size and age appear to have a negative association with discouragement. One possible explanation might be that older firms could establish a longer relationship with banks to lower the screening errors (Han et al., 2009), although this claim is not supported by the empirical analysis in both UK (Fraser 2009) and developing countries (Chakravarty and Xiang 2013). Moreover, the age effect indicates possible more severe credit constraints and deterred growth faced by start-ups (less than 2 years), calling for particular attention because of their pivotal role in creating job opportunities and driving innovation.

Our results also demonstrate a lower probability of discouragement and demand for SMEs that are profitable or running on a break-even basis. This lower demand is compatible with the pecking order theory that firms will utilise internal sources first and then seek bank debt as the first form of external finance. Similar to the case of discouragement, firms with better performance, an indicator to show stronger creditworthiness for repayment, are less likely to be refused by banks (Zhao and Jones-Evans, 2017). This reduces these firms' psychic application costs and leads to a lower discouragement level. This supports the findings of previous UK studies, e.g. Lee and Brown (2017) and Rostamkalaei (2017).

Surprisingly, firms with past business improvement are more likely to be discouraged, possibly because firms trying to improve their businesses are firms aware that there are some drawbacks in their management or technology, which need to be ameliorated or refined. This awareness potentially undermines their confidence in a successful application, increasing their psychic costs and resulting in a higher likelihood of discouragement. However, other kinds of business activities are unrelated to discouragement. We also find SMEs using a business account are less likely to be discouraged since banks can monitor these firms' behaviour more closely and thus are more ready for lending. Intuitively, SMEs receiving proactive approaches from banks are less likely to be discouraged, in agreement with the findings in Fraser (2014).

Owner/Manager characteristics

The owner/manager age, rather than gender, is found to have a bearing on discouragement. The insignificance of the gender effect conforms to the majority of UK investigations by, for example, Freel et al. (2012), Cowling, Liu, Minniti and Zhang (2016) and Rostamkalaei (2017). Despite the claims that females are more risk-averse towards investment (Watson, 2002; Watson and McNaughton 2007) and females have stronger desires to keep control of their businesses and thus are unwilling to accept the bank monitoring (Treichel and Scott, 2006), the related higher discouragement level might be offset by the actual lower rejection rate of female-owned/managed businesses (Cole and Dietrich, 2013). Younger entrepreneurs (18-30 years old) are, as expected, less likely to be discouraged since they tend to be over-optimistic (Parker, 2004) and more venture ambitious (Vos et al., 2007). This is in line with previous empirical evidence in the UK (Rostamkalaei, 2017) and US (Han et al., 2009; Cole and Sokolyk, 2016).

Different Determinants for Overdraft and Loan Discouragement

Firm Characteristics

Our results also show that limited liability companies are less likely to be discouraged from applying for overdrafts, possibly due to their perception that the limited liability represents good credibility (Storey, 1994) and this gives rise to a lower rejection rate. However, 'the protection offered by limited liability might be acting to reduce the commitment of borrowers to repay" (Cowling and Mitchell, 2003, p.67), triggering a higher default rate than the rate by sole traders and partnerships. Moreover, innovative SMEs face a higher probability of overdraft discouragement, possibly relevant to the higher rejection rate (Freel, 2007) and higher price (Nitani and Riding, 2013) relative to those of non-innovative firms. It is probably the case that the traditional high street banks experience difficulties in understanding the activities of innovative firms.

In contrast with the findings of Freel et al. (2012) and Lee and Brown (2017), the results indicate a significant effect of growth orientation on discouragement and this differs for overdrafts and loans. For overdrafts, firms planning to grow substantially are more likely to be discouraged while for loans, firms planning to grow (substantially or moderately) and exit are more likely to be discouraged. Slightly counter-intuitively, firms with a growth orientation, often believed to be optimistic, are linked with a higher likelihood of discouragement. One possible explanation is that the uncertainty and risk accompanied with the growth plan leads to reluctance on the part of banks to lend. Since overdrafts are typically renewed annually while loans last for several years, banks might be more willing to bear the risk of firms planning to grow moderately, i.e. relatively less uncertain and risky, by granting short-term rather than medium-term finance. Besides, in loan agreements, banks impose covenants, often related to financial ratios, to monitor the performance of the business. Once the borrower breaches the covenants, banks can put it into receivership, a condition which SMEs planning to exit the market over the next year are unwilling to accept. Hence, they are more likely to be discouraged from applying for loans.

Bank relationships and/or products

Remarkable differences appear when looking at the effects of explanatory variables on bank relationships. The two measures related to information asymmetry (multiple suppliers and credit card usage) are both significant for loan discouragement but always insignificant for overdraft discouragement. This indicates that for overdrafts, which banks can withdraw at short notice, improving information transparency does not play a vital role in alleviating discouragement. For loans, a more concentrated relationship with banks could encourage firms to apply, contrary to the recent findings in the US case (Han et al., 2009; Chakravarty and Xiang, 2013). This might be because, in the US, almost 25%[29] loan seekers have associations with more than one bank whereas only around 6% (see Table 3.6b) of UK loan seekers have multiple suppliers. Therefore, for UK SMEs, which focus more on their main bank, raising the information transparency seems more helpful and efficient in reducing screening errors and lowering the discouragement level. Again, inconsistent with the results of Han et al. (2009), firms using a credit card are less likely to apply for loans. One possible explanation is that banks can check credit card history via credit reporting agencies (e.g.

[29] This percentage is calculated according to the numbers in Table 2 of Chakravarty and Xiang (2013).

Experian) and firms using credit card might have a poor repayment history, leading to high rejection rates and their lack of confidence in applying. In this sense, it also points to the role of discouragement acting as a self-rationing mechanism prior to a loan application.

In addition, a previous refusal on a credit card application, bringing higher psychic application costs, is associated with a higher probability of loan discouragement, but is unrelated to overdraft discouragement. This might be attributed to their different application purposes. Term loans are generally used for firm expansion, whereas business overdrafts are typically used as working capital to maintain the daily operation of small businesses. Therefore, survival could be a problem if they do not apply for overdrafts, especially when further credit card borrowing is rejected. The pressure of survival outweighs the psychic costs caused by the previous refusal, driving firms to apply and leading to an insignificant relationship between the experience of credit card application and overdraft discouragement.

3.6.1 The Role of Financial Literacy

Our evidence indicates that financial literacy has a negative effect on overdraft discouragement but no effect on loan discouragement (see Table 3.8). However, as predicted in ***H3***, a more accurate self-assessment generated by financial literacy seem to have different effects on low- versus high-risk borrowers. To check whether financial literacy behaves in the way as expected, we carried out additional analysis. We split the full sample into two sub-samples using the external D&B risk rating. We identify low-risk borrowers as firms with minimal, low and average risk while high-risk borrowers as firms with above-average risk. Then we re-run the regressions in each sub-sample and report the results for overdrafts and loans in Table 3.9 and Table 3.10, respectively.

Table 3.9 Overdraft Results by Low- and High-risk Borrowers: Trivariate Probit Model with Sample Selection

	Low-risk borrowers (minimal, low and average risk)			High-risk borrowers (above average risk)		
	Discouragement	**Awareness**	Demand	**Discouragement**	**Awareness**	Demand
Financial literacy	**-0.0651**	**0.1631*****	-0.0989***	**0.0327**	**0.1681*****	-0.1149***
	(0.1108)	(0.0165)	(0.0207)	(0.0908)	(0.0284)	(0.0355)
Awareness of EFGS	**-0.5202***			**-0.9326****		
	(0.2823)			(0.3841)		
Firm characteristics						
Number of employees						
1-9	-0.3084***	-0.0104	0.2979***	-0.1507	-0.0006	0.2246***
	(0.1126)	(0.0314)	(0.0425)	(0.1720)	(0.0347)	(0.0431)
10-49	-0.4608***	-0.0232	0.2756***	-0.0350	-0.0288	0.2727***
	(0.1155)	(0.0336)	(0.0461)	(0.1821)	(0.0489)	(0.0583)
50-249	-0.3481**	0.0435	0.1300**	-0.1909	0.0734	-0.0624
	(0.1466)	(0.0375)	(0.0513)	(0.2035)	(0.0689)	(0.0870)
Business age						
2-5 years	-0.2880*	0.0079	0.0105	-0.1365	-0.0948**	-0.0590
	(0.1739)	(0.0468)	(0.0603)	(0.1045)	(0.0384)	(0.0480)
6-9 years	-0.4779*	-0.0156	-0.0021	-0.4213***	-0.0255	0.0074
	(0.2595)	(0.0455)	(0.0586)	(0.1551)	(0.0452)	(0.0560)
10-15 years	-0.5259**	-0.0063	0.0209	-0.4391**	0.0032	0.0982*
	(0.2588)	(0.0436)	(0.0564)	(0.1872)	(0.0466)	(0.0564)
>15 years	-0.6096**	0.0056	0.0778	-0.4489**	-0.0082	0.1442***
	(0.2585)	(0.0417)	(0.0538)	(0.1865)	(0.0437)	(0.0525)
Standard region						
East Anglia	0.1635	0.0433	-0.1943***	0.1596	0.0587	-0.0295
	(0.1402)	(0.0365)	(0.0441)	(0.1912)	(0.0639)	(0.0768)
East Midlands	0.1875	-0.0279	-0.1458***	-0.2294	0.0700	-0.1120
	(0.1351)	(0.0391)	(0.0467)	(0.2147)	(0.0668)	(0.0820)
North West	0.1623	-0.0142	-0.2094***	0.3332*	0.1000	-0.0109
	(0.1434)	(0.0372)	(0.0450)	(0.1947)	(0.0614)	(0.0735)
North/North East	0.1465	0.0378	-0.1372***	0.0970	-0.0123	0.0919
	(0.1545)	(0.0428)	(0.0509)	(0.2094)	(0.0754)	(0.0876)
Northern Ireland	0.0084	-0.0535	-0.0615	0.0761	-0.0456	-0.0181
	(0.1540)	(0.0439)	(0.0505)	(0.2299)	(0.0807)	(0.0940)
London	0.3374***	-0.0846**	-0.2720***	0.2007	-0.1438**	-0.1151
	(0.1214)	(0.0350)	(0.0421)	(0.1909)	(0.0604)	(0.0725)
South East	0.2064	-0.0153	-0.2182***	0.1385	0.0229	-0.0296
	(0.1317)	(0.0346)	(0.0413)	(0.1841)	(0.0593)	(0.0711)
South West	0.1701	0.0306	-0.0853**	0.3787*	0.0392	0.0424
	(0.1296)	(0.0367)	(0.0425)	(0.1953)	(0.0638)	(0.0757)
Wales	0.2062	-0.0380	-0.1989***	0.2270	-0.0112	0.0656
	(0.1373)	(0.0410)	(0.0491)	(0.1929)	(0.0709)	(0.0818)
West Midlands	0.0247	0.0311	-0.1471***	-0.2382	-0.0148	-0.1635**
	(0.1439)	(0.0367)	(0.0437)	(0.2208)	(0.0639)	(0.0783)
Yorkshire	0.2716**	0.0178	-0.1717***	0.2075	0.0614	-0.0150
/Humberside	(0.1311)	(0.0367)	(0.0439)	(0.1856)	(0.0626)	(0.0748)
Industry sector						
Construction	0.4978***	0.0085	-0.1529***	-0.2329	-0.0068	-0.1225*
	(0.1903)	(0.0360)	(0.0401)	(0.1701)	(0.0687)	(0.0739)
Health and social	0.6047***	0.0620	-0.3935***	-0.5301*	0.0643	-0.4118***
work	(0.1602)	(0.0387)	(0.0465)	(0.2790)	(0.0836)	(0.0972)
Hotels and	0.8060***	-0.0414	-0.2601***	0.0519	0.0709	-0.1963**
restaurants	(0.2666)	(0.0406)	(0.0458)	(0.1965)	(0.0745)	(0.0813)
Manufacturing	0.7698***	0.0193	-0.3746***	-0.1067	0.1374*	-0.1077
	(0.1968)	(0.0380)	(0.0446)	(0.1978)	(0.0773)	(0.0856)
Real estate renting	0.7284***	0.1394***	-0.3172***	-0.1260	0.1938***	-0.3070***
/business activities	(0.1949)	(0.0348)	(0.0404)	(0.2148)	(0.0693)	(0.0771)
Transport, storage /	0.7532***	0.0363	-0.2456***	-0.0888	0.0539	-0.2184***
communication	(0.2492)	(0.0399)	(0.0466)	(0.1969)	(0.0740)	(0.0827)
Wholesale/retail	0.5132***	0.0457	-0.2826***	-0.3036	0.0806	-0.1902**
	(0.1661)	(0.0378)	(0.0434)	(0.1895)	(0.0758)	(0.0834)
Other community,	0.7545***	0.0735*	-0.2657***	-0.2313	0.1045	-0.1904**
social/ personal service	(0.2341)	(0.0375)	(0.0433)	(0.2012)	(0.0783)	(0.0867)

(Continued)

Table 3.9 Continued

	Low-risk borrowers (minimal, low and average risk)			High-risk borrowers (above average risk)		
	Discouragement	**Awareness**	Demand	**Discouragement**	**Awareness**	Demand
Legal status						
Partnership	-0.3907***	0.0366	0.3137***	-0.2165	-0.0342	0.2533***
	(0.1118)	(0.0368)	(0.0421)	(0.1932)	(0.0613)	(0.0657)
LLP	-0.2672*	0.0045	0.1513***	-0.4165	0.0680	0.1435
	(0.1489)	(0.0422)	(0.0506)	(0.2765)	(0.0753)	(0.0885)
LLC	-0.1845	0.0599**	-0.0135	-0.1234	0.0803**	0.1366***
	(0.1187)	(0.0270)	(0.0341)	(0.1227)	(0.0350)	(0.0419)
Profitability						
Broken even	0.0337	-0.2213***	-0.3664***	-0.1356	-0.0766	-0.3235***
	(0.2431)	(0.0406)	(0.0478)	(0.1560)	(0.0507)	(0.0595)
Profit	-0.0744	0.0099	-0.3296***	-0.4124***	0.0565	-0.2901***
	(0.2531)	(0.0300)	(0.0336)	(0.0980)	(0.0375)	(0.0420)
Growth Orientation						
Grow substantially	-0.0295	0.0708**	0.2040***	0.2948**	0.1028**	0.2934***
	(0.1502)	(0.0283)	(0.0347)	(0.1179)	(0.0447)	(0.0537)
Grow moderately	-0.1815***	0.0351**	0.1190***	0.1625*	0.0585*	0.2036***
	(0.0648)	(0.0176)	(0.0223)	(0.0894)	(0.0302)	(0.0375)
Become smaller	-0.1341	0.0148	0.1928***	0.0371	0.0005	0.2431**
	(0.1707)	(0.0523)	(0.0619)	(0.2234)	(0.0878)	(0.1004)
Exit	-0.1461	0.0371	0.2982***	0.0795	-0.0308	0.2986***
	(0.1768)	(0.0487)	(0.0555)	(0.1884)	(0.0709)	(0.0789)
Business plan		0.1413***	0.0234		0.1671***	0.0696**
		(0.0168)	(0.0238)		(0.0279)	(0.0333)
Export	0.1921**	0.0761***	-0.0422	0.0587	0.0333	-0.0376
	(0.0970)	(0.0249)	(0.0314)	(0.1270)	(0.0463)	(0.0550)
Import	-0.0922	0.0606**	0.0494*	0.0802	0.0498	0.0284
	(0.0850)	(0.0241)	(0.0296)	(0.1164)	(0.0430)	(0.0508)
Management account		0.1557***	0.0813***		0.1543***	0.0316
		(0.0190)	(0.0232)		(0.0284)	(0.0354)
Improvement	-0.0879	0.0785***	0.1745***	0.1421	0.0930***	0.1180***
	(0.0974)	(0.0174)	(0.0215)	(0.0881)	(0.0293)	(0.0350)
Innovation	0.1487*	0.1031***	-0.0307	0.1462	0.0329	0.0084
	(0.0853)	(0.0200)	(0.0251)	(0.0997)	(0.0350)	(0.0421)
Business account	-0.5445**	-0.0062	0.1440**	-0.2062	-0.0930**	0.1711***
	(0.2125)	(0.0458)	(0.0624)	(0.1815)	(0.0436)	(0.0594)
Owner/Manager characteristics						
Gender						
Female	-0.0057	-0.0662***	-0.0032	-0.1756*	-0.0356	-0.0347
	(0.0732)	(0.0211)	(0.0261)	(0.1002)	(0.0338)	(0.0408)
Both (joint partners)	-0.0449	-0.0613	-0.1051*	-0.1271	0.1482	-0.1669
	(0.1737)	(0.0543)	(0.0605)	(0.3667)	(0.1108)	(0.1261)
Owner Age						
18-30 years	0.1482	-0.3265***	-0.3102***	-0.4472**	-0.4646***	-0.1604*
	(0.2302)	(0.0593)	(0.0798)	(0.2195)	(0.0773)	(0.0935)
31-50 years	0.1165	-0.2075***	-0.0879***	-0.3483**	-0.3063***	-0.0726
	(0.0999)	(0.0275)	(0.0338)	(0.1776)	(0.0607)	(0.0730)
51-65 years	0.0028	-0.0995***	-0.0415	-0.2686	-0.1534**	0.0216
	(0.1008)	(0.0265)	(0.0325)	(0.1793)	(0.0602)	(0.0722)

(continued)

Table 3.9 Continued

	Low-risk borrowers (minimal, low and average risk)			High-risk borrowers (above average risk)		
	Discouragement	**Awareness**	Demand	**Discouragement**	**Awareness**	Demand
Bank relationships and/or products						
Multiple suppliers	-0.2595	0.0891*	0.4155***	0.0028	0.2974***	0.5199***
	(0.1961)	(0.0517)	(0.0567)	(0.2722)	(0.0959)	(0.1016)
Use of credit card	-0.4404***	0.0716***	0.4158***	-0.1097	0.1589***	0.4953***
	(0.0869)	(0.0174)	(0.0208)	(0.2167)	(0.0341)	(0.0374)
Credit card application						
Unsuccessful	-0.1944	0.0259	0.1264	-0.0946	-0.1945	0.2132
	(0.3515)	(0.1244)	(0.1276)	(0.3500)	(0.1826)	(0.1632)
Not applied	0.3130***	0.0795**	-0.3162***	-0.1962	0.0479	-0.4789***
	(0.1113)	(0.0360)	(0.0379)	(0.1547)	(0.0621)	(0.0641)
Proactive approach	-0.3486***	0.2220***	0.1576***	-0.3256**	0.1935***	0.0259
	(0.1102)	(0.0193)	(0.0235)	(0.1477)	(0.0354)	(0.0423)
Constant	1.0996**	-0.8674***	-0.8412***	-0.1795	-0.8565***	-0.7617***
	(0.4641)	(0.0868)	(0.1061)	(0.7574)	(0.1328)	(0.1504)
Wave	Yes	Yes	Yes	Yes	Yes	Yes
Correlation coefficient ($\rho_{awaredem}$)	0.0710***			0.0685***		
Correlation coefficient ($\rho_{awaredis}$)	**0.2803**			**0.5451***		
Correlation coefficient (ρ_{demdis})	**-0.7260**			**0.5253**		
No. of observations	32299			12521		
Wald Chi-square test	3541.99***			1875.42***		

Notes: This table reports the estimated coefficients of a trivariate probit model with sample selection for business overdrafts by low- and high-risk borrowers. Standard errors are reported in parentheses. Low-risk borrowers refer to firms with minimal, low and average risk in D&B rating and high-risk borrowers refers to firms with above average risk in D&B rating. The dependent variables used in the model are whether a firm does not apply for fear of rejection even if it has a demand for overdrafts, whether the firm is aware of the Enterprise Guarantee Finance Scheme and whether the firm has a demand for overdrafts. The definitions of all control variables are provided in Table 3.5. The null hypothesis of the Wald test is that all coefficients, excluding the constant term, are equal to zero simultaneously. The data are collected during 2012Q4-2015Q4. *, **, *** indicate significance at 10%, 5% and 1% level, respectively.

Table 3.10 Loan Results by Low- and High-risk Borrowers: Trivariate Probit Model with Sample Selection

	Low-risk borrowers (minimal, low and average risk)			**High-risk borrowers** (above average risk)		
	Discouragement	**Awareness**	Demand	**Discouragement**	**Awareness**	Demand
Financial literacy	**-0.2540*** **	**0.1902*** **	-0.0621***	**0.1699*** **	**0.1742*** **	0.0089
	(0.0648)	(0.0133)	(0.0191)	(0.0528)	(0.0225)	(0.0310)
Awareness of EFGS	**0.7641**			**-1.4668*** **		
	(0.5331)			(0.1122)		
Firm characteristics						
Number of employees						
1-9	-0.0974	-0.0363	0.2051***	-0.2499***	0.0062	0.2656***
	(0.1423)	(0.0254)	(0.0400)	(0.0827)	(0.0278)	(0.0388)
10-49	-0.2183	-0.0382	0.2771***	-0.4146***	0.0105	0.3464***
	(0.1836)	(0.0272)	(0.0433)	(0.0957)	(0.0387)	(0.0527)
50-249	-0.5126**	0.0156	0.2852***	-0.3027**	0.0843	0.1415*
	(0.2325)	(0.0305)	(0.0474)	(0.1284)	(0.0540)	(0.0762)
Business age						
2-5 years	-0.0618	0.0149	-0.1852***	-0.0668	-0.0531*	0.0024
	(0.1376)	(0.0390)	(0.0521)	(0.0766)	(0.0309)	(0.0419)
6-9 years	-0.3018**	0.0159	-0.1536***	-0.1789**	0.0174	0.0459
	(0.1359)	(0.0379)	(0.0504)	(0.0887)	(0.0362)	(0.0498)
10-15 years	-0.4355***	0.0081	-0.2051***	-0.2725***	0.0372	0.1070**
	(0.1382)	(0.0366)	(0.0489)	(0.0895)	(0.0380)	(0.0511)
>15 years	-0.4414***	0.0388	-0.1723***	-0.3235***	0.0385	0.0848*
	(0.1280)	(0.0352)	(0.0467)	(0.1062)	(0.0358)	(0.0486)
Standard region						
East Anglia	-0.1328	0.0704**	-0.0646	0.0800	0.0634	0.0010
	(0.1448)	(0.0296)	(0.0423)	(0.1303)	(0.0507)	(0.0704)
East Midlands	-0.0333	-0.0120	-0.0374	0.1381	0.0796	-0.0869
	(0.1415)	(0.0317)	(0.0447)	(0.1504)	(0.0527)	(0.0748)
North West	-0.0047	-0.0328	0.0048	-0.0947	0.0111	0.0268
	(0.1389)	(0.0303)	(0.0421)	(0.1372)	(0.0490)	(0.0662)
North/North East	0.0349	0.0271	-0.0683	-0.1951	-0.0221	-0.0086
	(0.1614)	(0.0348)	(0.0497)	(0.1875)	(0.0598)	(0.0822)
Northern Ireland	0.1992	-0.0917***	0.0840*	0.1289	-0.0533	0.1706**
	(0.1434)	(0.0352)	(0.0470)	(0.1427)	(0.0620)	(0.0783)
London	0.0783	-0.0605**	-0.1132***	-0.0777	-0.1253***	0.0625
	(0.1336)	(0.0285)	(0.0408)	(0.1158)	(0.0479)	(0.0636)
South East	-0.1568	-0.0025	-0.0690*	-0.0012	0.0174	0.0040
	(0.1378)	(0.0280)	(0.0398)	(0.1245)	(0.0469)	(0.0637)
South West	-0.0282	0.0199	0.0912**	-0.0826	0.0324	0.0516
	(0.1386)	(0.0298)	(0.0403)	(0.1189)	(0.0505)	(0.0679)
Wales	-0.1005	-0.0308	-0.0070	-0.0094	0.0063	0.0352
	(0.1608)	(0.0332)	(0.0460)	(0.1315)	(0.0559)	(0.0744)
West Midlands	-0.1586	0.0285	0.0021	0.0006	0.0134	-0.0791
	(0.1461)	(0.0299)	(0.0417)	(0.1232)	(0.0498)	(0.0687)
Yorkshire	-0.0957	0.0016	0.0267	0.0450	0.0573	0.0178
/Humberside	(0.1449)	(0.0298)	(0.0415)	(0.1208)	(0.0493)	(0.0673)
Industry sector						
Construction	0.4102*	-0.0081	-0.3584***	0.2561*	0.0089	-0.1937***
	(0.2143)	(0.0285)	(0.0388)	(0.1335)	(0.0539)	(0.0660)
Health and social	0.1953	0.0419	-0.1966***	0.2574	0.0571	-0.1739**
work	(0.1726)	(0.0309)	(0.0403)	(0.1737)	(0.0667)	(0.0836)
Hotels and	0.4544***	-0.0218	-0.0754*	0.0518	0.0086	-0.0562
restaurants	(0.1549)	(0.0324)	(0.0404)	(0.1261)	(0.0590)	(0.0715)
Manufacturing	0.1934	0.0577*	-0.3024***	0.2377	0.1060*	-0.1132
	(0.1894)	(0.0301)	(0.0409)	(0.1558)	(0.0602)	(0.0753)
Real estate renting	0.3556*	0.1525***	-0.2879***	0.3286**	0.1748***	-0.2829***
/business activities	(0.1879)	(0.0275)	(0.0366)	(0.1293)	(0.0544)	(0.0687)
Transport, storage /	0.5087**	0.0120	-0.2378***	0.1964	0.0347	-0.0638
communication	(0.2008)	(0.0318)	(0.0425)	(0.1285)	(0.0585)	(0.0724)
Wholesale/retail	0.1769	0.0256	-0.2351***	0.1780	0.0402	-0.1104
	(0.1741)	(0.0302)	(0.0396)	(0.1369)	(0.0593)	(0.0732)
Other community,	0.3502*	0.0445	-0.2576***	0.1933	0.0618	-0.1838**
social/ personal service	(0.1889)	(0.0299)	(0.0399)	(0.1649)	(0.0620)	(0.0775)

(continued)

Table 3.10 Continued

	Low-risk borrowers (minimal, low and average risk)			High-risk borrowers (above average risk)		
	Discouragement	**Awareness**	Demand	**Discouragement**	**Awareness**	Demand
Legal status						
Partnership	-0.3153**	0.0493*	0.2225***	-0.2655***	0.0208	0.1473**
	(0.1466)	(0.0293)	(0.0382)	(0.1001)	(0.0475)	(0.0576)
LLP	-0.2510	0.0152	0.1290***	-0.1274	0.1088*	0.1310
	(0.1652)	(0.0354)	(0.0480)	(0.1979)	(0.0636)	(0.0798)
LLC	-0.1419*	0.0897***	-0.0603*	-0.0226	0.1288***	0.0293
	(0.0816)	(0.0217)	(0.0317)	(0.0692)	(0.0277)	(0.0379)
Profitability						
Broken even	-0.1203	-0.1949***	-0.3287***	-0.1213	-0.0776**	-0.3017***
	(0.1389)	(0.0313)	(0.0433)	(0.1604)	(0.0389)	(0.0503)
Profit	-0.5314***	0.0245	-0.2373***	-0.1885	0.0558*	-0.3012***
	(0.0832)	(0.0228)	(0.0292)	(0.1286)	(0.0288)	(0.0353)
Growth Orientation						
Grow substantially	0.0764	0.0803***	0.3276***	0.0194	0.1020***	0.3691***
	(0.1318)	(0.0237)	(0.0320)	(0.1290)	(0.0367)	(0.0478)
Grow moderately	0.0254	0.0406***	0.1643***	0.0642	0.0579**	0.1731***
	(0.0812)	(0.0141)	(0.0208)	(0.0787)	(0.0238)	(0.0337)
Become smaller	0.1190	0.0593	0.2449***	0.0686	-0.0546	0.3026***
	(0.1534)	(0.0391)	(0.0536)	(0.1780)	(0.0646)	(0.0771)
Exit	0.2251	0.0625	0.3538***	0.1244	0.0098	0.3492***
	(0.1503)	(0.0394)	(0.0509)	(0.1621)	(0.0557)	(0.0688)
Business plan		0.1555***	0.1206***		0.1825***	0.1138***
		(0.0135)	(0.0195)		(0.0214)	(0.0319)
Export	-0.1110	0.0701***	-0.1016***	0.0488	0.0693*	-0.0418
	(0.0961)	(0.0204)	(0.0304)	(0.0935)	(0.0379)	(0.0511)
Import	-0.0412	0.0463**	-0.0058	0.0542	0.0551	0.0096
	(0.0937)	(0.0199)	(0.0285)	(0.0895)	(0.0358)	(0.0477)
Management account	0.0524	0.1436***	-0.0019	0.1120**	0.1496***	-0.0627**
	(0.0766)	(0.0155)	(0.0220)	(0.0529)	(0.0226)	(0.0306)
Improvement		0.1129***	0.1363***		0.0888***	0.1372***
		(0.0139)	(0.0202)		(0.0235)	(0.0325)
Innovation	0.2007**	0.0714***	0.0183	0.0937	0.0355	0.0171
	(0.0787)	(0.0161)	(0.0225)	(0.0616)	(0.0274)	(0.0363)
Business account	-0.5504***	-0.0480	0.0683	-0.2532**	-0.0823**	-0.0131
	(0.1744)	(0.0367)	(0.0555)	(0.1243)	(0.0351)	(0.0499)
Owner/Manager characteristics						
Gender						
Female	0.0245	-0.0721***	-0.0396	-0.0202	-0.0456*	-0.0648*
	(0.0749)	(0.0170)	(0.0241)	(0.0699)	(0.0268)	(0.0362)
Both (joint partners)	0.1104	-0.0542	-0.1862***	0.2535	-0.0147	-0.3231***
	(0.1854)	(0.0420)	(0.0544)	(0.1782)	(0.0827)	(0.1103)
Owner Age						
18-30 years	-0.0043	-0.3230***	-0.0251	-0.2378	-0.4032***	-0.0130
	(0.2098)	(0.0493)	(0.0693)	(0.1599)	(0.0620)	(0.0874)
31-50 years	-0.0244	-0.1903***	0.0785**	-0.0854	-0.2292***	0.1547**
	(0.1211)	(0.0222)	(0.0327)	(0.1279)	(0.0487)	(0.0702)
51-65 years	0.0229	-0.0904***	0.0440	0.0111	-0.0719	0.1178*
	(0.1072)	(0.0214)	(0.0317)	(0.1265)	(0.0483)	(0.0701)

(continued)

Table 3.10 Continued

	Low-risk borrowers (minimal, low and average risk)			High-risk borrowers (above average risk)		
	Discouragement	**Awareness**	Demand	**Discouragement**	**Awareness**	Demand
Bank relationships and/or products						
Multiple suppliers	0.1011	0.0496	0.5346***	-0.0586	0.2500***	0.5502***
	(0.1798)	(0.0400)	(0.0455)	(0.1514)	(0.0711)	(0.0782)
Use of credit card	0.0778	0.0548***	0.2557***	-0.0672	0.0761***	0.2407***
	(0.0865)	(0.0137)	(0.0191)	(0.0634)	(0.0262)	(0.0332)
Credit card application						
Unsuccessful	0.4657	0.0091	0.4286***	-0.0089	-0.1199	0.2255
	(0.2847)	(0.1083)	(0.1066)	(0.2597)	(0.1470)	(0.1474)
Not applied	0.0338	0.0577**	-0.4084***	0.2986***	0.0343	-0.4343***
	(0.1610)	(0.0288)	(0.0335)	(0.1130)	(0.0519)	(0.0532)
Proactive approach	-0.3841***	0.2044***	0.2232***	-0.1913	0.1936***	-0.0389
	(0.1355)	(0.0154)	(0.0207)	(0.1637)	(0.0280)	(0.0391)
Constant	-0.8367	-0.9503***	-1.0176***	0.7235*	-0.9639***	-1.1821***
	(0.5825)	(0.0711)	(0.0950)	(0.3698)	(0.1066)	(0.1338)
Wave	Yes	Yes	Yes	Yes	Yes	Yes
Correlation coefficient ($\rho_{awaredem}$)		0.0666***			0.0705***	
Correlation coefficient ($\rho_{awaredis}$)		**-0.4369**			**0.8740*** **	
Correlation coefficient (ρ_{demdis})		**0.4229**			**0.3782***	
No. of observations		48816			19524	
Wald Chi-square test		4850.49***			2678.48***	

Notes: This table reports the estimated coefficients of a trivariate probit model with sample selection for term loans by low- and high-risk borrowers. Standard errors are reported in parentheses. Low-risk borrowers refer to firms with minimal, low and average risk in D&B rating and high-risk borrowers refers to firms with above average risk in D&B rating. The dependent variables used in the model are whether a firm does not apply for fear of rejection even if it has a demand for overdrafts, whether the firm is aware of the Enterprise Guarantee Finance Scheme, whether the firm has a demand for overdrafts and. The definitions of all control variables are provided in Table 3.5. The null hypothesis of the Wald test is that all coefficients, excluding the constant term, are equal to zero simultaneously. The data are collected during 2011Q3-2015Q4. *, **, *** indicate significance at 10%, 5% and 1% level, respectively.

In each sub-sample for overdrafts and loans, financially literate SMEs are more likely to be aware of EFGS, suggested by the significantly positive coefficient for financial literacy in equation (3.1). This again provides additional evidence supporting ***H1***. Our second hypothesis on overdrafts holds for both low- and high-risk borrowers while, for loans, only high-risk borrowers aware of EFGS are less likely to be discouraged. This suggests that raising the awareness of government initiatives could bring all borrowers back to the overdraft market but only high-risk borrowers back to the loan market. As intangible assets often constitute the majority of the assets in high risk-high growth firms (Berger and Udell, 1998), it is difficult for banks to understand the process, such as the innovations in management or technology. This informational opaqueness makes credit suppliers reluctant to lend, and these firms have to seek other financing sources (e.g. peer-to-peer lending). In this sense, our findings imply that raising the awareness of government initiatives, which encourages high-risk SMEs to take out loans, creates more opportunities for new high-growth firms and might be helpful to overcome the financing obstacles in the early stage of innovations.

Table 3.10 clearly shows that low-risk borrowers with financial literacy are more likely to apply for loans, whereas high-risk borrowers with financial literacy are more likely to be discouraged. Therefore, improving financial literacy could encourage creditworthy SMEs to apply for loans and discourage credit risky SMEs, making discouragement a more efficient self-rationing mechanism before loan application. Given the definition for financial literacy (see Table 3.5), we recommend that the authorities offer more facilities to empower SMEs to access to financial knowledge more conveniently (e.g. online) and at lower costs (or even free). However, such evidence in support of ***H3*** is not observed for overdrafts, although the signs of the insignificant coefficients for financial literacy are as expected: negative for low-risk borrowers and positive for high-risk borrowers.

3.7 Conclusions

This chapter empirically analyses UK small discouraged borrowers, the businesses that have a demand for bank debt but do not apply for fear of rejection. Although many studies investigate the credit rationing of SMEs in both developed and developing countries, only a handful addresses the issue of discouraged borrowers. Discouragement is prevalent in the UK market with the number of discouraged borrowers estimated to be twice that of refused borrowers in the Freel et al. (2012) study. In this sense, mitigating this latent credit constraint would benefit the growth of SMEs in the private sector and also the growth of the local economy. In light of such concerns, we explore the relationship between the Enterprise Finance Guarantee Scheme (EFGS), financial literacy and debt discouragement to test whether raising EFGS awareness and improving financial literacy could bring creditworthy discouraged borrowers back to the market.

Using the UK SME Finance Monitor 2011-2015, we apply a trivariate probit model with sample selection to deal with the potential endogeneity and selection bias problems. Financially literate SMEs are found to be more likely to be aware of EFGS, and aware SMEs are found to be less likely to be discouraged. We also find similar determinants for overdraft and loan discouragement. Younger and riskier SMEs with older owners and past business improvement are more likely to be discouraged. By contrast, profitable businesses receiving proactive approaches from banks are more likely to make applications.

Our evidence shows that raising EFGS awareness could bring all borrowers back to the overdraft market, but only high-risk borrowers back to the loan market. In addition, our findings are consistent with previous US and UK studies (e.g. Han et al., 2009; Cowling, Liu, Minniti and Zhang, 2016) that discouragement acts as an efficient self-rationing mechanism before application. We also discover a role for financial literacy in improving the efficiency of self-rationing for loans, since improving financial literacy could encourage low-risk borrowers to take out loans and discourage high-risk borrowers.

From a policy perspective, our analysis provides useful insights to the authorities on the characteristics of discouraged borrowers among UK SMEs. Our findings on a particular government initiative provide strong evidence for promoting their awareness. This could encourage discouraged borrowers back to the market, especially those high-risk SMEs, creating more financing opportunities for new high-growth firms and potentially mitigating financial barriers in the early stage of innovations. We also recommend that the authorities offer more facilities to enable SMEs to access financial knowledge more conveniently (e.g. online) and at lower costs (or even free). This would make discouragement more efficient and further reduce the supply-side costs when banks make assessments on loan applications. Finally, the government also aims to create a better environment for alternative financing and has launched several initiatives to allow SMEs better access to other sources, such as the Seed Enterprise Investment Scheme (SEIS) targeted at equity funding. In this sense, future studies on the relationship between bank debt discouragement and government initiatives on alternative financing are warranted. Our study also provides some avenues for future research on how to bring discouraged borrowers back to the market in the context of developing countries. We expect a similar but more intense role of financial literacy where discouragement is more prevalent but financial literacy is lower.

Chapter 4 Angels in the Crowd: Equity Crowdfunding Dynamics

4.1 Introduction

As a reaction to bank lending shortages in the wake of the financial crisis and a potential need for disintermediation in capital markets, several new players in entrepreneurial finance have emerged in recent years (Block et al., 2018). One of the most prominent funding alternatives for both investors and start-ups is equity crowdfunding (ECF) that builds on the ‘wisdom of the crowd’. In line with pecking order theory (Myers and Majluf, 1984), ECF is generally sought by seed and early-stage companies as a “last resort” after they use up their internal funds and debt capacity (Walthoff-Borm et al., 2018). With the rapid evolution of the ECF market and the sharp increase in the average amount raised, it has also attracted growth stage companies in recent years, helping to bridge the sizable second equity gap identified by Wilson et al. (2018).

Due to light-touch regulation (including prospectus exemption) and generous tax relief schemes, the UK has become the most developed ECF market in the world (Estrin et al. 2018). Three platforms (Crowdcube, Seedrs and SyndicateRoom) dominate the UK ECF market and accounted for 84% successful ECF campaigns in 2017 (Coakley et al., 2019). The Big 3 platforms employ the all-or-nothing (AON) model in which start-ups receive no funds if the amount pledged does not reach the target (Cumming, Leboeuf and Schwienbacher. 2019). Since the ECF market is new and there is no standard ‘optimal’ business model, platforms may introduce novelty into their own models (e.g. lead investor requirement, pooled investment vehicle, and secondary market establishment) and adopt business strategies from other platforms to strengthen their competitiveness.

In a pure ECF model (or a standard ECF model), the crowd of typically small investors (including friends and family) funds start-up campaigns (Vismara, 2016). In this setup, the ECF market is segmented from the traditional entrepreneurial market dominated by business angels and venture capital firms. One major innovation in the UK is that both markets have become linked by the rise of co-investment by institutional investors (mainly business angels[30]) to syndicate crowd investors and traditional professional investors. This funding strategy (an angel co-investment model) was implemented by SyndicateRoom from its establishment in late 2014. Since then, other platforms have explicitly or implicitly encouraged the involvement of angels or venture capital in the funding process. We refer to it as angels in the crowd.

Although growing numbers of empirical researches have started to investigate aspects of ECF campaigns in recent years, as Cumming, Vanacker and Zahra (2019) point out, most empirical studies examine the determinants of ECF campaign success (e.g. Ahlers et al., 2015; Piva and Rossi-Lamastra, 2018) and/or ECF funding dynamics (e.g. Vulkan et al., 2016; Hornuf and Schwienbacher, 2018a; Vismara, 2018) and many of them focus on the UK market (e.g. Vulkan et al., 2016; Vismara, 2016, 2018, 2019; Ralcheva and Roosenboom, 2019). Only a handful of studies discuss the role of angels in ECF market (e.g. Chen et al., 2016; Hornuf and Schwienbacher, 2016) and similarly, most empirical studies on this topic examines the (positive) role of angels on ECF campaign success (e.g. Ralcheva and Roosenboom, 2016; Kleinert et al., 2018). As far as we know, the relationship between angel co-investment and ECF funding dynamics has never been investigated. To fill in this gap in the literature, we aim to explore the role of angels in ECF funding dynamics in this chapter.

[30] Typically, business angels invest in smaller and early-stage businesses, whereas venture capitalists invest in larger and expansion-stage businesses. This is also the reason why institutional investors in ECF market are mainly business angels.

In the ECF funding dynamics literature, the Hornuf and Schwienbacher (2018a) study is the first paper to demonstrate the dynamic shape during an ECF campaign. Specifically, they investigate funding dynamics across four ECF platforms in Germany, by exploiting the cross-platform variation in allocation mechanisms – the first-come, first-served (FCFS) versus auction mechanisms – and examining their contrasting effects on funding dynamics. The dynamics exhibits an L-shaped pattern under the FCFS mechanism and a U-shaped pattern under an auction mechanism. By contrast, the allocation mechanism for all ECF platforms in the UK is the posted (fixed) price FCFS mechanism. Therefore, UK ECF campaigns may be expected to follow L-shaped dynamics given that more investors pledge in the early campaign days. Extending the Hornuf and Schwienbacher (2018a) study, this chapter answers the following questions. (1) What is the impact of angel co-investment on the L-shaped funding dynamics shown in an ECF campaign? (2) Will this impact vary in different situations, such as when the level of information asymmetry changes?

This chapter's main contribution to the literature is that it takes advantage of variation in funding mechanisms across UK platforms and investigates their effects on funding dynamics. More particularly, it contrasts the business angel co-investment funding models with the standard model and explores its impact on funding dynamics. We also show how this impact responds when the level of information asymmetry changes. The second contribution is that the UK ECF market operates a variation of the AON model that we call the AON+ model. The latter explicitly permits overfunding beyond the ex-ante target set at the campaign beginning. In addition to checking the dynamic shape at the campaign start, we also explore the dynamics after the onset of overfunding. To the best of our knowledge, this has not been examined before, although more investors are found to be attracted after overfunding in the Hornuf and Schwienbacher (2018a) study.

Employing the TAB database and UK Companies House websites, we obtain a sample of 21,223 daily observations from 497 (281 successful and 216 failed) campaigns on the three biggest UK platforms, spanning the period from July 2014 to December 2018. The rich dataset provides us, as far as we know, the largest sample for investigating funding dynamics. From a campaign-level analysis, we notice that campaigns with angel co-investment tend to be larger and the fundraisers running these campaigns tend to be bigger start-ups with a more diversified board.

In line with Hornuf and Schwienbacher (2018a), we investigate the dynamics of the number of investors. The number of investors attracted in each day during the campaign is utilised as the dependent variable, and negative binomial models are employed to carry out the empirical analysis. Our results confirm the L-shaped pattern at the campaign start and demonstrate a second L-shape after the funding target is exceeded (i.e. the overfunding stage), which is less pronounced than the first one. We also observe a more prominent L-shape when an angel co-invests alongside the crowd. However, this role of angels weakens when information asymmetry gets alleviated (e.g. by a successful initial ECF campaign or by successfully reaching the target).

The rest of this chapter is organised as follows. Section 4.2 provides a brief discussion of equity crowdfunding and angel co-investment in the ECF market. Section 4.3 sets out the key research hypotheses. Sections 4.4 describes the data and the variables employed in our regressions and presents some descriptive statistics. The empirical results and robustness tests are presented and discussed in Sections 4.5 and 4.6, respectively. Finally, Section 4.7 concludes and provides a discussion of the related policy issues.

4.2 Angel Co-investment in Equity Crowdfunding

4.2.1 Equity Crowdfunding in the UK

Crowdfunding is an umbrella term to describe a kind of alternative financing that an individual or a firm makes an open call via an Internet platform to raise money from a large group of investors who typically invest a small amount of investment. Equity crowdfunding is one form of crowdfunding where the fundraiser (a start-up rather than an individual) offers a percentage of equity or bond-like shares in exchange for the funding. Therefore, the investor's compensation is the fundraiser's future cash flow in ECF. This makes it different from other types of crowdfunding, where investors are compensated by philanthropy in donation-based crowdfunding, non-financial rewards (such as a thank-you card or a pre-purchased product) in reward-based crowdfunding, or fixed interests in lending-based crowdfunding (which is also called peer-to-peer lending or P2P).

Since the foundation of the first ECF platform Crowdcube in 2011, the UK ECF market has evolved to the largest and most developed ECF market (Estrin et al., 2018; Coakley and Lazos, 2019). The Big 3 ECF platforms in the UK employ several features leading to their success, such as a specified minimum investment of just £10 on Crowdcube and Seedrs to attract more crowd investors, although institutional investors can also invest via these platforms. However, SyndicateRoom sets a £1,000 minimum investment requirement, only allowing qualified investors and business angels (acting as lead investors). Another feature adopted by all Big 3 platforms is the AON model, which provides protection to investors, in the sense that their investment will be returned if the amount raised does not reach the target, a scenario indicating that most investors are not optimistic about the project. Overfunding is also permitted so that firms can choose to offer an extra percentage of equity in exchange for additional funding after the ex-ante target is exceeded. Therefore, we call this variation of AON model the AON+ model.

4.2.2 Angel Co-investment in equity crowdfunding

The pure ECF model (Vismara, 2016) is characterised by a large number of small investors, where the platform acts as an intermediary to connect entrepreneurs and crowds. This model excludes traditional institutional investors who typically invest a large amount of money. A prominent ECF innovation is co-investment by institutional investors (mainly business angels). In this co-investment funding model, crowds and business angels are syndicated, where the platform becomes multi-sided to connect entrepreneurs with angels and crowds. In the UK, SyndicateRoom pioneered this approach by requiring fundraisers to seek a lead investor (at least 25-40% of the total funding target) before their campaigns go online. Here an angel typically acts as the lead investor and conducts the due diligence together with the platform. Recently, Crowdcube also requires a 20% secure investment before a campaign goes public. Along similar lines, Seedrs requires start-ups to raise money from their network in the private launch of their campaigns to gain initial traction before going public. However, they do not specify any minimum sum that needs to be raised at this stage.

Several platforms also operate a syndicate investing strategy in other countries, such as OurCrowd in Israel and AngelList in US. The syndicate mechanism on OurCrowd is similar to that on SyndicateRoom. However, on AngelList, angels act as a syndicate lead to construct a portfolio with ECF campaigns. The crowd investors select the portfolio to invest and pay carry fees (usually 5-20%) to the lead angel (Agrawal et al., 2016). Hence, essentially, investors invest in the lead angels' experience and reputation on AngelList, rather than start-ups' quality and prospects on SyndicateRoom and OurCrowd.

Given that information asymmetry is one of the biggest challenges in ECF campaigns, the crowd can benefit from angel pre-campaigns due diligence (Chen et al., 2016) and post-campaign monitoring skills (Hornuf and Schwienbacher, 2016). It is also found that the syndicated ECF can reduce the local bias (Agrawal et al., 2016) that investors exhibit in investing geographically close firms (Hornuf and Schmitt, 2016). For the entrepreneurial firms, especially for those high-tech innovative firms, co-investment by angels helps them solve the double trust dilemma of innovation (Cooter and Edlin, 2013). On the one hand, the start-ups have to disclose information, via online platforms, to attract crowd investment. On the other hand, if too much information becomes publicly available, their innovative ideas might be replicated by other start-ups or large firms with no compensation. In this sense, the angel co-investment can reduce the severe information asymmetry, and start-ups have fewer worries about information leakage.

However, as more professional investors invest via ECF campaigns, some researchers argue that the ECF market may become dominated by large investors, thus destroying its initial democratising purpose (Zhang et al., 2015). A recent empirical study from Wang et al. (2019) finds a complementary relationship between angels and crowd investors on a UK platform and observes the information flow leveraged from angels. Hence, at least at this stage, professional investors are not crowding out crowd investors. They also establish that the large amounts pledged by angels have a more positive effect on other angels' investment than on crowd investment.

4.3 Hypothesis Development

Under the first-come first-served mechanism (common on UK ECF platforms), the funding dynamics during campaigns typically exhibits an L-shaped pattern because of the 'collective attention effect' (Hornuf and Schwienbacher, 2018a). Specifically, the number of pledges is typically high at the beginning of a new campaign when investors are informed, and then it decreases since the news decays as time elapses. Under the AON model, start-ups can collect the pledges only after the amount raised exceeds the funding target, after which they can choose to offer more equity in exchange for additional funding (i.e. overfunding) or close the campaign. This is what we call the AON+ model. Hornuf and Schwienbacher (2018a) argue that because the campaign becomes less risky once the funding target is reached, funding dynamics might differ before and after overfunding. Although they observe higher numbers of investors during the overfunding period, as far as we know, the specific pattern of overfunding dynamics has not been investigated.

Given that platforms will send advertising newsletters of overfunded campaigns to their registered crowd investors, the 'collective attention effect' might also lead to a similar L-shaped pattern after overfunding. However, it is plausible that fewer investors will be attracted after overfunding, thus leading to slightly lower L-shape dynamics than at the beginning of the campaign.

> ***H1:*** *Dynamics after overfunding follow an L-shaped pattern which is lower than the L-shape shown at the beginning of the campaign.*

4.3.1 The Role of Angels in Funding Dynamics

The rationale underlying a co-investment approach is that crowd investors trust that the angels (acting as lead investors in some situations) share the same interests so that they can benefit from their experience in selecting and monitoring high-quality start-ups (Agrawal et al., 2016). The involvement of angels can trigger herding behaviour, converting their expertise and experience to extensive pledges. Both experienced professional investors and inexperienced crowd investors are found to herd after angels, among whom herding is more prominent for professional investors (Wick and Ihl, 2018; Wang et al., 2019). Herding may be rational since crowd investors can, to some extent, avoid potential injudicious decisions when they piggyback on the "wisdom of crowd" (Hornuf and Schwienbacher, 2016).

Vulkan et al. (2016) underline the critical role of early funding in the first week in campaign success, and Vismara (2018) highlights the importance of early investors, especially the sophisticated early investors, in attracting late investors. Hence, we posit that the early funding from angels can provide initial traction and drive information cascades among investors. In addition, as Ralcheva and Roosenboom (2016) point out, the investment by angels, a creditable third-party (lead) investor, plays a certification role for the high quality of start-ups.[31] This reduces information asymmetries, leading to a higher probability of campaign success.

Considering rational herding behaviour, initial traction and certification effect, as well as the possibility that angels may inform their own social networks at the beginning of the campaign, L-shaped dynamics are expected to be pronounced when an angel co-invests alongside the crowd.

> ***H2:*** *Campaigns with angel co-investment exhibit a pronounced L-shaped pattern at the beginning of the campaign.*

The role of angels in funding dynamics may vary with the level of information asymmetries since herding behaviour becomes more pronounced when investors are faced with high uncertainty and risk and are in need of worthwhile signals (Wick and Ihl, 2018). In addition, the effect of signals (or certification) strengthens as the level of information asymmetry increases (Wang et al., 2019). Therefore, the impact of angels on funding dynamics potentially becomes weaker when information asymmetry is relatively low. As discussed above, in the AON+ model, reaching the funding target acts as an effective signal of the

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[31] Note that there are relatively few certification mechanisms for ECF campaigns in contrast to initial public offerings (IPOs) where lead underwriters and Top 4 auditors can act as certification mechanisms.

start-up's quality. This mitigates the severe information asymmetry in ECF campaigns, weakens the role of angels and contribute to a less pronounced L-shape in overfunding dynamics. Therefore, we propose the following hypothesis:

> ***H3:*** *Angels exert a weaker impact on the funding dynamics after the campaign reaches its funding target.*

Another situation when the level of information asymmetry reduces is in seasoned equity crowdfunded offerings (SECO), a follow-on campaign if the fundraiser has previously launched a successful campaign on the same platform. An increasing number of start-ups is engaging in SECO as second or third round financing. One of the reasons might be that they can raise money rapidly and cheaply in ECF campaigns (Estrin et al., 2018). Almost half of the seasoned campaigns in the UK occurred in the 12 months after the initial campaigns (Coakley et al., 2019). The success of initial campaigns can be recognised as a signal of firm's creditworthiness and thus as a signal, reduce the information asymmetry in seasoned campaigns. This leads to our final hypothesis:

> ***H4:*** *Angels exert a weaker impact on the funding dynamics in seasoned campaigns, relative to initial campaigns.*

4.4 Data and Variable Description

4.4.1 Data

The campaign data for the three biggest UK platforms are from the TAB database on Thomson Reuters Eikon App Studio. The database provides campaign-level characteristics

Table 4.1 Sample Selection Criteria

	Crowdcube	Seedrs	SRoom[a]	Total
Number of campaigns with data at the start date	631	204	114	949
-Campaigns lasting no more than 7 days	-16	-3		-19
-Campaigns with missing data in the first 7 days	-179	-85	-19	-283
-Campaigns with missing data in consecutive 7 days or more	-72	-13	-6	-91
-Campaigns with missing data at the end date	-12	-2	-14	-28
-Campaigns with "false" start date			-7	-7
-Campaigns with missing data on campaign characteristics	-19		-1	-20
-Campaigns with missing data on board characteristics		-3	-1	-4
Sample size *(Of which)*	**333**	**98**	**66**	**497**
Successful (Failed) campaigns	193 (140)	55 (43)	33 (33)	281 (216)
Seasoned (Initial) campaigns	23 (310)	12 (86)	9 (57)	44 (453)
# Observations				
Before interpolation	11606	4827	2361	18794
After interpolation	**13007**	**5790**	**2426**	**21223**

Notes: This table reports the sample selection process to obtain our final sample. [a]: SRoom represents SyndicateRoom

of both successful and failed campaigns from July 2011 to December 2018, as well as daily data on the cumulative number of investors and amount raised.

To control for the human capital of start-up directors, we scrape the data from UK Companies House, a public official website displaying the information of UK registered companies and the directors working in the companies. We start with a sample of 949 campaigns with data on the first day.[32] Table 4.1 presents an overview of our sample selection process.

First, we remove 302 campaigns with incomplete information in the first seven days (19 lasting no more than seven days and 283 with missing data in the first seven days). Then we interpolate the missing daily data. To ensure the validity of our interpolations, we exclude 91 campaigns with missing data on seven consecutive days[33] (or more) and 28 with missing data at the end date. We also take 7 campaigns out of our sample because of the

[32] The reason why we start here is related to the way we construct the proxy for angel co-investment. See more details in Section 4.4.2.2.

[33] If the data are missing on consecutive seven days (or more) but the data on the day before and after the missing data remain unchanged, we keep this campaign in our sample and presume that no additional investors pledged new funds.

‘false’ start date[34] and 24 because of their missing data or outliers[35] in control variables. This procedure produces a panel sample, consisting of 21,223 observations from 497 campaigns from July 2014 to December 2018, of which 281 are successful campaigns and 216 are failed campaigns. By contrast, in the Hornuf and Schwienbacher (2018a) sample, 81% of the 89 ECF campaigns are successful campaigns. Therefore, our sample is much larger and puts more weights on failed campaigns. This can offer a more balanced analysis by avoiding results skewed more towards successful campaigns.

4.4.2 Variable Description

4.4.2.1 Dependent Variables

Following Hornuf and Schwienbacher (2018a), the daily *Number of investors* is employed as the dependent variable to examine the funding dynamics in ECF campaigns. The difference in the cumulative number of investors on successive days is used to calculate the daily *Number of investors* on a given day. On average, an ECF campaign attracts 6.4 investors in a day, with 1989 investors at most on Crowdcube on November 28, 2017. Investors can withdraw their investment at any time before the campaign ends. Therefore, negative values appear for the dependent variable.

4.4.2.2 Key Explanatory Variables

The variables of interest are dummy variables to indicate a particular day during the campaign. To test our hypotheses, we construct 7 dummy variables for the first seven campaign days (Kuppuswamy and Bayus, 2018; Hornuf and Schwienbacher, 2018a) and

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[34] The database provides two files. One file includes the campaign characteristics, e.g. start date and end date. Another file includes the updated daily information. For these 7 SyndicateRoom campaigns, the updated daily information shows an earlier start date than the other file - hence ‘false’ start date.

[35] Four campaigns on SyndicateRoom offer more than 99% equity in exchange for funding. We treat these campaigns as outliers since generally, no fundraisers are willing to lose control of their businesses.

another 7 dummy variables for the first seven days after overfunding. The day on which the target is reached is deemed to be the first day in the latter context.

Another key explanatory variable is *Co-investment* (by angels) at the start date. All SyndicateRoom campaigns have an angel (or a venture capitalist) as a lead investor at the campaign start. Given that angels generally invest a large amount of money, we employ the ratio of the amount raised in the first day to funding target (*First-day-ratio*)[36] to identify co-investment on the Crowdcube and Seedrs platforms. Here we posit that investors putting large amounts of their own funds at risk behave similarly to angels (Wallmeroth, 2019; Wang et al., 2019). Accordingly, we construct a dummy variable equal 1 for all SyndicateRoom campaigns and the top 1/3 of the *First-day-ratio* (by year and platform) for the Crowdcube and Seedrs campaigns as a proxy for angel co-investment.

4.4.2.3 Control Variables

Considering that the determinants of campaign success might also impact the daily outcomes, we also control for campaign and board characteristics. Table 4.2 lists the definitions of all control variables with their respective descriptive statistics reported in Table 4.3.

Following Ralcheva and Roosenboom (2018), we add *Funding target* and *Equity offered* as control variables, which are decided by entrepreneurs in consultation with the platform. Under the ANO model in which the fundraiser will get nothing if the funding target is not reached, a higher target indicates entrepreneurs' confidence that their projects are good

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[36] The idea to employ the *first-day-ratio* to construct the proxy for *Co-investment* is inspired by the requirement on SyndicateRoom that the lead investor (typically a business angel) has to invest at least 25%-40% of the total funding target before the campaign goes online. We also considered employing the total amount raised in the first day and/or the average amount that an investor pledged in the first day (i.e. total amount raised in the first day/total number of investors in the first day) to construct the proxy. However, the proxy constructed by the latter two measures has a very high correlation with the dependent variable. To get rid of the possibility that our results are driven by the way we construct our proxy, we decide to employ *first-day-ratio*.

Table 4.2 Variable Description

	Description	Source
Number of investors	Total number of investors that pledged money in each day of the campaign	TAB
Campaign characteristics		
Co-investment	Dummy=1 if there is (at least) a co-investment by a business angel (or a venture capitalist) in the first day of the campaign (i.e. all campaigns on SyndicateRoom and the campaigns with top 1/3 first-day-ratio[a] on Crowdcube and Seedrs in each year); 0 otherwise	TAB
Funding target	Funding target of the campaign set by the fundraiser (in £1,000s)	TAB
Equity offered	Percentage of equity offered by the fundraiser in exchange for investors' pledges	TAB, Crowdcube and Seedrs websites
Seasoned campaign	Dummy=1 if the fundraiser had previously launched a successful campaign on the same platform; 0 otherwise	TAB
Information technology	Dummy=1 if the project to be funded in the campaign was classified as information technology sector in GICS; 0 otherwise	TAB
London	Dummy=1 if the fundraiser operates in London; 0 otherwise	TAB, UK Companies House
Overfunded	Dummy=1 if the total amount raised until a given day reached the funding target; 0 otherwise	TAB
Board characteristics		
Board size	Number of directors at the beginning of the campaign	UK Companies House
Average age	Average age of directors at the beginning of the campaign (in year)	UK Companies House
Age diversity	Range of age of directors at the beginning of the campaign (maximum age minus minimum age) (in year)	UK Companies House
Average tenure	Average tenure of directors at the beginning of the campaign (in year)	UK Companies House
Tenure diversity	Range of tenure of directors at the beginning of the campaign (maximum tenure minus minimum tenure) (in year)	UK Companies House
Common surname	Dummy=1 if any two (or more) directors have same surname; 0 otherwise	UK Companies House
Foreign nationality	Dummy=1 if any of the directors is not from UK; 0 otherwise	UK Companies House
Doctorate	Dummy=1 if any of the directors is titled "Dr" or "Professor"; 0 otherwise	UK Companies House

Notes: This table reports the definitions of the dependent variable and the independent variables used in the regressions. [a]: the first-day-ratio refers to the ratio of the amount raised in the first day to the funding target.

Table 4.3 Descriptive Statistics

	Obs.	Mean	Median	Std. dev.	Min.	Max.
Number of investors	21223	6.39	2	27.88	-11	1989
Campaign characteristics						
Co-investment	497	0.41	0	0.49	0	1
Funding target	497	392	300	459	40	6000
Equity offered	497	14.38	13.04	8.43	2.23	66.67
Seasoned campaign	497	0.09	0	0.28	0	1
Information technology	497	0.54	1	0.50	0	1
London	497	0.46	0	0.50	0	1
Overfunded	21223	0.24	0	0.43	0	1
Board characteristics						
Board size	497	2.43	2	1.51	1	11
Average age	497	43.39	43.65	9.97	22.77	77.67
Age diversity	497	9.02	3.67	11.18	0	46.92
Average tenure	497	3.20	2.15	3.17	0	21.74
Tenure diversity	497	1.37	0	2.60	0	19.26
Common surname	497	0.13	0	0.33	0	1
Foreign nationality	497	0.29	0	0.46	0	1
Doctorate	497	0.08	0	0.27	0	1

Notes: This table reports the descriptive statistics of the dependent variable and the independent variables. The definitions of all variables are provided in Table 4.2.

enough to attract enough money (Hornuf and Neuenkirch, 2017). Also, if the entrepreneurs are optimistic at the firm's prospect, they would retain more equity to guarantee more profits in the future (Vismara, 2016). In this sense, investors can use these two variables as signals to reduce information asymmetries. For *Equity offered*, we replace missing data from the Crowdcube and Seedrs official websites, although their websites only provide this information for successful campaigns. The fundraisers in our sample set an average target of approximately £392,000 and offer a mean 14.38% equity stake to the crowd for investment. The campaigns in our sample are much bigger than those in the Hornuf and Schwienbacher (2018a) sample (with an average target of €52k). *Seasoned campaign* and *Information technology* variables are also included to examine whether a successful initial campaign and a high-tech project play a positive role in attracting more investment. On average, only 9% fundraisers had previously launched a successful ECF campaign on the same platform, but more than half of the campaigns are information technology projects. ECF is an attractive financing alternative for innovative start-ups, especially when they face more difficulties in accessing bank credit (Freel, 2007). We also control for the location of the project (*London*), with almost half located in London, probably relevant to the fact that that is where Crowdcube and Seedrs' offices are located. *Overfunded* is the only time-variant control variable in our model. The amount raised exceeds the funding target in almost a quarter of all campaign days observed.

As previous studies (Ahlers et al., 2015; Piva and Rossi-Lamastra, 2018) point out, human capital (board characteristics) is an important determinant for campaign success since it is an indicator of the start-up's managerial competence and indicates its ability to survive, especially for early-stage start-ups. Specifically, we control for *Board size*, directors' age (*Average age* and *Age diversity*), and directors' tenure (*Average tenure* and *Tenure diversity*). On average, 2.43 directors aged 43.39 years work for 3.20 years in the start-ups. The board is diversified in the sense that the range of directors' age and tenure is 9.02 and 1.37 years, respectively. Following Wilson et al., (2018), we use *Common surname* as a proxy for family businesses. We also construct *Foreign nationality* and *Doctorate* to identify if there are foreign and highly-educated directors working in the start-ups. In our sample, 13% are family businesses, 29% employ directors from other countries and 8% employ directors with a degree that entitles them to employ the Dr. (or Professor) title. The correlation coefficients between all control variables and the variance inflation factors (VIFs) to deal with the multicollinearity concerns are reported in Table 4.4.

Most correlation coefficients are under 0.5, except for those between board size and board diversity (0.72 with directors' age diversity and 0.58 with directors' tenure diversity). A plausible explanation is that start-ups seek to bring more voices and absorb various opinions to avoid extreme decisions (Wilson et al., 2018). Then they employ more directors to make their board more diversified. Despite the high correlation, the VIFs for all control variables are smaller than 5, indicating that multicollinearity should not be an issue in our regressions.

Table 4.4 Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	VIF
(1) Co-investment	1													1.13
(2) Funding target	0.268***	1												1.22
(3) Equity offered	0.029	0.018	1											1.10
(4) Seasoned campaign	0.069	0.016	-0.163***	1										1.04
(5) Information technology	0.073	0.070	-0.040	0.004	1									1.05
(6) London	0.002	0.043	-0.056	0.008	0.004	1								1.11
(7) Board size	0.223***	0.314***	-0.089**	0.042	0.052	-0.084*	1							2.69
(8) Average age	0.115**	0.158***	-0.045	0.018	0.026	-0.195***	0.306***	1						1.33
(9) Age diversity	0.209***	0.265***	-0.063	0.060	0.090**	-0.096**	0.723***	0.332***	1					2.25
(10) Average tenure	0.036	0.084*	-0.160***	0.042	-0.036	-0.080*	-0.025	0.274***	0.011	1				1.29
(11) Tenure diversity	0.129***	0.268***	-0.155***	0.076*	-0.075*	-0.042	0.584***	0.342***	0.499***	0.288***	1			1.92
(12) Common surname	0.048	0.023	-0.028	0.030	-0.085*	-0.161***	0.210***	0.135***	0.237***	0.124***	0.154***	1		1.14
(13) Foreign nationality	0.067	0.149***	-0.103**	-0.014	0.056	0.152***	0.238***	-0.080*	0.168***	-0.085*	0.149***	-0.073	1	1.16
(14) Doctorate	0.141***	0.166***	-0.008	0.012	0.006	-0.127***	0.218***	0.206***	0.185***	0.050	0.245***	-0.024	0.085*	1.13

Notes: This table reports the correlation coefficients between the independent variables. The definitions of all variables are provided in Table 4.2. *, **, *** indicate significance at 10%, 5% and 1% level, respectively. VIF represents the variance inflation factor.

Table 4.5 Difference in Means: Co-investment vs. Traditional Campaigns

	Co-investment campaigns		**Traditional campaigns**			
	Obs.	Mean (a)	Obs.	Mean (b)	Difference (a-b)	t-statistics
Panel A Campaign-level comparison						
Campaign characteristics						
Funding target	206	538.30	291	288.45	249.85	5.45***
Equity offered	206	14.67	291	14.18	0.49	0.63
Seasoned campaign	206	0.11	291	0.07	0.04	1.48
Information technology	206	0.58	291	0.51	0.07	1.63
London	206	0.47	291	0.46	0.002	0.05
Board characteristics						
Board size	206	2.83	291	2.15	0.68	4.83***
Average age	206	44.74	291	42.42	2.32	2.64***
Age diversity	206	11.79	291	7.05	4.74	4.59***
Average tenure	206	3.34	291	3.10	0.23	0.81
Tenure diversity	206	1.76	291	1.09	0.68	2.78***
Common surname	206	0.15	291	0.11	0.03	1.04
Foreign nationality	206	0.33	291	0.27	0.06	1.48
Doctorate	206	0.13	291	0.05	0.08	2.96***
Panel B Daily-level comparison						
Number of investors	8096	9.24	13127	4.64	4.60	9.55***
#First day	206	99.60	291	37.71	61.89	3.76***
#Second day	206	21.86	291	12.10	9.76	3.75***
#Third day	206	13.77	291	7.64	6.13	3.90***
#Fourth day	206	11.30	291	6.62	4.68	3.17***
#Fifth day	206	10.54	291	6.16	4.38	2.56**
#Sixth day	206	9.77	291	5.18	4.59	3.34***
#Seventh day	206	8.91	291	4.99	3.92	3.33***
#Except first 7 days	6654	5.80	11090	3.38	2.42	14.73***

Notes: This table reports the difference in means between co-investment campaigns and traditional campaigns. Panel A shows the campaign-level comparisons and Panel B shows the daily-level comparisons. The definitions of the variables are provided in Table 4.2. **, *** indicate significance at 5% and 1% level, respectively.

4.4.3 Impact of Angels

Table 4.5 presents the results of equality of means between co-investment campaigns and traditional campaigns. Panel A presents the results for campaign and board (of director) characteristics, while Panel B gives daily-level comparisons for the number of investors.

The target capital in co-investment campaigns is almost double that in traditional campaigns. This difference is significant at the 1% level and is the only significant difference among all the campaign characteristics. It is consistent with evidence that angels tend to make relatively large investments in larger start-ups. By contrast, five out of the eight board characteristics exhibit significant differences, all at the 1% significance level.

Co-investment campaigns on average have larger boards, older directors, higher age and tenure diversity, and they employ double the number of experts (with doctor title) than their counterparts. The prevalence of significant board differences is consistent with the business angel and venture capital literature stressing these investors' careful scrutiny of and emphasis on the management team as part of their due diligence.

Panel B shows that the co-investment campaigns are significantly different from traditional campaigns in terms of a larger number of investors for all seven days tabulated. Co-investment campaigns, on average, attract almost twice as many daily investors. For individual days, the number of investors in the first seven days are significantly higher for angel co-investment campaigns than for other campaigns. The data exhibit downward trends in the first seven days that resemble an L-shaped pattern. However, the difference between these two groups declines in the first seven days, implying a pronounced L-shape for co-investment campaigns. This provides initial evidence on the impact of angels in funding dynamics (***H2***).

4.5 Empirical Results

Given the count data *Number of investors* has a higher variance than its mean (see Table 4.3), negative binomial models are employed for regressions. Its negative values are transformed to zero. To control for the unobserved heterogeneity among campaigns (e.g. nominee shareholder structure), we estimate negative binomial regressions with campaign fixed effects.[37] We also add platform dummies to control for the heterogeneity between platforms, such as different minimum investment requirements and different number of registered investors. Following Hornuf and Schwienbacher (2018a), year dummies are used

[37] One of the advantages of negative binomial regression with fixed effects is that it allows us to test the effect of observed time-invariant explanatory variables (Hornuf and Schwienbacher, 2018a).

to account for the rapid development of ECF market in recent years and dummies for the month of the year are used to account for the possibility of investors on vacation. In addition, investors' attention to ECF campaigns can be dispersed prior to or around weekends when they might be inclined to spend time shopping or with families and friends (Hornuf and Schwienbacher, 2018a). Taking these into consideration, our regression equation can be specified as follows:

$$\begin{aligned}\Pr(y_{i1}, y_{i2}, \dots, y_{iT}) \\ &= \mathrm{F}(DoD_{it} + CampaignCharacteristics_i + BoardCharacteristics_i \\ &+ Platform_i + DoW_t + MoY_t + Year_t + Campaign_i) \qquad (4.1)\end{aligned}$$

where y_{it} is the number of investors that pledged money in campaign i on day t. F(.) denotes the negative binomial distribution. For the independent variables, *DoD* includes dummies indicating a particular day during a campaign, *CampaignCharacteristics* and *BoardCharacteristics* represent the variables listed in Table 4.2, *Platform* includes the platform dummies, *DoW* includes the dummies for the day of the week, *MoY* includes the dummies for the month of the year, *Year* includes the year dummies and $Campaign_i$ captures the campaign fixed effects.

Table 4.6 reports the regression results, with the Wald test statistics given in the final rows. Figure 4.1 illustrates the dynamics for the predicted number of investors during a campaign. Panel A and Panel B are obtained using the estimates of Model (1) and Model (2) in Table 4.6, respectively.

Models (1) provides the results of our baseline regression for the daily number of investors. Co-investment campaigns tend to attract more investors as expected. The number of investors is significantly higher in the first seven days. The dynamics depicted in Figure

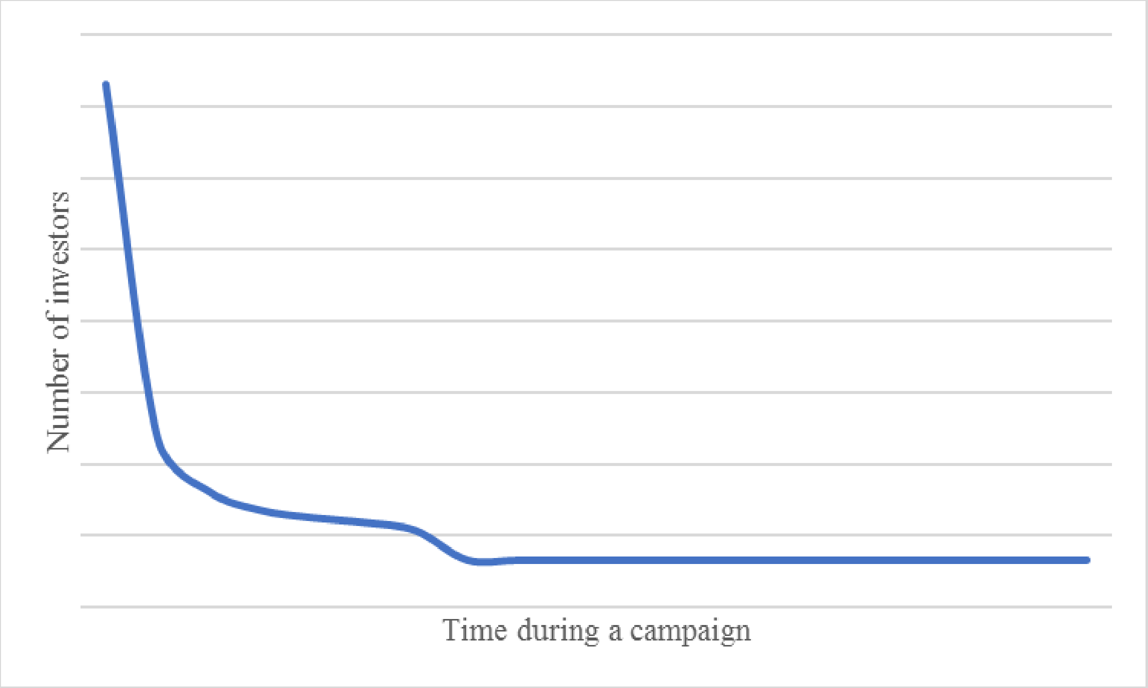
Table 4.6 Baseline Regression: Funding Dynamics

	Model (1)		Model (2)	
1st day	2.4149***	(0.0195)	1.9863***	(0.0293)
2nd day	1.2857***	(0.0278)	0.9660***	(0.0420)
3rd day	0.9032***	(0.0329)	0.6216***	(0.0490)
4th day	0.7252***	(0.0351)	0.4045***	(0.0544)
5th day	0.6446***	(0.0362)	0.3413***	(0.0557)
6th day	0.5912***	(0.0371)	0.3420***	(0.0556)
7th day	0.4901***	(0.0380)	0.1744***	(0.0592)
1st overfunded day			1.0860***	(0.0400)
2nd overfunded day			0.6187***	(0.0504)
3rd overfunded day			0.5318***	(0.0540)
4th overfunded day			0.4195***	(0.0583)
5th overfunded day			0.3023***	(0.0622)
6th overfunded day			0.3158***	(0.0635)
7th overfunded day			0.3035***	(0.0659)
Campaign characteristics				
Co-investment	0.1219***	(0.0359)	0.1944***	(0.0544)
Funding target	0.0002***	(0.0000)	0.0003***	(0.0001)
Equity offered	-0.0034*	(0.0021)	0.0055	(0.0034)
Seasoned campaign	0.4086***	(0.0534)	0.3638***	(0.0783)
Information technology	-0.0143	(0.0331)	0.1233**	(0.0506)
London	-0.1418***	(0.0334)	-0.3362***	(0.0502)
Overfunded	0.3516***	(0.0201)		
Board characteristics				
Board size	-0.0308*	(0.0161)	-0.0867***	(0.0273)
Average age	0.0089***	(0.0020)	0.0044	(0.0032)
Age diversity	-0.0040*	(0.0021)	0.0006	(0.0035)
Average tenure	0.0001	(0.0053)	-0.0153	(0.0098)
Tenure diversity	0.0098	(0.0083)	0.0172	(0.0126)
Common surname	-0.0155	(0.0532)	-0.0161	(0.0790)
Foreign nationality	0.1765***	(0.0365)	0.1037*	(0.0548)
Doctorate	-0.0464	(0.0581)	-0.0488	(0.0834)
Platform dummies	Yes		Yes	
Year dummies	Yes		Yes	
Month of the year	Yes		Yes	
Day of the week	Yes		Yes	
Observations (No. of campaigns)	21223 (497)		8082 (182)	
Log likelihood	-42995.19		-19519.51	
Wald test statistics *(All coefficients=0)*[a]	22254.63***		7588.43***	
Wald test statistics *(All first days at the beginning=0)*[b]	15760.48***		4796.05***	
Wald test statistics *(All first days after overfunding=0)*[c]			918.72***	

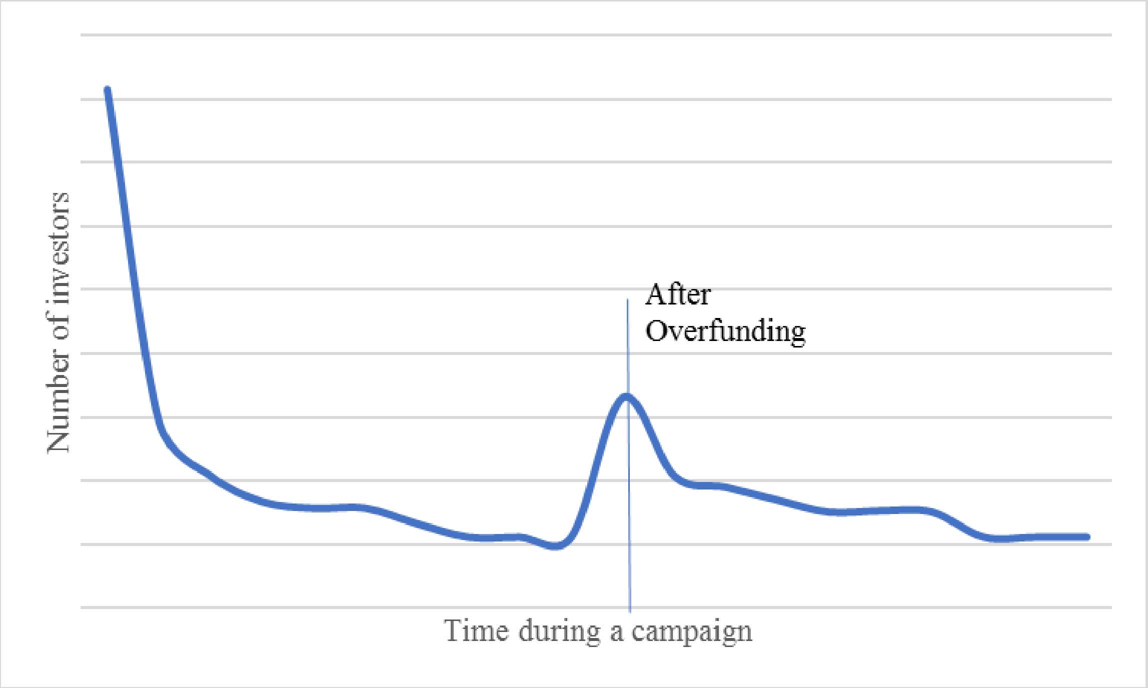
Notes: This table reports the estimated coefficients of negative binomial regressions with fixed effects, with the corresponding standard errors in parentheses. The dependent variable is the number of investors that pledged money in each day of the campaign. All campaigns are used in Model (1) while only successful campaigns are used in Model (2). The definitions of all control variables are provided in Table 4.2. [a]: The null hypothesis of the Wald test is that all coefficients, excluding the constant term, are equal to 0 simultaneously. [b]: The null hypothesis of the Wald test is that all coefficients of dummies indicating first seven days are equal to 0 simultaneously. [c]: The null hypothesis of the Wald test is that all coefficients of dummies indicating first seven days after overfunding are equal to 0 simultaneously. *, **, *** indicate significance at 10%, 5% and 1% level, respectively.

Figure 4.1 Predicted Daily Number of Investors

Panel A Dynamics in an ECF campaign



Panel B Dynamics in a successful ECF campaign



Notes: This figure shows the dynamics for the predicted number of investors that pledge money in each day during a campaign. Panel A shows the dynamics in an ECF campaign, where the predicted numbers are calculated using the estimates in Model (1) in Table 4.6. Panel B shows the dynamics in a successful ECF campaign, where the predicted numbers are calculated using the estimates in Model (2) in Table 4.6.

4.1 (Panel A) exhibits an L-shaped pattern, consistent with the finding of Hornuf and Schwienbacher (2018a).

To test our first hypothesis, ***H1***, we remove failed campaigns with no opportunity to enter the overfunding period as well as the campaigns with missing data in the first seven days after overfunding. To make a comparison between the dynamics after overfunding and at the start, we also exclude the campaigns if the first seven days after overfunding overlap with the first seven days at the start, i.e. excluding the campaigns reaching their targets in the first seven days. This leaves us 8,082 daily observations from 182 successful campaigns. The regression results are reported in Model (2), in which we do not include *Overfunded* to avoid possible multicollinearity issues.

We also observe a higher number of investors in the first seven days after the funding target is reached. As the coefficients after overfunding are generally smaller than their counterparts at the campaign start, the overfunding dynamics depicted in Figure 4.1 (Panel B) presents a relatively lower L-shaped pattern, providing evidence in support of ***H1***. In this sense, the dynamics show a double L-shaped pattern for successful campaigns and the overfunding day can be identified as another peak time during a campaign.

The regression results show significant effects for several control variables. They indicate a positive effect of Funding target which may be attributed to the size effect that cet par. larger targets require more funders (Vismara, 2016). Another explanation relates to the confidence implied by a higher target. Under the AON+ model, it is risky to set a higher target since start-up will get nothing if the target is not reached. In this sense, a higher target reflects an entrepreneur's confidence in her project. This acts as a good signal to future investors, resulting in a positive relationship. Surprisingly, London start-ups attract fewer investors. This could be explained by the local bias (Hornuf and Schmitt, 2016) where London start-ups mainly attract London investors, who are relatively wealthier and so pledge more funds, generating a smaller number of investors for a fixed funding target. Finally, the results reveal significantly positive coefficients for *Overfunded* and *Seasoned* campaign as expected. Reaching and exceeding the target capital in an initial campaign is an indicator of success and reduces information asymmetries. This, in turn, can encourage start-ups to engage in seasoned campaigns.

The board characteristic results show that the number of investors is significantly higher for smaller boards, inconsistent with the positive relationship found in previous literature (Ahlers et al., 2015; Hornuf and Schwienbacher, 2018b). This may be the case because it is less costly for smaller boards to reach agreements (Wilson et al., 2018). An alternative explanation derives from the non-necessity of excessive directors in start-ups, where investors might regard appointing too many directors as a waste of resources. The presence of foreign directors is associated with significantly more investors. One motivation for this is that investors may believe that start-ups can more readily expand their businesses to other countries and earn more profits. In addition, investors are attracted by higher age, a signal of directors having more experience, but discouraged by the potential cognitive conflicts caused by age heterogeneity (Goergen et al., 2015). However, these relationships do not hold for successful campaigns in Model (2).

4.5.1 The Role of Angels in Funding Dynamics

We split our sample into two subsamples to explore the impact of angels on L-shaped dynamics: co-investment campaigns which attract angel investment in the first day and traditional campaigns which do not. We re-run the regressions and report the results in Table 4.7. The predicted number of investors are displayed in Figure 4.2. Panel A is based on the estimates of Models (1) and (3) and Panel B is based on the estimates of Models (2) and (4).

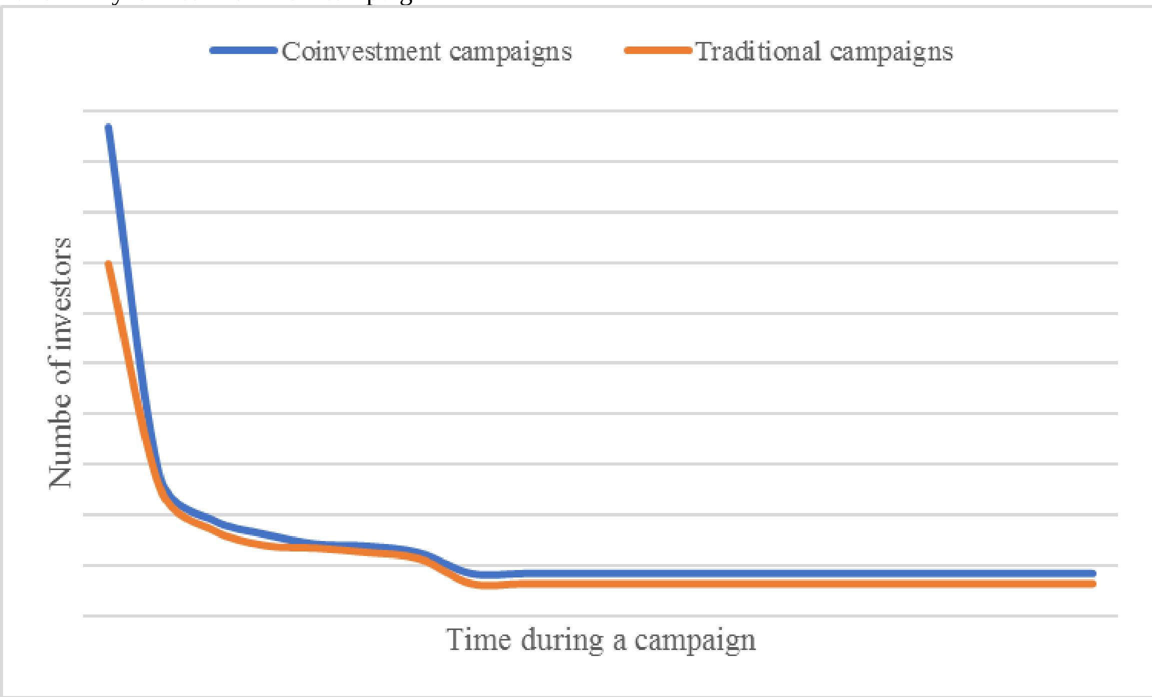
Table 4.7 Funding Dynamics: Co-investment vs. Traditional Campaigns

	Co-investment campaigns				Traditional campaigns			
	Model (1)		Model (2)		Model (3)		Model (4)	
1st day	2.4349***	(0.0312)	2.0830***	(0.0424)	2.3915***	(0.0254)	1.9055***	(0.0401)
2nd day	1.1755***	(0.0440)	0.9195***	(0.0635)	1.3747***	(0.0360)	0.9919***	(0.0548)
3rd day	0.8160***	(0.0509)	0.5477***	(0.0744)	0.9850***	(0.0429)	0.6722***	(0.0633)
4th day	0.6535***	(0.0540)	0.4224***	(0.0799)	0.7829***	(0.0461)	0.3679***	(0.0730)
5th day	0.5248***	(0.0570)	0.1640*	(0.0885)	0.7434***	(0.0468)	0.4868***	(0.0690)
6th day	0.4965***	(0.0576)	0.2800***	(0.0850)	0.6780***	(0.0485)	0.3816***	(0.0716)
7th day	0.3954***	(0.0588)	0.0853	(0.0922)	0.5741***	(0.0500)	0.2140***	(0.0766)
1st overfunded day			0.9170***	(0.0636)			1.2115***	(0.0504)
2nd overfunded day			0.4702***	(0.0791)			0.7405***	(0.0644)
3rd overfunded day			0.3925***	(0.0856)			0.6505***	(0.0686)
4th overfunded day			0.2963***	(0.0926)			0.5134***	(0.0747)
5th overfunded day			0.1591	(0.0988)			0.4246***	(0.0792)
6th overfunded day			0.2279**	(0.0953)			0.3890***	(0.0841)
7th overfunded day			0.1256	(0.1004)			0.4568***	(0.0858)
Campaign characteristics								
Funding target	0.0001***	(0.0000)	-0.0000	(0.0001)	0.0006***	(0.0001)	0.0004***	(0.0001)
Equity offered	0.0003	(0.0033)	0.0111*	(0.0061)	-0.0046*	(0.0027)	0.0019	(0.0044)
Seasoned campaign	0.3926***	(0.0835)	0.3605*	(0.1842)	0.4898***	(0.0784)	0.5477***	(0.1044)
Information technology	0.0208	(0.0551)	0.2202**	(0.0995)	-0.0102	(0.0432)	0.0350	(0.0636)
London	-0.1113*	(0.0569)	-0.5124***	(0.1016)	-0.1421***	(0.0436)	-0.2515***	(0.0633)
Overfunded	0.2503***	(0.0294)			0.4891***	(0.0277)		
Board characteristics								
Board size	-0.0304	(0.0236)	0.0214	(0.0520)	-0.0382	(0.0257)	-0.0860**	(0.0348)
Average age	0.0086**	(0.0037)	-0.0171**	(0.0072)	0.0073***	(0.0025)	0.0103***	(0.0037)
Age diversity	-0.0086***	(0.0032)	-0.0078	(0.0062)	0.0019	(0.0031)	0.0044	(0.0048)
Average tenure	0.0187**	(0.0080)	0.0228	(0.0173)	-0.0130*	(0.0074)	-0.0281**	(0.0136)
Tenure diversity	0.0249*	(0.0136)	0.0291	(0.0319)	0.0083	(0.0110)	0.0191	(0.0161)
Common surname	0.2766***	(0.0800)	0.2618	(0.1780)	-0.3165***	(0.0732)	-0.1963*	(0.1067)
Foreign nationality	0.2423***	(0.0585)	0.1628	(0.1170)	0.0805	(0.0508)	0.1083	(0.0724)
Doctorate	0.0661	(0.0870)	0.2011	(0.1715)	-0.1738**	(0.0832)	-0.0639	(0.1063)
Platform dummies	Yes		Yes		Yes		Yes	
Year dummies	Yes		Yes		Yes		Yes	
Month of the year	Yes		Yes		Yes		Yes	
Day of the week	Yes		Yes		Yes		Yes	
Observations (No. of campaigns)	8096 (206)		3238 (79)		13127 (291)		4844 (103)	
Log likelihood	-17295.76		-7330.14		-25551.28		-12092.02	
Wald test statistics *(All coefficients=0)*[a]	10495.60***		3837.26***		12402.81***		4270.46***	
Wald test statistics *(All first days at the beginning=0)*[b]	6219.87***		2500.35***		9305.89***		2408.36***	
Wald test statistics *(All first days after overfunding=0)*[c]			242.15***				757.04***	

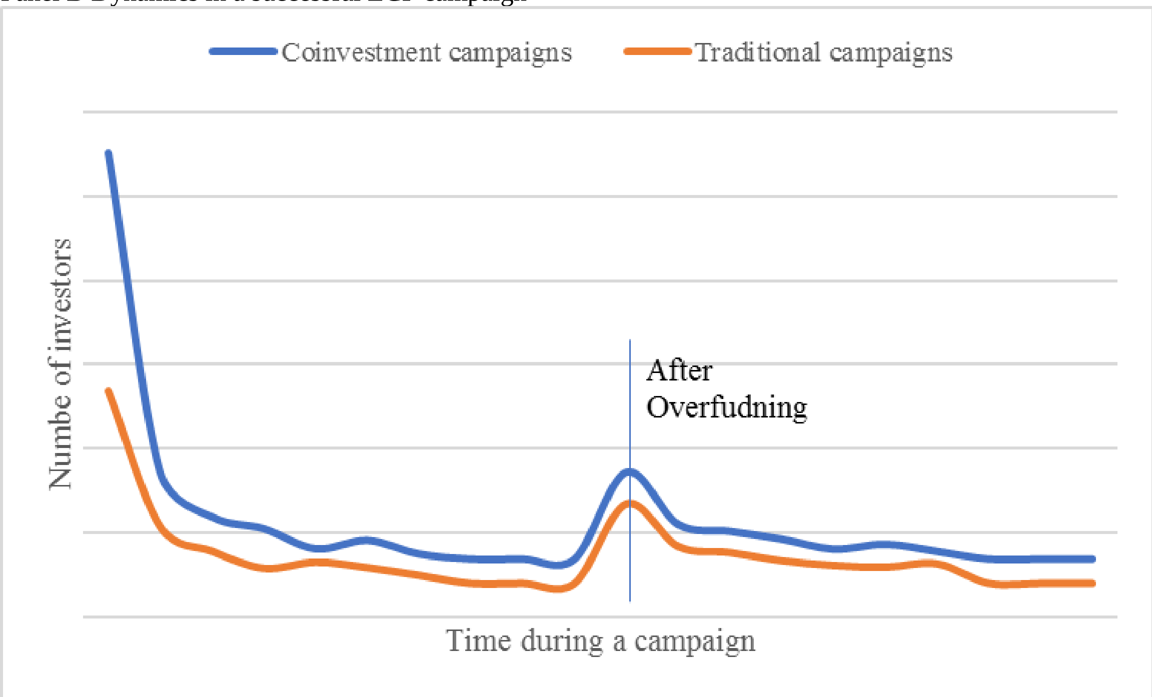
Notes: This table reports the estimated coefficients of negative binomial regressions with fixed effects, with the corresponding standard errors in parentheses. The dependent variable is the number of investors that pledged money in each day of the campaign. All campaigns are used in Model (1) and (3) while only successful campaigns are used in Model (2) and (4). The definitions of all control variables are provided in Table 4.2. [a]: The null hypothesis of the Wald test is that all coefficients, excluding the constant term, are equal to 0 simultaneously. [b]: The null hypothesis of the Wald test is that all coefficients of dummies indicating first seven days are equal to 0 simultaneously. [c]: The null hypothesis of the Wald test is that all coefficients of dummies indicating first seven days after overfunding are equal to 0 simultaneously. *, **, *** indicate significance at 10%, 5% and 1% level, respectively.

Figure 4.2 Predicted Daily Number of Investors: Co-investment vs. Traditional Campaigns

Panel A Dynamics in an ECF campaign



Panel B Dynamics in a successful ECF campaign



Notes: This figure shows the dynamics for the predicted number of investors that pledge money in each day during a campaign. Panel A shows the dynamics in an ECF campaign, with the blue line for a co-investment campaign and the orange line for a traditional campaign where the predicted numbers are calculated using the estimates in Model (1) and (3) in Table 4.7, respectively. Panel B shows the dynamics in a successful ECF campaign, with the blue line for a co-investment campaign and the orange line for a traditional campaign where the predicted numbers are calculated using the estimates in Model (2) and (4) in Table 4.7, respectively.

The dynamics for both subsamples show an L-shaped pattern at all campaign starts (Panel A) while another less pronounced L-shape is found after overfunding in successful campaigns (Panel B). The first L-shape at the start is more pronounced when an angel co-invests alongside the crowd in both Panel A and Panel B, providing strong evidence for our second hypothesis. However, for successful campaigns, dynamic shapes of co-investment and traditional campaigns are almost parallel after overfunding, implying the scant impact of angels when information asymmetries are mitigated by successfully reaching the target. This offers evidence in support of ***H3***.

We split our sample into initial and seasoned campaigns to test our last hypothesis and run regressions for all, co-investment and traditional campaigns in each subsample.[38] The results are reported in Table 4.8, and the predicted dynamics are shown in Figure 4.3. Panel A is based on the estimates of Models (2) and (5) and Panel B is based on the estimates of Models (3) and (6). We confirm the L-shaped dynamics in both initial and seasoned campaigns. The L-shape is found to be more pronounced when angels are involved. In addition, relative to initial campaigns (Panel A), the L-shape pattern when angels are involved is less pronounced in seasoned campaigns (Panel B). Therefore, our results suggest a weaker role of angels in ECF funding dynamics when information asymmetries are mitigated by the success of an initial campaign, supporting our ***H4***.

[38] As Table 4.8 shows, we only have 23 co-investment seasoned campaigns and 21 traditional seasoned campaigns. If we aim to test the overfunding dynamics in seasoned campaigns, we have to remove a few campaigns (similar to the procedure when we test ***H1***). This leads to an even smaller sample and estimation issues. Therefore, we do not look at overfunding dynamics here, but we would assume a little impact of angels after overfunding in both initial and seasoned campaigns, as found in Figure 4.2.

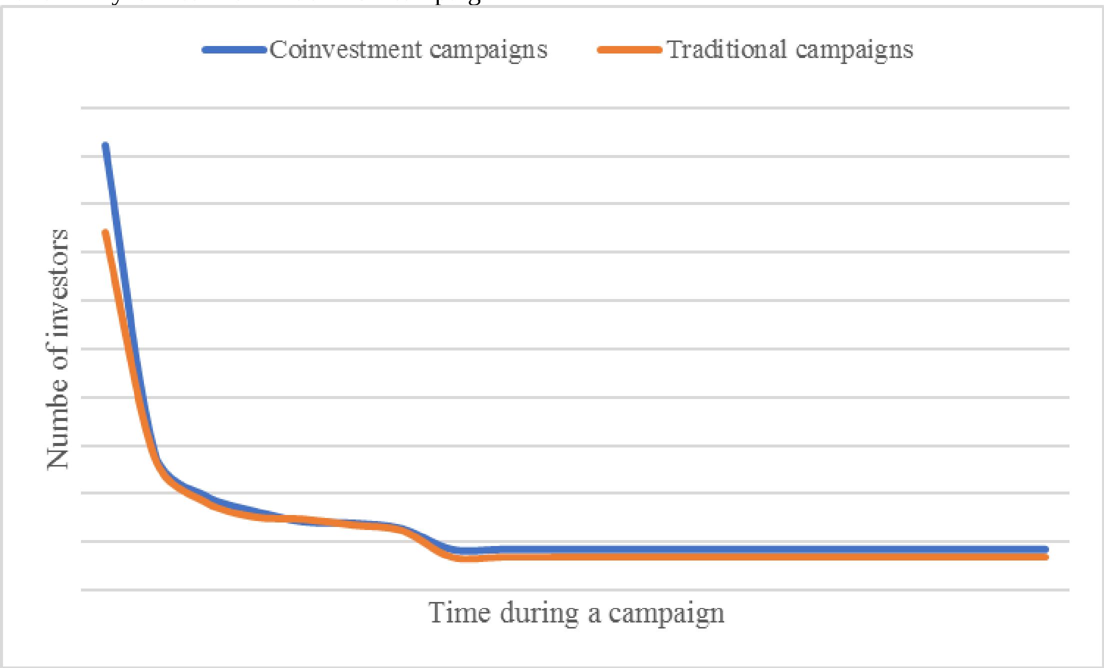
Table 4.8 Funding Dynamics in Initial and Seasoned Campaigns: Co-investment vs. Traditional Campaigns

	Initial campaigns						Seasoned campaigns					
			Co-investment campaigns		Traditional campaigns				Co-investment campaigns		Traditional campaigns	
	Model (1)		Model (2)		Model (3)		Model (4)		Model (5)		Model (6)	
1st day	2.3980***	(0.0208)	2.3800***	(0.0340)	2.3791***	(0.0268)	2.5502***	(0.0598)	2.5322***	(0.1089)	2.5803***	(0.0945)
2nd day	1.3098***	(0.0294)	1.2059***	(0.0470)	1.3848***	(0.0375)	1.1111***	(0.0868)	0.9642***	(0.1263)	1.3184***	(0.1286)
3rd day	0.9179***	(0.0349)	0.8386***	(0.0543)	0.9871***	(0.0450)	0.8451***	(0.0957)	0.7343***	(0.1305)	0.9761***	(0.1438)
4th day	0.7453***	(0.0371)	0.6605***	(0.0581)	0.7954***	(0.0481)	0.6790***	(0.1014)	0.6335***	(0.1328)	0.7111***	(0.1621)
5th day	0.6637***	(0.0383)	0.5137***	(0.0616)	0.7638***	(0.0487)	0.6090***	(0.1059)	0.6101***	(0.1369)	0.6218***	(0.1619)
6th day	0.6003***	(0.0394)	0.4926***	(0.0622)	0.6801***	(0.0507)	0.6238***	(0.1025)	0.5447***	(0.1362)	0.6873***	(0.1595)
7th day	0.5131***	(0.0404)	0.4065***	(0.0637)	0.5866***	(0.0521)	0.4135***	(0.1068)	0.3249**	(0.1370)	0.5138***	(0.1714)
Campaign characteristics												
Co-investment	0.1313***	(0.0379)					0.4883***	(0.1758)				
Funding target	0.0002***	(0.0000)	0.0002***	(0.0000)	0.0006***	(0.0001)	0.0007**	(0.0003)	0.0032***	(0.0008)	-0.0019	(0.0028)
Equity offered	-0.0022	(0.0021)	-0.0003	(0.0034)	-0.0037	(0.0028)	-0.0075	(0.0157)	-0.1258*	(0.0695)	0.0694	(0.0623)
Information technology	-0.0325	(0.0349)	0.0418	(0.0601)	-0.0074	(0.0452)	-0.0492	(0.1519)	0.8264*	(0.4877)	1.2637	(0.7747)
London	-0.1953***	(0.0354)	-0.2039***	(0.0624)	-0.1864***	(0.0460)	0.5601***	(0.1665)	0.0366	(0.4837)	0.9137***	(0.2526)
Overfunded	0.3357***	(0.0216)	0.2501***	(0.0313)	0.4680***	(0.0295)	0.4759***	(0.0591)	0.4715***	(0.0993)	0.5671***	(0.0967)
Board characteristics												
Board size	-0.0435***	(0.0169)	-0.0347	(0.0262)	-0.0520**	(0.0262)	0.1652**	(0.0709)	0.3809***	(0.1409)	-0.0699	(0.2246)
Average age	0.0086***	(0.0021)	0.0090**	(0.0040)	0.0070***	(0.0026)	-0.0040	(0.0088)	-0.0783**	(0.0319)	0.0160	(0.0131)
Age diversity	-0.0021	(0.0022)	-0.0115***	(0.0036)	0.0058*	(0.0031)	-0.0244**	(0.0101)	-0.0179	(0.0164)	-0.1654***	(0.0301)
Average tenure	-0.0018	(0.0054)	0.0228***	(0.0083)	-0.0153**	(0.0076)	0.0478	(0.0550)	-0.1107	(0.2333)	-0.0281	(0.0729)
Tenure diversity	0.0208**	(0.0086)	0.0443***	(0.0157)	0.0101	(0.0112)	-0.1078**	(0.0535)	-0.3427***	(0.0954)	1.1436***	(0.3853)
Common surname	-0.0498	(0.0568)	0.2426***	(0.0851)	-0.3941***	(0.0779)	0.6671***	(0.2541)	-0.4526	(0.5183)	1.1364**	(0.4808)
Foreign nationality	0.2354***	(0.0382)	0.4720***	(0.0641)	0.0624	(0.0517)	-0.7236***	(0.1841)	-1.4870***	(0.4830)	-0.0087	(0.6352)
Doctorate	0.0204	(0.0623)	0.2589***	(0.0991)	-0.1920**	(0.0861)	-0.4405	(0.2988)	-2.2585**	(0.9666)	1.8107*	(1.0025)
Platform dummies	Yes		Yes		Yes		Yes		Yes		Yes	
Year dummies	Yes		Yes		Yes		Yes		Yes		Yes	
Month of the year	Yes		Yes		Yes		Yes		Yes		Yes	
Day of the week	Yes		Yes		Yes		Yes		Yes		Yes	
Observations	19379		7318		12061		1844		778		1066	
(No. of campaigns)	(453)		(183)		(270)		(44)		(23)		(21)	
Log likelihood	-38725.68		-15188.71		-23350.01		-4176.94		-1985.30		-2112.45	
Wald test statistics *(All coefficients=0)[a]*	19389.57***		8812.46***		11212.37***		3602.98***		2502.57***		1547.78***	
Wald test statistics *(All first days =0)[b]*	13689.83***		5016.56***		8301.08***		1849.59***		590.34***		766.08***	

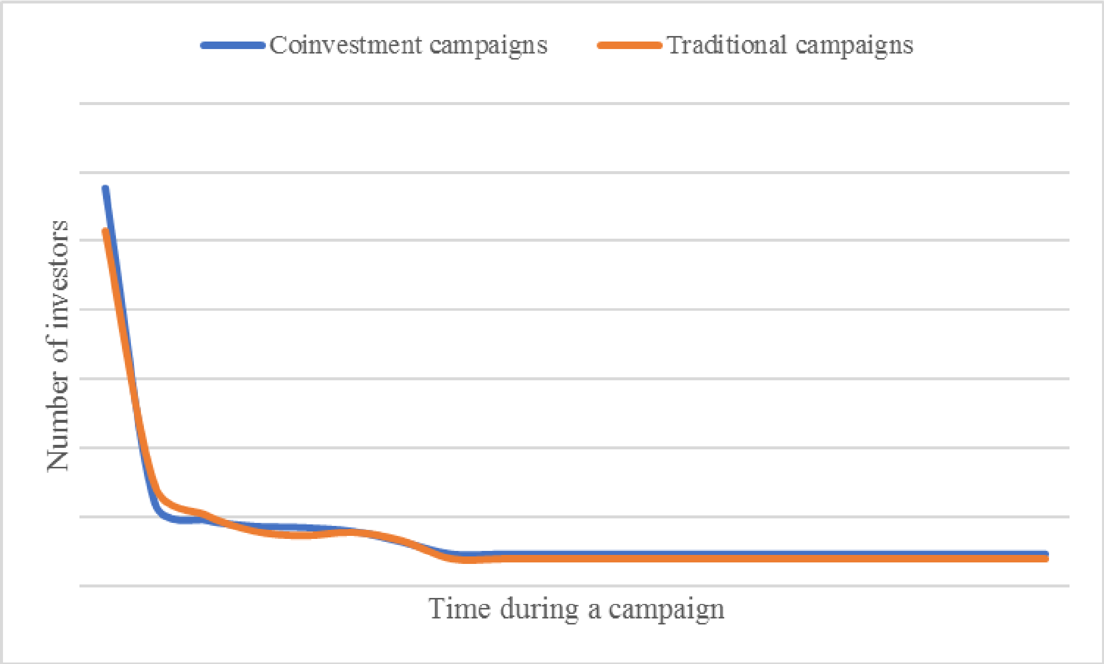
Notes: This table reports the estimated coefficients of negative binomial regressions with fixed effects, with the corresponding standard errors in parentheses. The dependent variable is the number of investors that pledged money in each day of the campaign. The definitions of all control variables are provided in Table 4.2. [a]: The null hypothesis of the Wald test is that all coefficients, excluding the constant term, are equal to 0 simultaneously. [b]: The null hypothesis of the Wald test is that all coefficients of dummies indicating first seven days are equal to 0 simultaneously. *, **, *** indicate significance at 10%, 5% and 1% level, respectively.

Figure 4.3 Predicted Daily Number of Investors in Initial and Seasoned Campaigns

Panel A Dynamics in an initial ECF campaign



Panel B Dynamics in a seasoned ECF campaign



Notes: This figure shows the dynamics for the predicted number of investors that pledge money in each day during a campaign. Panel A shows the dynamics in an initial ECF campaign, with the blue line for a co-investment campaign and the orange line for a traditional campaign where the predicted numbers are calculated using the estimates in Model (2) and (3) in Table 4.8, respectively. Panel B shows the dynamics in a seasoned ECF campaign, with the blue line for a co-investment campaign and the orange line for a traditional campaign where the predicted numbers are calculated using the estimates in Model (5) and (6) in Table 4.8, respectively.

4.6 Robustness Checks

Following Hornuf and Schwienbacher (2018a), we also examine the funding dynamics in the last seven days to confirm it shows an L-shaped, rather than a U-shaped pattern. We exclude campaigns with missing data in the last seven days and obtain a sample of 10,554 observations from 257 campaigns. The results are present in Table 4.9.

Although the number of investors is slightly higher in the last three days, this may be caused by those very cautious investors who watch closely and make investment decisions at the end of a campaign (Hornuf and Schwienbacher, 2018a). Even though we take dynamics after overfunding into consideration, the dynamics still show an L-shape at the campaign start and then a slightly lower L-shape after the amount raised reaches the funding target.

Next, we test if our results are robust to the threshold used in the *Co-investment* variable. In our analysis, we use the top 1/3 of the first-day-ratio as a proxy for angel co-investment on Crowdcube and Seedrs. We change the threshold to the top 1/4, 1/5 and 1/10 and report the results in Table 4.10, 4.11 and 4.12, respectively. We also predict the daily number of investors for each threshold and present the funding dynamics in Figure 4.4. The results are very similar to those using the top 1/3 in our naming analysis. Therefore, our findings do not depend on the threshold chosen to construct the proxy for our key explanatory variable.

An important concern is the endogeneity issue caused by the dual-class shares on Crowdcube, where fundraisers can offer investors Ordinary A-shares and Investment B-shares. Both shares give the same monetary benefits, but only A-shares offer voting and pre-emption rights. Start-ups place a threshold to distinguish them, and only if the investment is not lower than the threshold can the investor be allocated A-shares. In this sense, angels will prefer shares with voting rights and invest higher than the threshold, leading to a pronounced L-shaped dynamic pattern (***H2***). However, the average threshold on Crowdcube is £9k (Cumming, Meoli and Vismara, 2019), far lower than angels' average investment £75.5k (BBB and UKBAA, 2017). Therefore, angel investment is high enough and they do not have to exceed their budget to obtain voting rights. We also try to deal with this issue empirically. We exclude Crowdcube campaigns from our sample and re-run the regressions. Table 4.13 and Figure 4.5 show that we obtain similar results. Therefore, even if dual-class shares may affect our results, it is believed to have little impact, and our finding is robust when it does not exist.

Finally, we extend the study of Hornuf and Schwienbacher (2018a) to look at the dynamics for the daily amount raised as a robustness check, employing OLS regressions with fixed effects.[39] The results are shown in Table 4.14. Although the dynamics also exhibits an L-shaped pattern, the amount raised is only significantly higher in the first two days. One possible explanation is that the 'collective attention effect' works among crowd investors but not professional investors who will spend more time and pay more attention to search valuable investment opportunities. Therefore, as time passes, despite fewer crowd investors, professional investors enter to pledge a large amount of money, leading to a significant change in the number of investors but only a slight change in the amount raised.

[39] Unlike negative binomial regressions, OLS regressions do not allow us to incorporate time-invariant explanatory variables. Hence, the time-invariant variables are removed for estimation reasons.

Table 4.9 Robustness Check: Funding Dynamics in the Last 7 Days

	Model (1)		Model (2)	
1st day	2.3065***	(0.0234)	2.1234***	(0.0451)
2nd day	1.0844***	(0.0345)	0.8859***	(0.0674)
3rd day	0.7528***	(0.0403)	0.5918***	(0.0779)
4th day	0.5526***	(0.0445)	0.4067***	(0.0881)
5th day	0.4700***	(0.0460)	0.2498***	(0.0925)
6th day	0.4472***	(0.0466)	0.3602***	(0.0873)
7th day	0.3519***	(0.0475)	0.1011	(0.0964)
1st overfunded day			0.7987***	(0.0706)
2nd overfunded day			0.3612***	(0.0843)
3rd overfunded day			0.2885***	(0.0881)
4th overfunded day			0.1290	(0.0954)
5th overfunded day			0.0806	(0.0969)
6th overfunded day			0.1182	(0.0951)
7th overfunded day			0.0171	(0.0973)
7th last day	-0.0558	(0.0521)	-0.0943	(0.1039)
6th last day	-0.0186	(0.0518)	-0.0420	(0.1009)
5th last day	-0.0091	(0.0517)	0.2060**	(0.0912)
4th last day	0.0084	(0.0507)	-0.0326	(0.1017)
3rd last day	0.1019**	(0.0493)	0.1665*	(0.0920)
2nd last day	0.3806***	(0.0437)	0.3980***	(0.0844)
1st last day	0.6915***	(0.0387)	0.9757***	(0.0662)
Campaign characteristics				
Co-investment	0.1131**	(0.0526)	0.4199***	(0.1529)
Funding target	0.0002***	(0.0000)	0.0002	(0.0002)
Equity offered	-0.0011	(0.0030)	-0.0213***	(0.0076)
Seasoned campaign	0.2059***	(0.0696)	-0.4333**	(0.2158)
Information technology	0.1334***	(0.0495)	-0.0799	(0.1260)
London	-0.1076**	(0.0490)	-0.0344	(0.1340)
Overfunded	0.3946***	(0.0243)		
Board characteristics				
Board size	-0.0959***	(0.0232)	0.0038	(0.0665)
Average age	0.0101***	(0.0033)	-0.0079	(0.0103)
Age diversity	-0.0008	(0.0031)	0.0095	(0.0114)
Average tenure	-0.0070	(0.0089)	0.0151	(0.0253)
Tenure diversity	0.0296***	(0.0104)	-0.0259	(0.0256)
Common surname	-0.0341	(0.0798)	0.1270	(0.2032)
Foreign nationality	-0.0418	(0.0543)	-0.3594**	(0.1736)
Doctorate	-0.2219***	(0.0686)	-0.2304	(0.2002)
Platform dummies	Yes		Yes	
Year dummies	Yes		Yes	
Month of the year	Yes		Yes	
Day of the week	Yes		Yes	
Observations (No. of campaigns)	10554 (257)		2337 (53)	
Log likelihood	-23255.60		-5379.64	
Wald test statistics *(All coefficients=0)*[a]	14494.26***		4270.32***	
Wald test statistics *(All first days at the beginning=0)*[b]	9909.93***		2293.83***	
Wald test statistics *(All first days after overfunding=0)*[c]			143.61***	
Wald test statistics *(All last days=0)*[d]	384.96***		239.11***	

Notes: This table reports the estimated coefficients of negative binomial regressions with fixed effects, with the corresponding standard errors in parentheses. The dependent variable is the number of investors that pledged money in each day of the campaign. All campaigns are used in Model (1) while only successful campaigns are used in Model (2). The definitions of all control variables are provided in Table 4.2. [a]: The null hypothesis of the Wald test is that all coefficients, excluding the constant term, are equal to 0 simultaneously. [b]: The null hypothesis of the Wald test is that all coefficients of dummies indicating first seven days are equal to 0 simultaneously. [c]: The null hypothesis of the Wald test is that all coefficients of dummies indicating first seven days after overfunding are equal to 0 simultaneously. [d]: The null hypothesis of the Wald test is that all coefficients of dummies indicating last seven days are equal to 0 simultaneously. *, **, *** indicate significance at 10%, 5% and 1% level, respectively.

Table 4.10 Robustness Check: Proxy for Angel Co-investment (top 25%)

	Baseline regression		Co-investment campaigns		Traditional campaigns	
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
1st day	2.4113***	1.9842***	2.4280***	2.0130***	2.4053***	1.9833***
2nd day	1.2831***	0.9662***	1.1791***	0.9161***	1.3468***	0.9847***
3rd day	0.9009***	0.6234***	0.8129***	0.5722***	0.9619***	0.6457***
4th day	0.7230***	0.4056***	0.6525***	0.4208***	0.7621***	0.3845***
5th day	0.6443***	0.3430***	0.5845***	0.2563**	0.6845***	0.3986***
6th day	0.5899***	0.3435***	0.5025***	0.3338***	0.6425***	0.3639***
7th day	0.4886***	0.1718***	0.4318***	0.0970	0.5341***	0.2104***
1st overfunded day		1.0777***		0.8947***		1.1609***
2nd overfunded day		0.6136***		0.4433***		0.6834***
3rd overfunded day		0.5212***		0.2896***		0.6349***
4th overfunded day		0.4107***		0.2332**		0.4921***
5th overfunded day		0.2985***		0.1339		0.3882***
6th overfunded day		0.3046***		0.1343		0.3927***
7th overfunded day		0.2895***		0.0193		0.4340***
Campaign characteristics						
Co-investment	0.2159***	0.4039***				
Funding target	0.0002***	0.0003***	0.0001***	0.0002*	0.0004***	0.0001*
Equity offered	-0.0033	0.0040	0.0056	0.0079	-0.0098***	-0.0026
Seasoned campaign	0.4221***	0.3893***	0.5727***	0.4244	0.3705***	0.3941***
Information technology	-0.0277	0.0854*	-0.0818	-0.2602*	0.0256	0.1257**
London	-0.1387***	-0.3216***	-0.0083	0.0018	-0.2510***	-0.4123***
Overfunded	0.3411***		0.2888***		0.4113***	
Board characteristics						
Board size	-0.0357**	-0.0878***	-0.0541**	0.0107	-0.0578**	-0.1221***
Average age	0.0093***	0.0038	0.0130***	-0.0119	0.0063***	0.0099***
Age diversity	-0.0032	0.0028	-0.0008	0.0141*	-0.0021	0.0040
Average tenure	-0.0002	-0.0104	0.0267***	0.0779***	-0.0159**	-0.0473***
Tenure diversity	0.0110	0.0154	0.0107	-0.0030	0.0154	0.0391***
Common surname	-0.0255	-0.0467	0.2710***	-0.1849	-0.1930***	-0.1385
Foreign nationality	0.1868***	0.1219**	0.2654***	0.0311	0.1580***	0.0951
Doctorate	-0.0701	-0.1061	0.0408	-0.2135	-0.1701**	-0.1090
Platform dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Month of the year	Yes	Yes	Yes	Yes	Yes	Yes
Day of the week	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21223	8082	6577	2385	14646	5697
(No. of campaigns)	(497)	(182)	(173)	(59)	(324)	(123)
Log likelihood	-42985.37	-19507.24	-13749.25	-5042.09	-29130.58	-14407.33
Wald test statistics *(All coefficients=0)*[a]	22316.08***	7645.05***	8378.68***	2478.96***	14376.75***	5318.98***
Wald test statistics *(All first days at the beginning=0)*[b]	15662.23***	4829.55***	4509.79***	1458.58***	10834.34***	3269.98***
Wald test statistics *(All first days after overfunding=0)*[c]		902.79***		164.96***		786.21***

Notes: This table reports the estimated coefficients of negative binomial regressions with fixed effects. The dependent variable is the number of investors that pledged money in each day of the campaign. All campaigns are used in Model (1), (3) and (5) while only successful campaigns are used in Model (2), (4) and (6). The definitions of all control variables are provided in Table 4.2. [a]: The null hypothesis of the Wald test is that all coefficients, excluding the constant term, are equal to 0 simultaneously. [b]: The null hypothesis of the Wald test is that all coefficients of dummies indicating first seven days are equal to 0 simultaneously. [c]: The null hypothesis of the Wald test is that all coefficients of dummies indicating first seven days after overfunding are equal to 0 simultaneously. *, **, *** indicate significance at 10%, 5% and 1% level, respectively.

Table 4.11 Robustness Check: Proxy for Angel Co-investment (top 20%)

	Baseline regression		Co-investment campaigns		Traditional campaigns	
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
1st day	2.4159***	1.9925***	2.5109***	2.1082***	2.3819***	1.9508***
2nd day	1.2858***	0.9637***	1.1881***	0.9039***	1.3429***	0.9943***
3rd day	0.9034***	0.6234***	0.8302***	0.5635***	0.9533***	0.6394***
4th day	0.7257***	0.4048***	0.6802***	0.4263***	0.7548***	0.3887***
5th day	0.6470***	0.3435***	0.6283***	0.2578**	0.6713***	0.3839***
6th day	0.5924***	0.3407***	0.5421***	0.2439**	0.6277***	0.3759***
7th day	0.4910***	0.1712***	0.4614***	0.0652	0.5248***	0.2035***
1st overfunded day		1.0795***		0.9254***		1.1307***
2nd overfunded day		0.6196***		0.5477***		0.6387***
3rd overfunded day		0.5198***		0.2435**		0.6123***
4th overfunded day		0.4126***		0.2592**		0.4654***
5th overfunded day		0.2978***		0.0616		0.3772***
6th overfunded day		0.3057***		0.0699		0.3826***
7th overfunded day		0.2928***		-0.0229		0.3964***
Campaign characteristics						
Co-investment	0.1315***	0.4914***				
Funding target	0.0002***	0.0003***	0.0002***	0.0000	0.0004***	0.0001
Equity offered	-0.0035*	0.0032	0.0056	0.0041	-0.0088***	-0.0022
Seasoned campaign	0.4224***	0.4078***	0.6632***	1.8282***	0.3603***	0.3488***
Information technology	-0.0241	0.0629	-0.0647	-0.9392***	0.0236	0.1027*
London	-0.1346***	-0.3201***	-0.1261*	0.2380	-0.1952***	-0.3835***
Overfunded	0.3516***		0.3035***		0.4209***	
Board characteristics						
Board size	-0.0317**	-0.1010***	-0.0808***	-0.0920	-0.0406*	-0.1187***
Average age	0.0091***	0.0039	0.0194***	-0.0246**	0.0039*	0.0083**
Age diversity	-0.0035	0.0023	-0.0001	0.0273***	-0.0020	0.0033
Average tenure	-0.0002	-0.0162	0.0183*	0.1116***	-0.0090	-0.0507***
Tenure diversity	0.0092	0.0203	0.0302*	-0.0847*	0.0099	0.0464***
Common surname	-0.0164	-0.0515	0.3516***	-0.2038	-0.2008***	-0.1149
Foreign nationality	0.1830***	0.1392**	0.3795***	0.1920	0.1431***	0.0915
Doctorate	-0.0421	-0.0631	-0.3209***	0.5913**	-0.0484	-0.1058
Platform dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Month of the year	Yes	Yes	Yes	Yes	Yes	Yes
Day of the week	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21223	8082	5686	2016	15537	6066
(No. of campaigns)	(497)	(182)	(153)	(50)	(344)	(132)
Log likelihood	-42995.85	-19505.10	-11510.97	-4035.26	-31341.31	-15378.18
Wald test statistics *(All coefficients=0)*[a]	22250.09***	7659.24***	7528.25***	2332.57***	15521.40***	5802.01***
Wald test statistics *(All first days at the beginning=0)*[b]	15789.96***	4874.49***	4063.36***	1459.62***	11435.68***	3505.00***
Wald test statistics *(All first days after overfunding=0)*[c]		908.92***		152.23***		810.60***

Notes: This table reports the estimated coefficients of negative binomial regressions with fixed effects. The dependent variable is the number of investors that pledged money in each day of the campaign. All campaigns are used in Model (1), (3) and (5) while only successful campaigns are used in Model (2), (4) and (6). The definitions of all control variables are provided in Table 4.2. [a]: The null hypothesis of the Wald test is that all coefficients, excluding the constant term, are equal to 0 simultaneously. [b]: The null hypothesis of the Wald test is that all coefficients of dummies indicating first seven days are equal to 0 simultaneously. [c]: The null hypothesis of the Wald test is that all coefficients of dummies indicating first seven days after overfunding are equal to 0 simultaneously. *, **, *** indicate significance at 10%, 5% and 1% level, respectively.

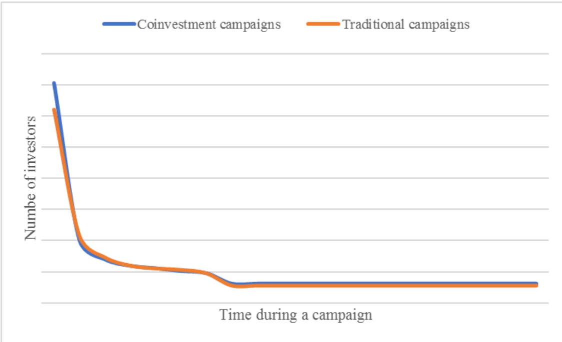
Table 4.12 Robustness Check: Proxy for Angel Co-investment (top 10%)

	Baseline regression		Co-investment campaigns		Traditional campaigns	
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
1st day	2.4184***	1.9821***	2.8627***	2.0384***	2.3606***	1.9796***
2nd day	1.2895***	0.9657***	1.2612***	0.7001***	1.3237***	1.0036***
3rd day	0.9061***	0.6202***	0.7741***	0.3043*	0.9511***	0.6592***
4th day	0.7286***	0.4025***	0.7222***	0.4178***	0.7593***	0.4076***
5th day	0.6500***	0.3522***	0.6804***	0.4698***	0.6558***	0.3527***
6th day	0.5949***	0.3399***	0.5084***	-0.0155	0.6291***	0.3833***
7th day	0.4937***	0.1764***	0.4812***	0.1762	0.5047***	0.1884***
1st overfunded day		1.0938***		1.2146***		1.0806***
2nd overfunded day		0.6246***		0.6307***		0.6300***
3rd overfunded day		0.5334***		0.3060*		0.5583***
4th overfunded day		0.4237***		0.3646*		0.4295***
5th overfunded day		0.3071***		0.1854		0.3231***
6th overfunded day		0.3201***		0.3177*		0.3162***
7th overfunded day		0.3075***		0.1198		0.3278***
Campaign characteristics						
Co-investment	0.0249	0.3199**				
Funding target	0.0002***	0.0004***	0.0007***	0.0005	0.0002***	0.0004***
Equity offered	-0.0033	0.0052	0.0115**	0.0160	-0.0074***	0.0052
Seasoned campaign	0.4161***	0.3668***	0.5643***	3.0592***	0.3792***	0.3219***
Information technology	-0.0109	0.1264**	-0.2946***	0.3903	0.0279	0.1416***
London	-0.1352***	-0.3309***	0.0127	0.2402	-0.2191***	-0.3527***
Overfunded	0.3655***		0.4587***		0.3874***	
Board characteristics						
Board size	-0.0281*	-0.0916***	-0.1691***	-0.3706**	0.0044	-0.0871***
Average age	0.0092***	0.0053*	0.0118*	0.0022	0.0042*	0.0055*
Age diversity	-0.0036*	0.0010	0.0341***	0.0300*	-0.0043*	-0.0032
Average tenure	0.0008	-0.0144	-0.0128	0.0434	0.0030	-0.0218**
Tenure diversity	0.0075	0.0157	-0.0229	-0.0553	0.0030	0.0255**
Common surname	-0.0147	-0.0266	0.2949*	0.0645	-0.1107*	0.0380
Foreign nationality	0.1715***	0.1154**	0.1564	0.4975	0.1895***	0.1224**
Doctorate	-0.0435	-0.0605	-0.3063*	1.2759***	-0.0729	-0.1308
Platform dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Month of the year	Yes	Yes	Yes	Yes	Yes	Yes
Day of the week	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21223	8082	3866	1264	17357	6818
(No. of campaigns)	(497)	(182)	(109)	(32)	(388)	(150)
Log likelihood	-43000.83	-19522.79	-6516.26	-1960.57	-36271.49	-17493.87
Wald test statistics *(All coefficients=0)*[a]	22205.83***	7532.60***	6458.86***	1086.74***	17952.25***	6790.48***
Wald test statistics *(All first days at the beginning=0)*[b]	15861.04***	4757.76***	3733.85***	496.89***	12966.29***	4274.29***
Wald test statistics *(All first days after overfunding=0)*[c]		941.41***		112.63***		843.70***

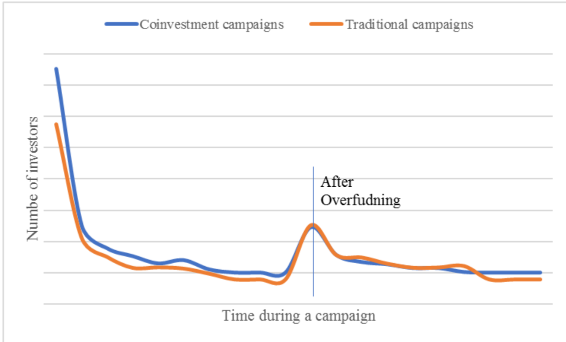
Notes: This table reports the estimated coefficients of negative binomial regressions with fixed effects. The dependent variable is the number of investors that pledged money in each day of the campaign. All campaigns are used in Model (1), (3) and (5) while only successful campaigns are used in Model (2), (4) and (6). The definitions of all control variables are provided in Table 4.2. [a]: The null hypothesis of the Wald test is that all coefficients, excluding the constant term, are equal to 0 simultaneously. [b]: The null hypothesis of the Wald test is that all coefficients of dummies indicating first seven days are equal to 0 simultaneously. [c]: The null hypothesis of the Wald test is that all coefficients of dummies indicating first seven days after overfunding are equal to 0 simultaneously. *, **, *** indicate significance at 10%, 5% and 1% level, respectively.

Figure 4.4 Robustness Check: Different Proxies for Angel Co-investment

Panel A Proxy: Top 25%

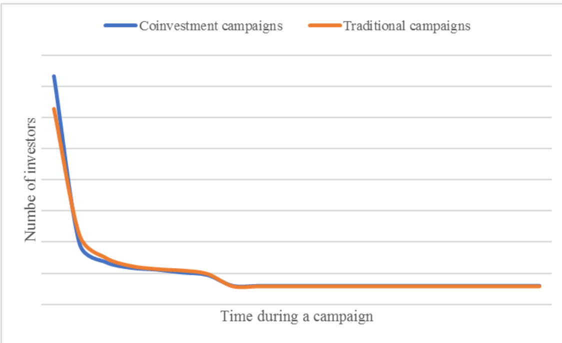


Dynamics in an ECF campaign

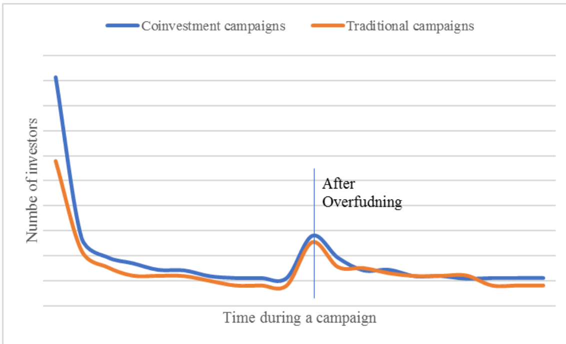


Dynamics in a successful ECF campaign

Panel B Proxy: Top 20%

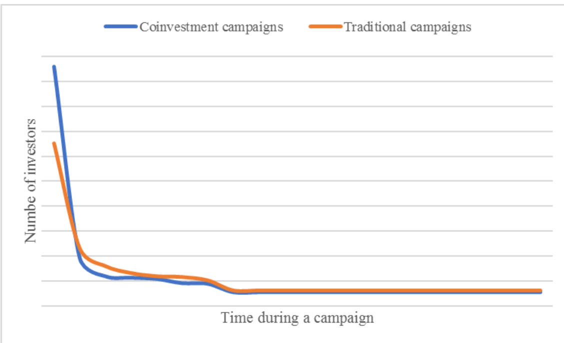


Dynamics in an ECF campaign

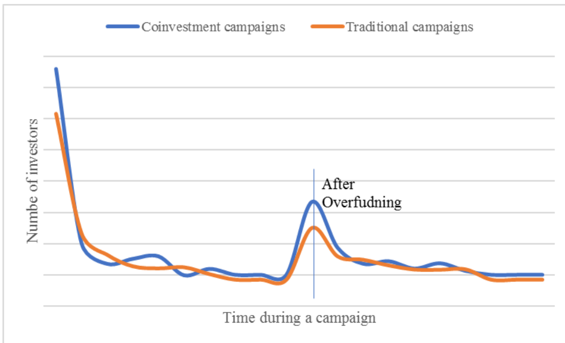


Dynamics in a successful ECF campaign

Panel C Proxy: Top 10%



Dynamics in an ECF campaign



Dynamics in a successful ECF campaign

Notes: This figure shows the dynamics for the predicted number of investors that pledge money in each day during a campaign. The figure on the left-hand side in each panel shows the dynamics in an ECF campaign while the figure on the right-hand side in each panel shows the dynamics in a successful ECF campaign, with the blue line for a co-investment campaign and the orange line for a traditional campaign. The predicted numbers in Panel (A), (B) and (C) are calculated using the estimates in Table 4.10, 4.11 and 4.12, respectively. The predictions on the left-hand side are based on the Model (3) and (5) in the corresponding tables while the predictions on the right-hand side are based on the Model (4) and (6) in the corresponding tables.

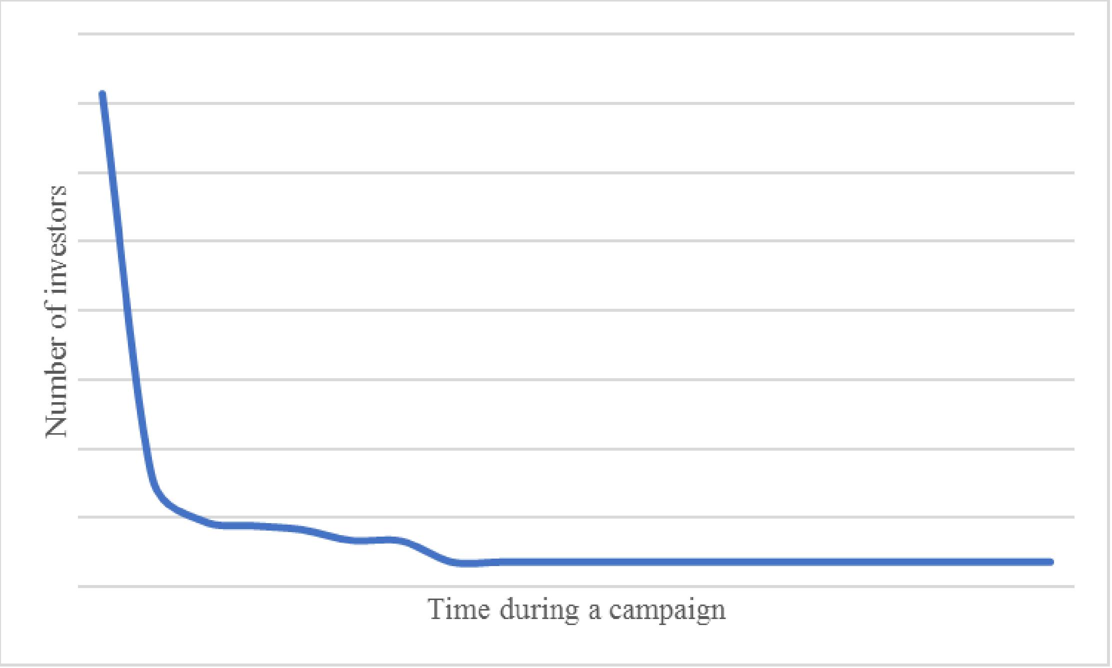
Table 4.13 Robustness Check: Excluding Campaigns on Crowdcube

	Baseline regression		Co-investment campaigns		Traditional campaigns	
	Model (1)		Model (2)		Model (3)	
1st day	3.0077***	(0.0394)	2.9376***	(0.0561)	3.0551***	(0.0631)
2nd day	1.4888***	(0.0640)	1.3096***	(0.0925)	1.7894***	(0.0876)
3rd day	0.9914***	(0.0756)	0.8367***	(0.1078)	1.1966***	(0.1043)
4th day	0.9122***	(0.0791)	0.7836***	(0.1112)	1.1099***	(0.1088)
5th day	0.8465***	(0.0804)	0.8062***	(0.1093)	0.9011***	(0.1162)
6th day	0.6326***	(0.0872)	0.5420***	(0.1190)	0.7815***	(0.1223)
7th day	0.6202***	(0.0876)	0.4757***	(0.1236)	0.8492***	(0.1190)
Campaign characteristics						
Co-investment	0.0523	(0.0780)				
Funding target	0.0004***	(0.0000)	0.0001**	(0.0001)	0.0016***	(0.0002)
Equity offered	-0.0088**	(0.0041)	0.0115*	(0.0061)	-0.0414***	(0.0073)
Seasoned campaign	0.8517***	(0.1076)	1.4379***	(0.1939)	0.9382***	(0.1500)
Information technology	0.0028	(0.0703)	0.6319***	(0.1452)	-0.1434*	(0.0862)
London	-0.0661	(0.0686)	-0.2204*	(0.1264)	0.0010	(0.0905)
Overfunded	0.0355	(0.0447)	-0.1373**	(0.0607)	0.0514	(0.0643)
Board characteristics						
Board size	-0.1176***	(0.0376)	-0.1352**	(0.0576)	-0.1026*	(0.0576)
Average age	0.0237***	(0.0040)	0.0379***	(0.0077)	0.0169***	(0.0051)
Age diversity	-0.0010	(0.0042)	-0.0090	(0.0066)	-0.0155**	(0.0069)
Average tenure	0.0347***	(0.0095)	0.0403***	(0.0152)	0.0207	(0.0143)
Tenure diversity	0.0512***	(0.0191)	0.0995***	(0.0312)	0.0965***	(0.0358)
Common surname	-0.1650	(0.1194)	-0.2113	(0.2076)	-0.5283***	(0.1937)
Foreign nationality	0.3333***	(0.0725)	0.4280***	(0.1224)	0.1133	(0.1105)
Doctorate	-0.0781	(0.1152)	0.2284	(0.2558)	-0.3221*	(0.1681)
Platform dummies	Yes		Yes		Yes	
Year dummies	Yes		Yes		Yes	
Month of the year	Yes		Yes		Yes	
Day of the week	Yes		Yes		Yes	
Observations	8216		4147		4069	
(No. of campaigns)	(164)		(97)		(67)	
Log likelihood	-12329.17		-5816.24		-6405.61	
Wald test statistics *(All coefficients=0)*[a]	9058.57***		4918.74***		4873.64***	
Wald test statistics *(All first days at the beginning=0)*[b]	5919.10***		2816.65***		2444.42***	

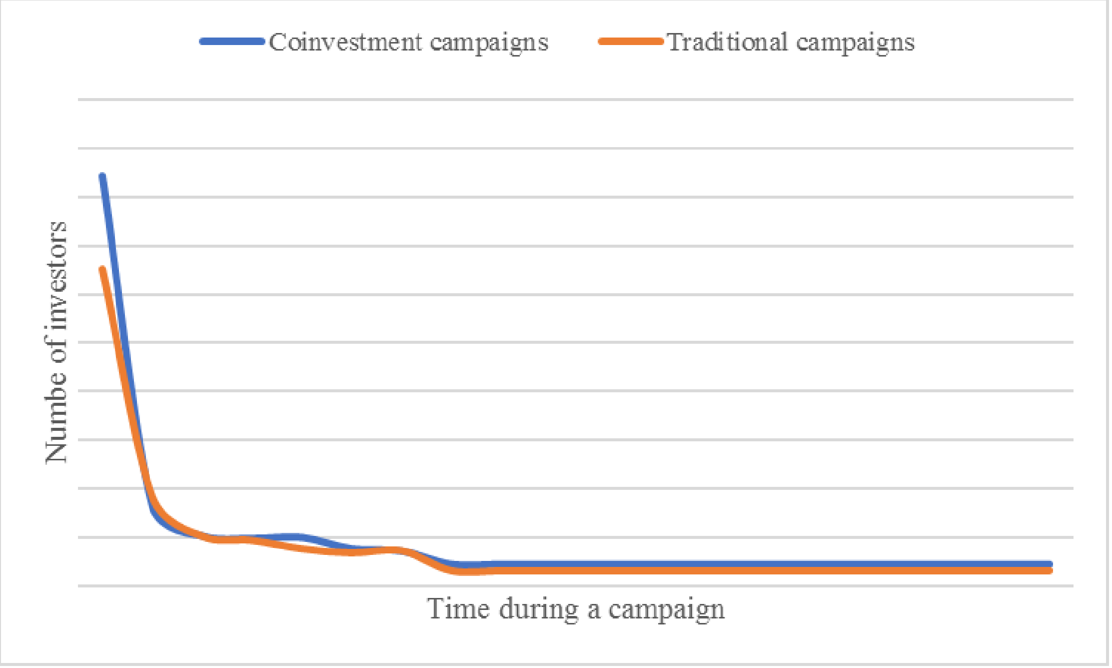
Notes: This table reports the estimated coefficients of negative binomial regressions with fixed effects, with the corresponding standard errors in parentheses. The dependent variable is the number of investors that pledged money in each day of the campaign. The definitions of all control variables are provided in Table 4.2. [a]: The null hypothesis of the Wald test is that all coefficients, excluding the constant term, are equal to 0 simultaneously. [b]: The null hypothesis of the Wald test is that all coefficients of dummies indicating first seven days are equal to 0 simultaneously. *, **, *** indicate significance at 10%, 5% and 1% level, respectively.

Figure 4.5 Robustness Check: Excluding Campaigns on Crowdcube

Panel A Dynamics in an ECF campaigns on Seedrs/SRoom



Panel B Dynamics in a co-investment campaign vs. a traditional campaign on Seedrs/SRoom



Notes: This figure shows the dynamics for the predicted number of investors that pledge money in each day during a campaign. Panel A shows the dynamics in an ECF campaign, where the predicted numbers are calculated using the estimates in Model (1) in Table 4.13. Panel B also shows the dynamics in an ECF campaign, with the blue line for a co-investment campaign and the orange line for a traditional campaign where the predicted numbers are calculated using the estimates in Model (2) and (3) in Table 4.13, respectively.

Table 4.14 Robustness Check: Funding Dynamics for Daily Amount Raised

	Model (1)		Model (2)	
1st day	191.5789***	(3.3688)	151.9724***	(3.8372)
2nd day	7.0338**	(3.3629)	5.3220	(3.8334)
3rd day	3.3839	(3.3590)	4.2492	(3.8294)
4th day	0.8477	(3.3540)	1.8622	(3.8285)
5th day	0.6159	(3.3518)	-0.7349	(3.8275)
6th day	0.3456	(3.3498)	0.4130	(3.8256)
7th day	0.1654	(3.3473)	-1.1964	(3.8262)
1st overfunded day			54.1560***	(3.8796)
2nd overfunded day			2.0496	(4.0227)
3rd overfunded day			0.0444	(4.1259)
4th overfunded day			-0.0907	(4.1942)
5th overfunded day			-1.2855	(4.3113)
6th overfunded day			0.7308	(4.4228)
7th overfunded day			-1.0954	(4.6168)
Overfunded	1.4739	(1.8803)		
Year dummies	Yes		Yes	
Month of the year	Yes		Yes	
Day of the week	Yes		Yes	
Observations (No. of campaigns)	21223 (497)		8082 (182)	
F statistics *(All coefficients=0)*[a]	121.14***		54.90***	
Wald test statistics *(All first days at the beginning=0)*[b]	466.54***		226.17***	
Wald test statistics *(All first days after overfunding=0)*[c]			28.03***	

Notes: This table reports the estimated coefficients of OLS regressions with fixed effects, with the corresponding standard errors in parentheses. The dependent variable is the amount of investment that investors pledged in each day of the campaign. All campaigns are used in Model (1) while only successful campaigns are used in Model (2). The variable definitions are provided in Table 4.2. [a]: The null hypothesis of the F test is that all coefficients, excluding the constant term, are equal to 0 simultaneously. [b]: The null hypothesis of the Wald test is that all coefficients of dummies indicating first seven days are equal to 0 simultaneously. [c]: The null hypothesis of the Wald test is that all coefficients of dummies indicating first seven days after overfunding are equal to 0 simultaneously. *, **, *** indicate significance at 10%, 5% and 1% level, respectively.

4.7 Conclusions

This chapter investigates funding dynamics in equity crowdfunding and particularly whether angel co-investment may influence these dynamics. The descriptive statistics show when an angel co-invests alongside the crowd in an ECF campaign, the campaign tend to be larger and the fundraiser tends to have a larger and more diversified board. This suggests that the funding dynamics may be distinctive. Following Hornuf and Schwienbacher (2018a), we investigate the dynamics of the daily number of investors. The empirical results confirm the L-shaped pattern of prior studies but in addition show a further (less pronounced) L-shaped pattern after the funding target is exceeded (i.e. overfunding). The latter could be explained by the 'collective attention effect' (Hornuf and Schwienbacher, 2018a) that the number of investments is high when potential investors are informed of this news and then decreases as time elapses. The results also indicate a more pronounced L-shape for campaigns with angel co-investment. However, angels are found to exert a weaker impact on funding dynamics in seasoned ECF campaigns and after overfunding. This is consistent with the idea that herding behaviour is less pronounced (Wick and Ihl, 2018) and signals become less effective (Wang et al., 2019) when information asymmetry is mitigated.

From a practical perspective, the analysis provides useful insights to both platform and fundraisers. For platform, our findings that angels play an important role in funding dynamics provide evidence of its benefits, especially when information asymmetries are severe. Acting as an intermediary, platforms can have more connections with angels (or venture capitalists) and construct a stronger network between fundraisers and professional investors. These platforms are also encouraged to set up channels for angels to exhibit more information on their knowledge and experience, lending their reputation to protect the interests of inexperienced crowd investors.

Finally, it is worth stressing the difference between angel co-investing on ECF platforms and angel syndicate platforms. AngelList is a good example of the latter where lead angels construct a portfolio with ECF campaigns to attract investors with relatively high carry fees (usually 20%) as the payoff. By contrast, crowd investors on UK platforms do not pay additional fees to angels but confer on them greater power on the start-up’s board under the nominee shareholder structure. In the latter context, the co-investing angel typically acts as the representative of all crowdfunding investors. The nominee shareholder structure plays a crucial role in corporate governance in the sense that it allocates the same rights to the crowd and angels. This could be a digital solution to potential conflicts between these two parties. Via this channel, angels can leverage their initial investment to become a “blockholder” to exercise more influence on start-up policy and have a stronger monitoring impact on firm performance. Further studies can analyse the mechanisms underlying these two different approaches and its influence on firm performance or investors’ return.

Chapter 5 Concluding Remarks

5.1 Conclusions

Small businesses have a vital role to play in the economy. In recent years a growing number of studies has been devoted to the topic of small business financing. Nowadays there is even more interest as innovations in FinTech give more options to small businesses to raise external capital, and platforms introduce new business models as attractions, some of which challenge (even threaten) traditional financing sources. To gain a better understanding of this area, this thesis investigates issues on external debt and equity finance for UK small businesses. Despite the many changes, banks are still the main provider of financing for small businesses.

Therefore, we first look at the bank credit market conditions that small businesses faced after the global financial crisis and then discuss how to bring discouraged borrowers back to bank borrowing. In addition to bank finance, we also explore issues on a new alternative financing source (equity crowdfunding) that small businesses can seek if bank credit is difficult to access or they are discouraged from applying.

For bank finance, considering the difference between business overdrafts and term loans in application purpose, duration and bank monitoring power and so on, we analyse these two facilities separately in this thesis. Relative to the years just after the global financial crisis (2010-11), the rejection rates of both facilities started to fall in 2014 until the Brexit referendum in 2016. Among UK SMEs, start-ups and micro firms are found to benefit most. However, exporting SMEs, which suffer from the depreciation of sterling, seem to experience especially tough times around Brexit, calling for more attention to help alleviate credit constraints.

The improved lending conditions suggest the potential effectiveness of government initiatives for supporting SME finance. We also examine whether government initiatives, such as the Enterprise Finance Guarantee Scheme, can help reduce the discouragement level, i.e. if they can encourage more SMEs, which have demand but do not apply for fear of rejection, back to borrowing. Our results confirm its effectiveness (via awareness) in both overdraft and loan markets, especially on potential high-growth firms. Moreover, we also find an important role for financial literacy in discouragement in the sense that it encourages low-risk borrowers to apply but discourages high-risk borrowers.

When it is difficult for small businesses to access bank credit, such as for innovative firms, or when they are discouraged from applying, they can seek financing from other sources. An emerging financing alternative is equity crowdfunding (ECF), in which the funding dynamic shows an L-shaped pattern that more investors are attracted at the beginning of a campaign. One of the trends in ECF market is that more and more business angels co-invest alongside the crowd. Their co-investments lead to a pronounced L-shaped dynamic, especially in the case of high information asymmetries. This shows the advantages of syndicates between institutional and crowd investors. However, the platform needs to provide suitable protection to inexperienced crowd investors, and we suggest asking angels to disclose more information, such as their investment history and achievement, when they invest in an ECF campaign.

5.2 Limitations and Future Research

The main limitation of this thesis derives from the data limitation and it provides several avenues for future research once the data become available. In our first study, we only access the data till the end of 2017 and observe stable rejection rates for both overdrafts and loans in the Brexit referendum year (2016) and its immediate aftermath, suggesting an insignificant impact in the short term. An immediate avenue is to investigate whether the uncertainty brought by Brexit will change the bank credit market in the medium term if the survey continues to be carried out for a few years (possibly 3-5 years) after Brexit. In the second study, we emphasise the vital role of financial literacy in awareness of government schemes and discouragement. It will be valuable to extend our finding to developing countries, where discouragement is more prevalent but financial literacy needs to be raised. Since we use the same data source in our first two studies, they may suffer from similar limitations. Although we include many explanatory variables to control for the heterogeneity among small businesses, some factors related to bank debt rejections and/or discouragement are still omitted, such as owner/manager’s ethnicity and credit history. A relatively new dataset, Longitudinal Small Business Survey (LSBS) supported by the Department of Business Innovation and Skills (BIS), started its first wave survey in 2015 and provided yearly panel data for UK SMEs. This dataset allows us to run regressions with fixed effects and might be helpful for future research in this area.

Finally, in equity crowdfunding, the effect of angel characteristics on funding dynamics needs further investigations. Although more and more institutional investors enter this market, their data are still difficult to collect. This justifies why our study constructs proxies for angels’ investments. Besides, during our data cleaning, we observe two specific firms launching their first ECF campaigns successfully on one platform but moving to another platform to seek ECF as a second or third round financing. The underlying reasons deserve more analysis and in-depth interviews might be favoured in this context.

Another interesting issue to be better understood is the role of gender in ECF funding dynamics. A preliminary analysis from Vismara et al. (2017) suggests female entrepreneurs attract almost twice as many female investors relative to male entrepreneurs. Future studies can examine what it might bring to the funding dynamics and analyse what happens if the entrepreneur and the angel have the same gender, especially when they are both females.

Overall, this thesis empirically investigates three issues on external debt and equity for UK small businesses which are typically informationally opaque and more likely to encounter financing obstacles relative to large firms. The thesis provides a comprehensive analysis on what happens to bank lending conditions after the global financial crisis and around the Brexit referendum, how to bring discouraged borrowers back to the bank debt market and the role of angels in equity crowdfunding dynamics. Based on the findings, it makes several recommendations to both policymakers and firms, aiming to alleviate the financing constraints faced by UK small businesses. These are designed to promote their growth and foster the development of the whole economy.

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