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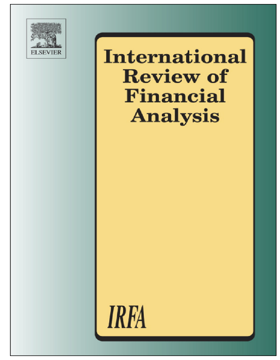

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Xiaodong Wang, Liang Han, Xing Huang

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Bank Competition, Concentration and EU SME Cost of Debt

Xiaodong Wang
Henley Business School, University of Reading, Reading, RG6 6UD, U.K,
Xiaodong.Wang@pgr.reading.ac.uk

Liang Han
Corresponding Author. Henley Business School, University of Reading, Reading, RG6 6UD, U.K,
Liang.Han@henley.ac.uk

Xing Huang
Portsmouth Business School, University of Portsmouth, Portsmouth, PO1 3DE,
Xing.Huang@port.ac.uk

Abstract

Despite the plentiful debate on the effects of bank competition on SME access to finance and growth, only few studies have explored the impacts on SME cost of debt. This study examines how bank market power affects the credit costs of SMEs by using unique matched SME-bank data from 17 EU countries. We show that bank market power reduces the cost of debt for SMEs. Such a favorable effect is stronger for SMEs that are less informationally transparent, and in the economies subject to less credit information depth and business extent of disclosure. These findings support the Information-based Hypothesis, whereby market power motivates banks to invest in soft information acquisition and to build lending relationships to reduce information costs. In addition, we show that despite the favorable effects of relationship lending brought by bank market power, SME credit conditions worsen in a more concentrated banking market.

Keywords: Bank market power, Cost of debt, EU countries, Financing constraints, SME

JEL: G10, G21, M21

Declarations of interest: none

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1: Introduction

Financing obstacle has been identified as one of the most serious problems for Small and Medium-sized Enterprises (SMEs) in the EU countries (Survey on the Access to Finance of Enterprises, SAFE). Existing literature has shown ample evidence that financing is a crucial determinant of SME survival and growth (e.g. Ayyagari et al., 2011; Campello and Larrain, 2016) and SME sector makes a great contribution to a country's economic stability and employment creation (e.g. Duygan-Bump et al., 2015).

In the EU countries, because of the limited capability of SMEs accessing other sources of finance, bank finance[1], as well as trade credit, are still the dominant sources of external financing (e.g. Siedschlag et al., 2014; Brown and Lee, 2014, Palacin-Sanchez et al., 2018).

SMEs are not scaled-downed version of larger enterprise, and compared with the latter, SMEs generally have more difficulties in obtaining bank credit, especially cheap credit (Yoshino and Taghizadeh-Hesary, 2018) because[2], first, SMEs are more likely to be informationally opaque due to their lack of information infrastructure and credit history. For example, due to SMEs' lower external monitoring and narrow reporting needs (e.g. audited financial statements), they are more likely to be lacking of observable signals for credibility, resulting in an asymmetric information problem and that banks' close and continuous observation become costly for borrowers of small loans (Yoshino and Taghizadeh-Hesary, 2018). Second, unlike large enterprises, SMEs are generally less capable of providing sufficient collaterals for coverage of their risk. This becomes even more troublesome since the existence of the asymmetric information problem between banks and SMEs, and high transaction costs may lead to more collateral requirements for lending to SMEs (Yoshino and Taghizadeh-Hesary, 2018). Third, the Moral Hazard problem (Holmstrom and Tirole, 1998) happens when borrowers intentionally exercise deviated effort or take on higher business risk after the issuance of a loan. This is because a borrower's expected return is an increasing function against project risk, but a decreasing function for its lenders. This dilemma can be alleviated when the borrower's after-contract activities can be properly monitored by banks at a low cost. However, due to the

[1] The EU banking market is larger in size compared with the US. As of 2017, banking assets were equivalent to 280% of GDP for the EU, peaked at 340% back in 2012, but only 88% for the US (source: European Central Bank).

[2] We thank an anonymous referee for suggesting the points in relation to the reasons of SMEs' financing constraints.

disproportionally higher costs of due diligence and low transparency of SMEs, such a problem may not be easily managed by banks. For all these reasons, bank lending to SMEs is considered to involve higher costs and credit risk, therefore banks are generally more reluctant to extend loans to SMEs, making SMEs more likely to face credit constraints (e.g. high interest rate) (Yoshino and Taghizadeh-Hesary, 2016).

Due to the great contribution of SME sector to the EU economy[3], the importance of bank financing in SME growth and the intrinsic financing constraints of SMEs, plenty of studies have attempted to investigate how to improve SME credit availability and to tackle their credit constraints. The potential impacts of banking sector e.g. market power of banks and the market structure of banking industry, on SME finance have attracted considerable attention during the past decade, although the empirical findings are mixed. For example, banks with greater market power may cut credit supply to SMEs (Love and Peria, 2014; Leon, 2015) but bank competition may also reduce SME credit availability (Alvarez and Bertin, 2016; Ratti et al., 2008).

The theoretical foundations of the contrasting evidence are mostly built on the Market Power Hypothesis (MPH) and the Information-based Hypothesis (IBH). The former one (MPH), which is derived from the standard industrial organization models, suggests that market power enables firms to engage in anti-competitive behavior (e.g. Vatiero, 2010). Under the banking context, increased market power could result in restricted loan supply and manipulated lending rates, thereby aggravating borrowers' financing constraints (Ryan et al., 2014). On the other side, a decrease in bank's market power enhances competition and increases the overall efficiency of a banking industry, therefore facilitating credit access (Meslier et al., 2020; Love and Peria, 2014), and ultimately leading to a stronger economic growth (Caggiano and Calice, 2016). While, the latter hypothesis (IBH, Petersen and Rajan, 1995) conjectures that, in the presence of information asymmetries and agency costs, fiercer competition may reduce the incentives of, or make it more costly for banks to invest in private information acquisition, and reduce the quality of screening and monitoring. In contrast, stronger market power enables banks to build lending relationships that reduce the information asymmetries and agency costs between banks and borrowers, to efficiently allocate resources to more informationally opaque borrowers (e.g. SMEs), and to

[3] According to European Commission, there were 23.9 million EU SMEs in 2016, accounted for 99.8% of all EU enterprises, provided over 93 million jobs (66.6%) and €4,030 billion (56.8%) of gross value added.

establish a lending relationship for subsequent periods informational rents (Ryan et al., 2014), therefore easing credit constraints (Han et al., 2015; Meslier et al., 2020).

Prior literature has focused substantially on the quantity (amount) of finance available to SMEs. For example, SME financing constraints are mostly reflected by the lack of access to bank finance and low financing quantity fulfilment (e.g. exclusion, loan turndowns, low bank debt usage). However, what is under-studied is the bank market power effects on SME cost of credit - another major element composing financing obstacles. Price-related obstacles (e.g. high interest rate) are not always numerically reflected in SME access to finance measures such as the ones in Love and Peria (2014) and Mudd (2013). In this study, instead of focusing on whether an SME has applied bank finance, or if it has successfully accessed to finance, our interest is placed on the cost of bank debt. For SMEs, although high credit cost may reflect higher risk, it could also be one of the hindrances impairing their survival and development, even though they might have obtained an adequate amount of finance (Vos et al., 2007). High credit costs may also lead to SMEs being able to afford only partial finance, therefore impeding their investment opportunities. In addition, the Moral Hazard dilemma (Holmstrom and Tirole, 1998) suggests that because of the different expected return functions between borrowers and creditors, borrowers could be incentivized to adventure on upwardly deviating risk-taking level to compensate the high interest cost after the issuance of loans, increasing the uncertainty of repayments and therefore damaging the financial stability of a banking industry. For all these arguments, a thorough empirical investigation on the effects of bank market power would deepen our understanding on the mechanisms of how small business loans are priced and how SME credit conditions could be improved.

Our study, as the first empirical study based on cross-country matched firm-bank relationship, examines the disaggregate level (individual bank-year level) market power effects on SME cost of debt using data from EU countries. In addition to providing novel evidence to the SME financing constraints literature from a perspective of cost of bank debt, we also extend the existing literature by the following ways. **First**, we distinguish the effects of bank market power and of bank concentration on SME credit cost by accounting for the fact that bank concentration might be an inappropriate measure of competition (e.g. Bolt and Humphrey, 2015). Our unique matched bank-firm database also allows us to detect the direct and varied bank market power effects on SMEs in a country at a disaggregate level, where the country-level measures are widely criticized in the literature (e.g. Ratti et al., 2008; Ergungor, 2004; Alvarez and Bertin, 2016). **Second**, given the advantages of using financial reporting data and the implicit measure of SME debt interest rate under the absence of loan-level data, our panel-structured data consists of a richer number of observations than most of the existing papers in relevant to SME financing constraints (e.g. Mudd, 2013; Leon, 2015). This large disaggregate-level dataset enhances the external validity of the results, allows us to control for intrinsic industry-level financing cost differences and other factors affecting SME credit cost (e.g. financing capability, risk), and allows us to assess if information and institutional development would moderate the bank market power effects. **Third**, we make distinctions between the different types of SME financing constraints, focus exclusively on the cost of bank debt, and deepen the understanding of bank competition effects on SME finance. Our empirical evidence is based on objective indicators of SME cost of debt, rather than indirect financing constraints proxies such as the use of trade credit (e.g. Carbo-Valverde et al., 2009), manager's self-assessment (e.g. Beck et al. 2004;), or estimations based on sensitivity analysis (e.g. Ryan et al., 2014; Agostino and Trivieri, 2010). **Fourth**, unlike Giannetti and Ongena (2009) and Rice and Strahan (2010) who examined the bank competition effects on SME cost of credit in scenarios with exogenous shocks on bank competition (i.e. foreign bank entry, relaxation of banking restriction), our cross-country study does not focus on a specific event but on the market power of banks in general, enhancing the validity of policy implications

In examining the bank market power effects on EU SME cost of bank debt, our principal findings from a matched bank-firm sample composed of 77,911 SMEs in 17 EU countries are that, disaggregate-level bank market power reduces the cost of debt of SMEs and, relives the financing constraints of SMEs in the EU. This favorable effect is more pronounced for those SMEs who are smaller and more informationally opaque, and in the economies which are subject to higher degree of credit information obstacles and less informationally transparent because banks investing in relationship-based lending techniques becomes more effective. Our empirical findings do not show support to the Market Power Hypothesis but in favor of the Information-based Hypothesis where due to the crucial role of information, greater bank competition reduces the market power of banks and impedes banks from investing in private (soft) information acquisition or building relationship with smaller and less transparent firms. We also find little supporting evidence on the hypotheses proposed by Ergungor (2004), Ruckes (2012) and Boyd and De Nicolo (2005). In addition, we show that SMEs are charged higher costs on debt in a more concentrated banking market despite the favorable effects of relationship lending, suggesting that SME credit availability is more constrained along with the leading banks expanding their market shares.

The remainder of the paper is organized as follows. Section 2 reviews relevant studies and theories. Section 3 describes data and methodologies. Section 4 presents the findings and Section 5 summarizes.

2: Literature Review

Recent studies examining the factors affecting SME credit costs have largely focused on the firm-level determinants such as financial reporting quality (Bauwhede et al., 2015), executive gender (Mascia and Rossi, 2017), and firm performance (Hyytinen and Pajarinen, 2007). Many other studies have also focused on the macroeconomic determinants of SME credit costs such as economic stress (Ferrando et al., 2017), unemployment rate (Carroll and McCann, 2016) and cultural differences (Chui et al, 2012). There are only handful studies examining the banking effects on SME credit allocation, such as Hubbard et al. (2002) which focused on bank capital and risk, Bremus and Neugebauer (2018) on banking market integration, and Carroll and McCann (2016) on bank profitability and cost structure. However, studies examining the bank competition effects on SME lending price in particular are rare although many have paid attention to such effects on SME access to finance and financing constraints.

Several theoretical frameworks have offered implications on the relationship between bank market power and SME cost of debt. Ruckes (2004) and Demiroglu et al. (2012), for instance, have shown that bank's changes in credit standards over different economic conditions could be an intermediary factor, through variations of price competition, explaining the relationship between bank market power and SME cost of debt. Borrower's credit risk declines when economic outlook improves and vice versa. When the economy is in recession, pricing competition among creditors are less attractive and banks become protective by increasing interest rates charged on high-risk borrowers (e.g. SMEs). However, since the screening process of SME lending is costly (Ruckes, 2004), under favorable economic conditions, the likelihood of firms' default rate declines and creditor's screening and monitoring processes are less marginally beneficial, leading to fiercer competition on prices. Therefore, economic condition is expected to be negatively related to SME cost of credit and the effect of bank market power on SME borrowing cost is diminished under sound economic conditions and vice versa. Evidence from Boyd De Nicolo (2005) supports a contrasting conjecture that bank market power is a result of bank's technology advantage on loan screening and monitoring and, a bank with such technology advantage has greater discourse power; and therefore the cost efficiency could be shifted to borrowers with higher credibility by reducing interest or non-interest costs for long-term prosperity. Hence, such a conjecture implies that bank market power would be negatively related to the cost of credit, and such a favorable effect would be stronger for creditworthy borrowers such as those with better credit rating scores.

Furthermore, as introduced in Section 1, two most widely discussed contrasting hypotheses, Market Power Hypothesis (MPH) and Information-based Hypothesis (IBH), could potentially explain the mechanisms through which bank market power could affect SME finance although neither directly emphasizes on the cost of credit. MPH, which is based on the conventional industrial organization theory, suggests that market power enables firms to engage in anti-competitive behavior (e.g. Vatiero, 2010) and, bank market power, for example, could result in restricted loan supply and manipulated lending rates, worsening the financing constraints of borrowers. Whilst, IBH (Petersen and Rajan, 1995) conjectures that with information asymmetries and agency costs, banks with a market power have stronger incentives to invest in private information acquisition from borrowers, to build lending relationship to reduce agency costs, to efficiently internalize the costs of private information collection, and to extract informational rents in subsequent periods with reduced financing obstacles especially for informationally opaque firms (Ryan et al., 2014; Han et al., 2015; Meslier et al., 2020). Although IBH does not specify particularly on how bank market power could affect SME finance, it is expected that relationship lending could alleviate the financing constraints and credit costs of SMEs. Finally, Ergungor (2004) states that bank's lending activities are either transaction-based or relationship-based, and competition reduces bank's profits from both lending techniques but the effect varies between the two alternatives. An increase in competition reduces a bank's profits from transaction lending more than its profits from relationship lending. Therefore, competition encourages banks to shift from transaction to costly relationship loans.

Empirical studies examining the above theories on the relationship between bank competition and SME finance provide fairly mixed results. Mudd (2013) and Love and Peria

(2014) have shown that bank competition improves SME's access to finance but only non-structural bank competition measure (e.g. Lerner index) is found to be significant in the latter study. By measuring the level of perceived financing obstacle facing SMEs, Beck et al. (2014) show that obtaining finance becomes more difficult for SMEs operating in more concentrated banking markets although their interpretation on concentration measure is likely to be biased due to the scales of different economies (e.g. Belize vs France). Basing on the concept of discouragement as a type of financing obstacles, Leon (2015) documents that SMEs borrowing discouragement reduces in the countries where banking markets are more competitive but such a finding is not affected by the concentration level of a banking market.

Besides these cross-country studies, single country studies in China (Chong et al., 2013), Italy (Agostino and Trivieri, 2010), Belgium (Degryse and Ongena, 2007) and UK (Degryse et al., 2015) generally back the argument that bank market power impedes SMEs to obtaining formal bank finance. Ryan et al. (2014) use financial reporting data find that the sensitivity of dependence of investment on internal fund is more significant in less competitive banking market. The improvement of SME credit availability in these studies supporting MPH are defined as better access to finance, less application rejections and discouragements, and less dependency on internal funds for investment opportunities.

In sharp contrast, Ratti et al. (2008) indicate that bank market power increases banks' incentive to acquire private information on potential borrowers and hence relaxes SME financing constraints although they criticize themselves that country level competition measure could be subject to strong bias. Similar supporting evidence on IBH is also available from Latino countries (Alvarez and Bertin, 2016), UK (Abunakr and Esposito, 2012) and Philippine (Tacneng, 2014), where bank competition does not necessarily improve credit availability to SMEs due to the special role of asymmetric information. There are also studies (e.g. Di Patti and Dell'Ariccia, 2004; Cetorelli and Gambera, 2001) which suggest non-linear relationship between bank market power and SME access to finance. Carbo-Velverde et al. (2009) show that bank market power as measured by Lerner index is negatively related to SME credit availability but concentration measures suggest an opposite result, highlighting the different concepts between bank competition and concentration.

Above studies have investigated the bank competition effects on SME financing constraints in terms of credit accessibility but only a few have focused specifically on the cost of debt. Rice and Strahan (2010) report that in a large U.S. small business sample, in states with stronger bank competition (open to branching), credit supply expands and small firms borrow at a lower price but the amount that SMEs borrow does not alter. Interestingly, their competition measure (branching restrictiveness) is not associated with the state-level banking concentration, and concentration has no impact on SME loan price. Using the same data, Bonini et al. (2016), however, show that relationship lending is not associated with the rent extraction derived from information lock-in. In contrast, high banking market concentration appears to be a cause of SME high borrowing costs but this unfavorable effect can be fully compensated if the relationship of an SME-bank pair is long and comprehensive.

In the European markets, bank competition reduces SME cost of credit if concentration measure is assumed to reflect the degree of contestability (Carroll and McCann, 2016). However, Mascia and Rossi (2017) conclude, in sharp contrast, that SMEs operating in more concentrated banking markets have lower financing costs. They also find that a bank's lending standards and credit risk taking level do not affect SME credit costs. Finally, Giannetti and Ongena (2009) show that an increase in bank competition and reduction in market power as a result of foreign bank lending in Eastern European countries stimulate firm's access to finance and reduces borrowing costs for large firms (employees>250), but not for small firms.

Among the literature reviewed, only Giannetti and Ongena (2009) and Rice and Strahan (2010) address the competition effects on SME cost of debt although they aim at specific events which cause the changes of bank competition (i.e. foreign bank entry, relaxation of banking restriction). Other studies only examine the banking market concentration effects and provide inconsistent empirical evidence. However, due to the fact that bank concentration may proxy market conditions only rather than bank market power (Ergungor, 2004; Stein, 2002), measuring bank market power is more challenging according to the concept of market contestability (Bolt and Humphrey, 2015). For example, the theoretical foundation of using concentrations as a measure of competition (structure-conduct-performance paradigm, SCP) has been rejected by Claessens and Laeven (2004) and Northcott (2004). In addition, Berger (1995) argues that due to the high correlation with other factors, the relation between banking market structure and monopoly profit could be biased. Lapteacru (2014) has shown that in European market, concentration is not an ideal measure of bank market power or banking market competition.

Existing literature has also shown that concentration measure (e.g. HHI) is not significantly correlated with other non-structural measures (e.g. Lerner Index) (Bolt and Humphrey, 2015).

In this study, we add to the literature related to SME financing constraints by asking for the first time, how does bank market power affect the cost of bank debt of SMEs by using unique matched SME-bank disaggregate-level data from 17 EU countries.

3: Data, Variables, and Model Specification

3.1 Data source and matching

SME survey data has the deficiencies such as small sample size (e.g. Small Business Survey) and cross-sectional nature (e.g. SAFE), and therefore we obtain firm-level financial reporting data from Orbis Amadeus[4]. According to EU law, small and medium-sized enterprises are made up of firms which employ fewer than 250 persons and have an annual turnover not exceeding 50 million euros[5]. We also exclude sample firms which do not meet the criteria in some particular ways[6]. Bank-level accounting data are collected from *Fitch Connect* and bank specialization data from *Orbis BankFocus*. Bank-level data can be directly matched with the firm data but generating variable such as bank market power (Lerner index) requires full bank data including those banks which are not matched with our SME sample[7]. Macroeconomic and banking market data used for controlling economic and time-series heterogeneities are collected from Heritage Foundation, World Bank, European Commission (AMECO), European Central Bank (ECB) and Eurostat. Data are matched with SMEs through country code and year.

We follow existing literature (Kalemli-Ozcan et al., 2019; Marco, 2019; Ongena and Sendeniz-Yuncu, 2011; Giannetti and Ongena, 2012; Barbiero et al., 2016) to define an SME-bank relationship at disaggregate level. Consistent with above literature, Kompass database provides creditor information of European SMEs and the main bank is defined as the bank which

[4] 99% of the samples in Amadeus are private firms and, we use the sub-subscription of Amadeus because the full subscription contains too many micro-firms with low quality data (e.g. non-genuine values, blank spaces).
[5] Estimation, which is based on turnovers, total assets, and employees at two-digit NACE1 and UK SIC 07 industry-level, is used to define the size of a firm when information on the number of employees and/or amount of turnover is not available.
[6] We screen the samples on their activity locations (e.g. overseas territories), industries, legal forms, and creditor information. Details are available from authors on request.

[7] We add only cooperative banks, savings banks, and commercial banks in both the matched bank-firm sample and the bank-only sample.

is the most preferred debt lender which also provides depositing, liquidity management and other services. Such a firm-bank relationship is very sticky and bank switching is very rare in the EU countries (Chodorow-Reich, 2014; Ongena and Smith, 2001), particularly as shown from the Amadeus database (Giannetti and Ongena, 2012; Marco, 2019 and Kalemli-Ozcan et al.,2019). In addition, in European countries, bank finance is the most important source of SME finance and therefore debt financing data of SME samples from Amadeus is a valid reflection of lending from their main banks (Fungacova et al., 2017). It is possible that SMEs may over-report or hide identity of their main banks for strategic reasons (Yosha, 1995; Diamond, 1991). However, this is not a concern in our sample because the Kompass database has access to credit registry information (Brown, 2009; Ongena and Sendeniz-Yuncu, 2011; Giannetti and Ongena, 2012). Another concern is the multiple banking relationships reported by SMEs in several countries[8]. We match the first bank listed by firms because as instructed by Kompass, bank ranking follows the order of importance as an external financier and financial services provider but not alphabetically or by preference (Giannetti and Ongena, 2012; Kalemli-Ozcan et al., 2019).

Our final sample consists of 3,319 banks in the bank-only database where 528 banks are directly matched[9] with 77,911 SMEs in 17 EU countries[10] over the period of 2007 to 2015. Barclays plc serves the greatest number of SMEs in our sample and a typical bank works as the primary creditor for 143 firms and the median number is 25. Around 79% of the SMEs are from big four countries, i.e. UK, France, Spain, and Germany, and 24% of them operate in manufacturing industry and 32% in wholesale and retail industry.

3.2 Variables

3.2.1 Dependent variables

[8] The number of relationship banks reported by firms in Kompass varies across countries. The whole sample has the median number of bank relationships of 1 and mean value 1.17. Full breakdown of the multiple-bank reporting across countries is available on request from the authors.

[9] We manually match Fitch Connect and Amadeus databases instead of using text-processing application such as OpenRefine. Manual matching process takes account of reporting formats inconsistency caused by usage of abbreviation and different Unicode, as well as the actual lending business of banks and potential uncertainty.

[10] Banking concentration data obtained from the Global Financial Development is not available for Estonia and Iceland, Amadeus does not have debt information for Danish SMEs and Kompass does not have bank-firm relationship information for the remaining 11 EEA countries.

Banking finance is a dominant source of SME finance in the European countries, but measuring borrowing cost at firm-level is challenging without loan level data. Given the fact of SMEs' limited accessibility to other sources of finance and the potential role of banks' incentives of assimilating soft information, and in the absence of loan-level data, we follow recent studies, such as Giannetti and Ongena (2009), Hernandez-Canovas and Martinez-Solano (2010), Bauwhede et al. (2015) and Chui et al. (2016), to measure the cost of debt using the ratio of financial expense to average short-term and long-term debt[11] (%). Financial expenses (or interest payment) reported by SMEs are mostly loan expenses because they lack access to non-bank funding sources. This ratio is an implicit interest rate measure and thus cannot be viewed as the actual interest rate charged on loans. It is an index reflecting the level of borrowing costs across SMEs and lower values indicate lower cost of debt and vice versa. An advantage of using this implicit measure is that it enables us to conduct a large sample study to enhance the external validity of the results. However, the measure is prone to outliers coming from errors due to loan repayment, received interest incomes or other costs unrelated to borrowing. Therefore, the computed ratio as an index is likely to be higher than real cost of debt. We follow aforementioned papers and exclude samples with cost of debt variable higher than a value of 0.5 or lower than the left 1st percentile of all observations. Statistics for the main variables at country level are reported in Table 1.

(Please insert Table 1 about here)

3.2.2 Bank market power and concentration

Bank competition (or market power) measured at country-level is empirically unable to capture the direct and distinct effects of banks with different levels of market power on firms in a country. For examples, there could be banks with significant market power in a banking market that is deemed as competitive, and if two banking markets have a similar level of competitiveness, regression analysis could not detect the level of disparity within a country. Moreover, country-level measure matched with firm-level data could overstate the significance of coefficients as the degree of freedom is miscalculated (Ergungor, 2004). Hence, examining the impacts of bank market power on SME cost of credit requires a measure at the disaggregate level.

[11] Follow Fungacova et al. (2017), bank debt in the Amadeus is decomposed between short-term loans and long-term debt and bank debt is the sum of these two components.

Empirically, there are three indicators that can be used to measure market power at bank-level, Panzar-Rosse H-statistics (Ranzar and Rosse, 1987), Boone indicator (Boone, 2008) and Lerner index (Lerner, 1934). The validity of the H-statistics is conditional on the prerequisite that the tested sector must be in a long-run equilibrium (Bikker et al., 2012). We test this in our sample countries by using bank profitability models proposed by Athanasoglou et al. (2008) and Tabak et al. (2015). Similar to Lepetit et al. (2018), our results indicate that the condition is not met[12]. The Boone indicator measured at bank level lacks of literature support and its theoretical foundation has been challenged by the assumption of the causality between bank efficiency and market power (Cipollini and Fiordelisi, 2012 and Phan et al., 2016). We therefore adopt the most widely-used bank-level market power measure Lerner index[13] (Appendix A). The Lerner index measures a bank's level of market power by relating price to marginal cost. A higher value approaching one indicates a greater market power. The use of Lerner index as a proxy for bank market power for the investigation of SME cost of debt is challenged by the nature that the variable itself is pricing power related. However, as reasoned by Fungacova et al. (2017), this is not a concern because the variable reflects the market power of an individual at bank-level, which is not specifically refined at SME lending market, and we also control for the price-related variables at both macroeconomic and banking levels, and address the endogeneity concerns later in Section 3.3.

Maudos and Guevara (2007) have criticized the derivation of Lerner index as described in Appendix A that banks' market power on lending market could be overestimated because banks' deposit market pricing power is transferrable to the lending market, and this bias could be enlarged if a bank's lending price is sensitive to its marginal cost. Turk-Ariss (2010) proposes a simple solution to drop the cost of fund from the trans-log cost function[14]. However, Forssbeck and Shehzad (2015) state that the solution is subject to two inadequacies. First, the Turk-Ariss Lerner index could be upwardly biased and the cost to output ratio could be underestimated

[12] The assumption of the test is that bank profitability should not be statistically correlated with input prices under long-term equilibrium. Full testing approaches and results are available on request from the authors.

[13] Practical limitations of Lerner index are that, first, Lerner index could be overstated because risk preferences of banks on taking disparate projects are likely to be related to pricing decisions. Second, Bulow and Klemperer (2002) find that competitive banking markets do not necessarily prevent banks from obtaining market power.

[14] The cost of funds reflects the bank market power on the deposit market (Maudos and Guevara, 2007; Turk-Ariss, 2010).

because the trans-log cost function is estimated with only one input price since the function has to hold assumption of homogeneity in input prices. Second, dropping price of fund is only applicable when the assumption that marginal cost is irrelevant to the cost of fund and deposit rate holds. Empirically, both Adams et al. (2002) and Forssbeck and Shehzad (2015) have shown that bank market power of deposit market is not associated with the market power in lending market. For all these reasons, we measure the market power of a bank specifically at the lending market by following Forssbeck and Shehzad (2015, Appendix A).

Section 2 has discussed the difference between the concepts of bank competition and concentration, two banking characteristics that are not substitutable. For example, leading banks in a concentrated banking market are not guaranteed to have higher market power. However, banking market concentration could affect the amount of SME credit supply and the effectiveness of relationship lending (e.g. Beck et al., 2004, Ratti et al., 2008). We therefore use macro-level variable Herfindal-Hirschman index (HHI) to examine the banking market concentration effects on SME cost of debt[15]. HHI is the sum of the squared values of each bank's market share (total assets) in a banking market with a value ranging from zero to one indicating a banking market from least to most concentrated. We also apply widely used concentration-n (3 or 5) ratios for robustness check which are defined as the sum of total assets of three or five largest banks in a banking market as a share of total banking industry assets. However, HHI is a superior proxy to concentration-n ratios because HHI takes account not only the leading banks but also the remaining market participants where concentration-n ratios partially ignore the market share of smaller participants in a particular market.

3.2.3 Control variables

To account for sample heterogeneity and to address the concern of omitted variable endogeneity, we control other factors that affect the cost of bank debt, in addition to our main interested variables. The selection of controlling factors is established on the principle that borrowers' interest rates reflect a bank's perceived (credit) risk level, and the demand and supply in the lending market. Hence, we select control variables based on the theoretical foundation of the factors affecting SME credit risk (financing capability), credit demand, and credit supply by

[15] Ideally, concentration should be measured at regional-level since not all banks are operating at country level, but such data are not consistently available across our sample countries.

following existing empirical work in relevance to the studies of SME cost of debt (e.g. Bonini et al., 2016; Bauwhede et al., 2015; Chui et al., 2016; Mascia and Rossi, 2017; Rice and Strahan, 2010; Rostamkalaei and Freel, 2016). However, control variables are added subject to the following limits and considerations. First, data availability. We acknowledge that some factors, e.g. entrepreneur's characteristics, have been documented to be crucial determinants of SME borrowing cost (e.g. Mascia and Rossi, 2017; Rostamkalaei and Freel, 2016, 2017), but we do not have these data available. Second, the considerations of multicollinearity and firm-level variables' inner relatedness. Last but not least, the trade-off between the number of control variables and the number of observations that can be taken into regression analysis, as small and micro businesses in our sample have plenty of missing accounting values.

We include ten firm- and industry-level control, explained as follows. Firm's size and age are expected to be negatively related to cost of debt, as size and age are an inverse proxy of bankruptcy cost (Berger and Udell, 1995), and a proxy of borrower bargaining power (Howorth and Moro, 2012). Larger, or more mature firms are also less opaque with more public information available for credit risk assessment (Bonini et al., 2016). Moreover, consistent with relationship theory, more mature firms may have longer-standing relationships with their banks so that private (soft) information may be more readily available (Bauwhede et al. 2015). Next, we include a dummy variable to capture whether an SME is innovative or not[16]. A positive sign is expected as innovative firms are more likely to be informationally opaque and high in business success uncertainty, therefore less attractive to banks due to higher and more professional skill-based screening and monitoring costs involved in credit assessment. Cash-richness (cash/total assets net cash) and short-term liquidity position (current assets net stock/current liabilities) are expected to be negatively related to cost of debt because these two can be an indicator of lower repayment risk. In addition, according to pecking order theory, cash-rich and liquid firms prefer to generate funds internally (Meuleman and Maeseneire, 2012), resulting in a lower demand on bank credit and therefore, higher bargaining power when bank credit is needed. We also control for asset structure (tangible assets/total assets) because firms with higher tangibility are more capable of providing collaterals that would reduce the risk and control moral hazard (Howorth and Moro, 2012). Collateral also acts as a signaling device of the default risk of loan applications,

[16] The dummy variable is coded as 1 if an SME has ever had a patent or a trademark; 0 otherwise. We acknowledge that R&D expenses could be a better indicator but only 8% of our sample report such data. One limitation of our binary measure is that the data is time-invariant.

as the level of collateralization is negatively related to the riskiness of the borrower's investment project (Bester, 1985). The usage of trade credit (net trade credit scaled by total assets) is also controlled for by following Casey (2014) and McGuinness et al. (2018). Under the substitution hypothesis (Carbo-Valverde et al., 2016), which is empirically tested in the EU SME sector by Palacin-Sanchez et al. 2018, trade credit is a substitute for bank credit especially when a firm has less capability in accessing bank credit, or when the bank lending is tightened or costly. In addition, Carbo-Valverde et al. (2009) believe that under normal market condition, the usage of trade credit is an indicator for firm credit constraints (e.g. high credit cost) because the implicit assumption is that trade credit is an expensive form of short-term external finance alternatives. Hence, a positive association between trade credit usage and cost of debt is expected but the relation could be bilateral. Moreover, we control for depreciation rate and working capital (both scaled by total assets) into regressions by following Chui et al. (2016) and Peel (2019). Depreciation rate is expected to be positively associated with credit cost and negatively for the working capital, because SMEs with higher depreciation cost and lower amount of working capital are higher in repayment risk to the banks. Last, we control for the growth opportunity at industry-level. We follow Behr et al. (2013) and Degryse et al. (2012) and measure the growth opportunity of an industry by the weighted averaged sales growth rate in the main tests, and by intangibility ratio at industry-level (Di Patti and Dell' Ariccia, 2004) in the robustness tests. From the view of credit demand, Michaelas et al. (1999) show that firms with growth opportunities are more likely to exhaust internal funds and access to external financing. On credit supply side, since the expected return functions differ between borrowers and lenders, the agency theory suggests that small firms are likely to increase their risk-taking level due to the intensifying incentive of growth, and thus banks react by increasing credit price. However, Fungacova et al. (2015) argue that firms with better growth opportunities aim to minimize agency conflicts and thus they rely less on bank debt and are less sensitive to bank credit supply. All other time-invariant characteristics of individual SME that are not picked up by explanatory variables are assumed to be absorbed by individual fixed-effects, otherwise as remainder disturbances in the error term.

At macroeconomic level, we include real GDP growth rate to capture general economic condition (Mudd, 2013) and the ratio of domestic credit to private sector by banks (% of GDP) for the degree of banking development and bank credit supply (Delis and Kouretas, 2011). A negative sign is expected for these two variables. On the credit supply side, the general default risk of SME borrowers decreases in time of economic boom, so that banks may increase their credit supply for SMEs by reducing lending standards (e.g. cheaper credit). The latter variable is a direct indicator of an economy's amount of bank credit supply. Following Mascia et al. (2017), we include two price related variables, inflation rate (GDP deflator) and bank's net interest margin to control for lending price variation since the cost of debt dependent variables are implicit measures which are not directly observed (e.g. loan level data). These price measures must be strongly positive and both statistically and economically significant otherwise the dependent variable is not properly generated. Last, bank size is measured by logarithm of total assets in thousands of dollars to control for bank size effect. Definitions and sources of variables are reported in Appendix B and their descriptive statistics are presented in Table 2.

(Please insert Table 2 about here)

3.3 Baseline models, specifications, and validity

We employ the following baseline model (Eq. 1) to investigate the effects of bank-level market power and banking market concentration on SME cost of debt. In the equation, Y_{ijcts} are cost of debt measures for firm i in industry j country c and at time t, and the subscribe b denotes the bank which is matched with firm i. θ_{ijc}s are potential firm fixed effects, or industry-level and country-level dummies in random-effect models. τ_t is the potential time fixed-effect. Matrix BMP and BMC are bank market power and banking market concentration variables. F, M and B' are sets of firm and industry specific, country-level and remaining bank-level determinants[17]. $\boldsymbol{\varepsilon}_{ijct}$ is a disturbance term consisting of unobservable individual time-invariant specific effect, potential time-effect, and remainder disturbance.

$$Y_{ijct}\left(\frac{financial\ expenses}{average\ total\ debt}\right) = \alpha + \beta_1 BMP_{bt} + \beta_2 BMC_{ct} + C_1 F_{ijct} + C_2 M_{ct} + C_3 B'_{bt} + (\theta_{ijc}) + (\tau_t) + \varepsilon_{ijct} \quad (1)$$

[17] Our correlation matrix, available from authors on request, does not indicate concerns of multicollinearity and all variables are correlated with coefficients under 0.5. We manually manage outliers from both firm and bank databases instead of using winsorization or extremity truncation. Our approach ensures the data quality without sacrificing too many observations or altering original data. Less than 0.3% of our initially obtained data are dropped.

The baseline equation (cost of debt models) is estimated using fixed-effect estimator as Hausman test suggests that within-groups estimator is more consistent. We also estimate the equation by random-effect maximum likelihood estimator to allow adding time-invariant binary independent variable (e.g. innovation) and controlling dummies[18].

We examine the validity of our data and model specification before moving onto empirical analysis. Reverse causality and variable omission are two causes of endogeneity. Our empirical models are not subject to reverse causality issue because, first, our market power measure is calculated at bank-level from Fitch Connect database; while cost of debt is an estimated firm-level characteristic generated from the Amadeus database. It is therefore unlikely that cost of debt measure can reversely affect bank market power measures (Mudd, 2013; Leon, 2015; Fungacova et al., 2017; Love and Peria, 2014). Second, the amount of SME lending accounts for only a small fraction of banking business and thus bank characteristics such as market power can hardly be affected by SME lending, especially when our analysis adopts a representative sample instead of all the firms in the economy. Third, there is no evidence suggesting that SME cost of debt measures would directly influence the variables used to derive our market power indicators (e.g. Lerner index, Appendix A). The endogeneity concern of omission variable is also of little concern because, first, control variables are comprehensively entered our regression analysis according to relevant theories and extant literature to capture different aspects of cost of debt heterogeneities. Second, the panel structure of our data allows firm-level fixed-effects to remove all time-invariant unobservable effects that could be possibly related to variables on both sides. In addition, we instrument the market power variables and carry out the Durbin-Wu-Hausman test and the result does not suggest the existence of endogeneity. Nevertheless, the endogeneity concern is empirically addressed in our robustness test section and we treat banking concentration as an exogenous variable as it is measured at country-level.

Although our models are not subject to reverse causality issue, another econometrical concern could arise on the basis of selection bias where the findings between bank and firm variables in our regressions may reflect pre-existing bank-firm relationship so that certain types of firms tend to cooperate with banks with certain characteristics. This selection bias concern

[18] Results do not vary if using basic generalized method of moments random-effect estimator or Swamy-Arora random-effect estimator.

matters only at cross-sectional dimension because the panel setting of our data controls for the time-series variations. To address this problem, we carry out the Intraclass Correlation Coefficient test (ICC) to examine how strongly units (SMEs) with a fixed degree of relatedness (e.g. firm size, age) in a same group (a bank) resemble each other. Test results[19] indicate that our sample does not suffer from selection bias.

4: Empirical Results

4.1 Baseline results

We present our baseline results in Table 3. From left to right, all models include inflation variable as it is a basic control for our implicit cost of debt measure[20]. Model 1 only includes bank market power measure and basic firm-level controls (size and age), Model 2 include full firm-level controls, and the following two models respectively take in macroeconomic (including HHI index) and bank controls. Model 5 comes with a full variable set. The reason for gradually adding controls into the models is to examine the stability of our main interested parameters to be estimated. Model 6 is the simplified version where three variables that could potentially induce econometrical problems are removed[21]. Model 7 is estimated using random-effect maximum-likelihood estimator for comparison and allows for the existence of time-invariant

[19] ICC response groups are classified into three. They are SME attributes that are not able to be influenced by banks (e.g. industry, age), less likely to be influenced (e.g. size) and those could be influenced by banks (e.g. leverage, solvency ratio). All these attributes are directly accessible from their financial reports. Bank characteristics are not categorized because a bank by its identity has already defined a group of banking characteristics that are tested with response groups. Test results indicate that apart from a small group of similar sized SMEs tend to work with certain banks in Cyprus and Latvia, there is little evidence that other SMEs with similar characteristics are intraclass-correlated to any individual bank. More details on ICC are available from Marchenko (2006) and our full test results are available from authors on request.

[20] Results do not change if we use different interest rate variables instead of inflation. In fact, the inflation and interest rate variables in our sample are highly correlated. We also exclude time fixed-effects in Models 1 - 6 by following Baum (2006) which suggests that time fixed-effects must be removed if macroeconomic factors are controlled for because those factors do not vary across firms. Results do not significantly vary if time fixed-effects are added.

[21] In the simplified model, firm age, trade credit usage and country-level bank development variables are dropped because of the following reasons. Age variable is not an ideal control in panel data setting as it rises with the same increment along with time moving forward across all the cross-sections. Trade credit usage could bring reverse causality issue as discussed in Section 3.2.3. Last, the calculation of bank development variable captures both financial market development and the importance of banking industry (Delis and Kouretas, 2011) and, these two may have offsetting effects on our dependent variable.

variable Innovation. Any model with a prime sign (’) is the same as a specific model except for the Lerner index being substituted by lending market Lerner index (see Appendix A).

The primary purpose of this study is to investigate the effects of disaggregate level bank market power and country level banking market concentration on SME cost of debt. Starting with bank market power, Lerner index and that for lending market have significantly negative coefficients with similar magnitudes across all models. Our Lerner index variable has a mean value of 0.23, median 0.24 and standard deviation 0.12, which are similar to those of the sample adopted in Love and Peria (2014). As previously explained, the dependent variable, cost of debt is an index-based implicit measure reflecting the level of cost rather than an actual observation on lending price; therefore results cannot be directly interpreted as the actual changes in interest rate. Hence, using the simplified Model (6) as an example, the coefficients of Lerner index and lending market Lerner index are respectively -2.88 and -3.65, suggesting that a one-standard-deviation rise in the Lerner index (Lending market Lerner) leads to an approximately -4.2% (-5.3%) deviation from the mean value of cost of debt measure, and -6.2% (-7.8%) from its median value. Alternatively, considering a case in which Lerner index increases from sample’s 25th percentile (less market power) to 75th percentile position (greater market power), cost of debt index decreases by 10.7% if the base is also chosen at 25th percentile (3.33) or 4.0% for the base at 75th percentile (8.93). Given the fact that the changes of credit costs should be mainly determined by macroeconomic conditions (e.g. monetary policy) and firm-level attributes (e.g. size, tangibility, credit history), the effects of market power on SME cost of debt are therefore economically meaningful.

Our baseline results have shown that bank market power at disaggregate level reduces the cost of debt of SMEs, supporting the Information-based Hypothesis (IBH) whereby competition increases the SME credit cost and financing constraint because in the presence of information asymmetries and agency costs, market power incentivizes banks to build lending relationship and to invest in private information acquisition, reducing lending barriers between lenders and borrowers especially to informationally opaque firms, e.g. SMEs. Our baseline results show little evidence supporting the Market Power Hypothesis (MPH) and the argument by Ergungor (2004). Finally, this study examines the banking market concentration effects on SME cost of debt. In Table 3, all the coefficients of HHI are of similar magnitude and statistically significant at 1% level. Using Model 6 as an example, ceteris paribus, SMEs operating in a less concentrated banking market (25th percentile of HHI, 4.97) have lower cost of debt by -8.4% (-12.3%) deviation of the mean (median) value of the cost of debt (COD) compared to those in a more concentrated banking market (75th percentile of HHI, 6.79). Numerical results conclude that SME cost of debt is higher in a more concentrated banking market.

In terms of other explanatory variables, at firm-level, an SME is credited cheaper along with aging and / or growing in total assets as expected. Model 7 shows that cost of debt is higher for innovative firms[22] and this is because innovation activities are less transparent and have higher uncertainty. Cash-richness variable as a proxy of credit demand and business risk is not significant across all models, but liquidity ratio is negatively associated with cost of debt. SMEs with higher tangibility are likely to have lower interest costs because tangibility proxies a firm's capability of providing collateral and the collateralization level can be a signal of the riskiness of the borrower's investment project. Models 2-5 show that trade credit usage is positively related to the cost of debt as expected. In addition, in most models, deprecation rate and working capital as (inverse) measures of firm risk are positively (negatively) associated with SME cost of debt as expected. Finally, SMEs operating in industries at the time of higher growth opportunity are likely to be charged at higher interest premium. The possible reasons are that small firms tend to exhaust internal funds and depend more heavily on external finance when facing a growth opportunity. In addition, due to the different expected return functions between SME borrowers and their lenders, banks may have to react by increasing credit risk premium to compensate the extra risk exposed.

For bank and country variables, two lending price related controls are indeed strongly and significantly linked to the cost of debt measure, as they are pure controls for SME funding price at macroeconomic and bank level. They are more appropriate to be entered in estimations as control variables rather than to be price-adjustment factors because the dependent variable is index-based but not an actual observation (Hail and Leuz, 2006). An interesting finding is that larger banks are more likely to charge higher interests. This result eliminates the concern that the negative bank market power effect could be a reflection of bank size effect[23]. Finally, as

[22] This variable (innovation) is only examined in Model 7 because time-invariant dummy variable is not allowed in fixed-effect models.
[23] We also checked our bank-only dataset that the bank market power and bank size variables used in our study are not statistically associated, confirming the independence of the interpretations made on these two sets of bank-level variables.

expected, GDP growth rate and a proxy for bank credit supply, are both found to have a favorable impact on reducing SME cost of debt.

(Please insert Table 3 about here)

4.2 Robustness tests

By following our baseline Model 6 (Table 3), we employ different approaches to test the robustness of our baseline results.

First, we test if the baseline findings are driven by a specific group of firms (Table 4). Our SME samples are regrouped by country, year, industry, and total debt ratio factors. Specifically, the sample is grouped into big-4 countries and others[24] (Model 1), financial crisis period (2007-09) and post-financial crisis period (2010-15)[25] (Model 2), operating in the industries of manufacturing, wholesale and retail trade, and others (Model 3) and lower and higher level of total debt ratio[26] (Model 4). Table 4 shows that the coefficients of Lerner index and HHI are all consistent with those of baseline models and they are all statistically significant at 1% level. Results do not change if we replace Lerner index by that of lending market and replace HHI by concentration-3 ratio, confirming that our findings from baseline models are not driven by a specific group of firms. We also group our sample by bank specializations (commercial bank vs. cooperative bank vs. savings bank) and complete the regressions by using a Lerner index (Appendix A) that is adjusted for the inclusion of bank specialization dummies. Our baseline findings (not reported) do not alter.

(Please insert Table 4 about here)

Second, we test the robustness of our baseline models by using alternative cost of debt (COD) variables. In Table 5, we adopt four measures that are slightly different from the COD used in baseline models. All in percentages, COD1P is redefined as the total interest payment divided by average total bank debt (Model 5). COD2 (Model 6) is the same as COD but instead

[24] Big four countries in this sample are France, Germany, UK, and Spain according to their size of economies and contribution rates of the number of SMEs in the full sample.
[25] Results do not vary if the sample is regrouped into two equal halves (2007-11 vs. 2011-15) along the time.
[26] Total debt ratio is measured as the sum of short-term loans plus long-term loans divided by total assets. The threshold (less vs. more) for our sample is 21.7% as it equally divides our SME sample into two. Results still hold if the threshold is amended to 15% or 25%.

of scaling the financial expenses to average debt, it uses average liabilities. COD1NA (Model 7) and COD1NAL (Model 8) are defined respectively by dividing financial expenses to current and lagged total bank debt where the baseline model (COD) uses average total bank debt. The coefficients of Lerner index and HHI provide same conclusion as the baseline models.

Models 9 and 10 adopt two cost of debt dependent variables that are adjusted respectively by interest rate and inflation rate. Following Carbo-Valverde et al. (2009), we define the interest rate adjusted cost of debt ratio COD.CV as the difference between the ratio of financial expenses to average bank debt and country-year level mean value of nominal long-term and short-term interest rates (Source: AMECO database by European Commission). Following Chui et al. (2016), we measure the real cost of debt (inflation adjusted cost of debt, RCOD) as $[(1+COD)/(1+0.5*\pi_t+0.5*\pi_{t-1})]-1$, where COD is the average cost of debt explained previously and π is inflation rate. Bank net interest margin and inflation rate variables are dropped since these price related variables are adjusted in dependent variables. The estimated coefficients are negative and significant for Lerner index and positive and significant for the HHI, confirming that bank market power relieves SME financing constraint in terms of cost of debt and SMEs are charged at a higher interest rate in a more concentrated banking market[27].

We next translate the cost of debt index into growth. The dependent variable in Model 11 is a binary variable (COD.LDVM) which is coded as one if an SME experiences increased rate of implicit cost of debt measure (COD); 0 otherwise. Around 46% of observations show increasing financing cost in our sample. A limited dependent variable model (LDVM) is estimated using random-effect panel Probit estimator[28]. Estimation output shows that the probability of a rise in financing cost of an SME decreases by approximately 4.3% if the Lerner index increases by one-standard-deviation. In Model 12, dependent variable (COD.GR) is a two-year moving average growth rate of the ratio of financial expenses to total assets. We use two-year moving average instead of arithmetic average because it reduces the skewness by big jumps in the regression analysis. Estimation output shows that bank market power reduces the growth

[27] Using price adjusted measure is exposed to one major concern that, in the absence of direct loan level data, the cost of debt values are implicit estimations reversely calculated from financial reporting data. However, interest rate and inflation rate data are actual values. Subtracting actual price-related macroeconomic observations from estimated values would generate biased results since two values are not at the same level of scope. The bias is predicted to be that adjustments are less effective because of the disproportionately higher value ranges of reversely estimated cost of debt ratios (Hail and Leuz, 2006).

[28] Results do not vary if using fixed-effect panel logit estimator.

rate of SME credit cost. Although these two interpretations are made on growth rate, they are translated aligning with our main findings, according with the Information-based Hypothesis.

The statistics (not reported) show that SME credit costs vary significantly across industries and we address the concern of industry-level natural difference in cost of debt by introducing another dependent variable COD.delta, which is calculated as the difference of the COD from industry weighted averaged value across years (Model 13). This variable eliminates the natural heterogeneities of financing costs across different industries and a positive value implies that an SME at a time is financed with higher price than the industry 'standard' and vice versa for negative value. Estimation results align with our baseline findings.

The last model in Table 5 (Model 14) uses a dependent variable named COD.CV.adj, which is based on COD.CV. It considers the debt maturity and the interest rate adjustment factor is weighted by short-term debt ratio to short-term interest rate and long-term debt ratio to long-term interest rate. Same as above, price related controls are dropped and Lerner index is still significantly negative but not for HHI.

Moreover, we substitute all the Lerner index in Model 5 to 14 by lending market Lerner index and our earlier results hold (not reported). In addition to substituting dependent variable, recall that we adopt different methods when estimating the Lerner index (see Appendix A), we substitute alternative Lerner indices into the baseline Model 6 (Table 3), and all of them entered negatively and significantly. Also, in baseline Model 6, results do not change if we replace HHI by concentration-3 ratio (0.021^{***}) or concentration-5 ratio (0.011^{***}). Additionally, we substitute each of our control variables by their alternative measures[29]and our baseline findings still hold.

(Please insert Table 5 about here)

Third, although the coefficients of correlation between two market power variables and HHI are both less than 0.03, and literature as discussed in Section 2 has shown that bank concentration is not statistically correlated with non-structural measures (e.g. Lerner index) and the SCP paradigm is rejected, we still address the potential causality concern when both being added into the regression. In Table 6, Models 15, 16 and 17 considers HHI, Lerner index and lending market Lerner index, respectively. Results show that all coefficients of such measures are close to those in baseline Model 6 (Table 3), providing additional supporting evidence that

[29] Alternative measures for each of our control variables are available from authors on request.

bank market power and concentration are not conflictual when both being added to the estimations.

Fourth, we examine if cost of debt is determined by bank market power as a reflection of other observable or unobservable bank effects by estimating Model 18 in Table 6 with bank fixed-effects. The joint t-tests for bank dummies (not reported) are significant, suggesting that, not unexpectedly, there are other bank effects being associated with cost of debt. However, the coefficients of our main regressors are still highly consistent with baseline estimations in terms of magnitude and statistical significance. This confirms that the key findings are not biased reflections of other banking effects.

Fifth, we address the potential endogeneity concern by re-estimating our main specification using an instrumental variable approach and a lagged variable approach. We follow Anginer et al. (2014) to instrument bank market power variable by lagged growth of gross loan rate[30] (Model 19) and lagged Lerner index (Model 20). The principles are that the former assumes that expanding gross loans would generate more bank market power and the latter is a classic econometric solution to address endogeneity. In addition to the instrumental variable estimations used to pull the trigger on potential endogeneity, we lag our main independent variables by one-year to address the concern of reverse causality in Model 21. All the main regressors from Model 18, 19 and 20 are significant at 1% level and have the signs consistent with our main estimations, confirming the robustness of our key results.

In addition, we include the squared term for the market power variable in Model 22 (Table 6) to consider possible non-linearity. If the collinearity problem between its quadratic form and itself is to be ignored (coefficient of correlation >0.8), estimation outputs indicate that, because the symmetry axes (turning points) is not located in a meaningful area, this result does not support an inverse u-shaped relationship. Because the squared term and the linear term are both negative and significant, it supports the linear relation observed in the baseline estimations.

Last, we substitute Lerner index by lending market Lerner index, and HHI by concentration-3 ratio in Models 18-22, and our results remain unchanged. For Model 21, we also test lagging all the control variables by one year and results still hold. Finally, we check the possible debt composition effects on the main findings based on baseline Model 6 by including short-term debt ratio (ratio of short-term debt to total debt) and a variable that controls for

[30] Estimation result does not change if we instrument Lerner index by current growth of gross loan ratio.

observations which do not have long-term debt (14% of the regression sample), and our baseline results are still robust.

(Please insert Table 6 about here)

4.3. Heterogeneity tests

The favorable effects of market power on SME cost of debt concluded above may vary over certain firm and country features. In Tables 7 and 8, we report the results of testing the heterogeneity of market power effects by employing both interactive term and grouping approaches based on the baseline Model 6 in Table 3 to ensure result validity and robustness.

Theoretically, innovative SMEs are higher in information opaqueness and therefore the IBH effect should be stronger for such SMEs. We group samples into non-innovative (38,638 obs.) and innovative (11,990 obs.) SMEs. Results in Table 7 show little significant difference in the values of Lerner index coefficients. The interaction terms of innovation dummy and bank market power are not significant in the next two columns, all suggesting that the degree of bank market power effects on cost of capital is not statistically dependent on firm's innovation activities. The possible reason of this statistically insignificant results is that, unlike using R&D expenses as a proxy for firm innovation, our time-invariant binary variable is less econometrically favorable because of the low numerical variations.

Although all firms in our sample are SMEs, their size varies significantly. The sample is regrouped into three (Model 2) as micro firms (<10 employees and turnover <2m euros), small firms (10-49 employees and turnover <10m euros) and medium-sized firms (50-249 employees and turnover<50m euros). After excluding size control variable, the trend of Lerner index coefficient values is interpreted as stronger favorable effects of market power on cost of debt for smaller firms. This is in line with the IBH since smaller firms' credit approval is more dependent on soft and private information processed by creditors and SMEs normally lack of formal credit history. This argument is supported by the positively significant coefficients of bank market power and size interaction terms in the full sample regressions.

(Please insert Table 7 about here)

It is expected that SMEs with higher level of information opacity would benefit more from increasing level of bank market power as suggested by IBH because banks' investment in soft information acquisition could be more effective to them. We follow Bonaccorsi di Patti and Dell'Ariccia (2004) and use the ratio of total assets to fixed assets as a proxy of private information at industry level[31]. SMEs are grouped into three from less to more informationally opaque (Model 3, 3', 3''). Meanwhile, interaction terms of bank market power and opacity are positively significant with meaningful values of coefficients. Regression outcomes conclude that the favorable effect of bank market power on cost of credit is stronger for SMEs with higher level of opacity, supporting IBH. However, the cost of debt is generally higher for less informationally opaque SMEs, offsetting the desirable bank market power effects.

We have also tested the Boyd and De Nicolo (2005) hypothesis discussed in Section 2. Such hypothesis holds when the favorable effects of bank market power on SME credit cost is stronger for creditworthy firms. With the absence of credit rating data, we use risk-related variables such as firm profitability, turnover, liquidity, and solvency ratios. In a short remark[32], all these risk-related variables are not found to have moderating effects on the relation between bank market power and SME credit cost, thus we conclude that bank market power effect is more sensitive to the information opaqueness of SMEs rather than to their risk-level. Hence, the Boyd and De Nicolo (2005) hypothesis is not empirically valid in our sample.

In terms of macroeconomic characteristics (Table 8), it is not ideal to group our sample by country-level variables and therefore we examine the moderating effects by interaction terms only. The significantly negative coefficients on the interaction term of Lerner index and HHI specify that the favorable effects of bank market power on investing in private information acquisition and building relationship lending are stronger in concentrated banking markets although banking concentration increases SME financing constraints.

Beck et al. (2004) suggest that bank competition effects on SME finance can be either enhanced or mitigated by the economic framework. We test such moderating effects represented by economic growth and financial development. As reviewed in Section 2, Ruckes (2004) and Demiroglu et al. (2012) conjecture that the effect of bank market power on SME borrowing cost is diminished under sound economic conditions. However, we do not find support to their hypothesis as the interaction terms of bank market power and economic growth indicator in Model 5 are not statistically significant. Empirical evidence has also shown that financial

[31] Alternatively, we use the ratio of intangible assets to total assets at industry-level, and results hold.
[32] Results are not presented due to space limit but available on request from authors.

development soothes the bank competition effect on SME finance (Love and Peria, 2014) and financial development is also associated with lower information asymmetries because of the higher quality of bank risk assessment processes (Godlewski and Weill, 2011). It is therefore hypothesized that in countries with better financial development, the beneficial effects of banks with a greater market power assimilating soft information on informationally opaque firm are attenuated. The interaction terms in Model 6 are positively entered, being translated as supporting evidence on such a hypothesis.

Finally, we examine two information related institutional factors that could potentially modify the market power effect. One is an index for the depth of credit information (CID) at country level, ranging from 0 to 8 indicating low to high level of rules affecting the scope, accessibility, and quality of credit information available through public or private credit registries, to facilitate lending decisions. The other one is an index for business extent of disclosure at country level ranging from 0 to 10 indicating low to high level of the extent to which investors are protected through disclosure of financial information. Both indices measure the strength of information in an economy and our empirical results in Models 7 and 8 show that both factors weaken the market power effect, bolstering the Information-based Hypothesis.

(Please insert Table 8 about here)

5: Conclusion

Due to the great contribution of SME sector to the EU economy, the importance of bank financing in SME growth and the intrinsic financing constraints of SMEs, this paper focuses on the banking effects on SME financial constraints by studying the impacts of bank market power and banking market concentration on the cost of debt of SMEs in 17 EU countries over the period of 2007 to 2015. Our sample contains 77,911 SMEs being matched with 528 banks and, our market power measures are derived from a sample of 3,319 banks from the 17 countries.

Our main finding is that bank market power at disaggregate level reduces the cost of debt of SMEs. Numerically, the cost of debt for a typical SME reduces by 6.2% of the median value when the bank market power increases by one-standard-deviation. Or, from the probability perspective, the probability of a rise in financing cost of an SME reduces by approximately 4.3% if the Lerner index increases by one-standard-deviation. The favorable effects of bank market power on SME cost of debt are more pronounced for those SMEs who are smaller and more informationally opaque. The favorable effects are also stronger within economies where banking markets are more concentrated, and subject to higher degree of information obstacles and less informationally transparent since banks investing in relationship-based lending techniques becomes more effective. These findings support the Information-based Hypothesis where due to the crucial role of information asymmetries, greater competition reduces the market power of banks and impedes banks from investing in private (soft) information acquisition or building relationship with smaller and less transparent firms

Our results are not consistent with Rice and Strahan (2010) and Giannetti and Ongena (2009) that advocate the favorable effects of tackling bank market power on SME debt interest rates. Our study shows little evidence supporting Market Power Hypothesis as empirically concluded in Love and Peria (2014) and Mudd (2013), both suggesting that competition relaxes SME credit constraint with an emphasis on the access to finance by SMEs. This is because our sample contains only those observations which have accessed debt finance and they are less likely to be financially constrained compared with those who have not accessed debt finance. Samples used in Love and Peria (2014) and Mudd (2013) include a higher proportion of SMEs that are more likely to be financially constrained or even excluded. This could have suggested that bank market power at disaggregate level negatively affects the probability and usage of debt finance, especially for those SMEs who are more credit constrained and financially excluded. However, for those SMEs who has gained access to finance, bank market power promotes relationship lending activities and reduces SME cost of debt. In addition, our empirical evidence does not support the hypotheses proposed by Ergungor (2004), Boyd and De Nicolo (2005), and Ruckes (2004) and Demiroglu et al. (2012), as detailed in Section 2.

Besides the primary findings, our empirical results also show that cost of debt finance is higher for those SMEs which are younger, smaller, and involving in innovation activities. Other firm characteristics, such as liquidity, tangibility, trade credit usage, depreciation rate and working capital are all influential factors of cost of debt finance as expected. SMEs operating in industries at the time of higher growth opportunity are likely to be charged at higher costs. In addition, we show that in general, larger banks provide credit at a higher price and SME credit availability is more constrained in a more concentrated banking market, indicating the different effects of concentration and competition on SME finance.

Our paper is the first study investigating the bank market power effect on SME credit cost at firm-bank level in the EU. The implications for policy makers are that pro-competitive policies that suppress bank market power could reduce the incentives and necessities of banks in investing in private information acquisition and relationship lending. However, bank competition has substantial merits under general economic theories such as increasing financial stability in European countries (Fiordelisi and Mare, 2014; Leroy and Lucotte, 2017). In terms of the SME sector, prior literature has also shown that bank competition could reduce financial exclusion and increase credit availability (e.g. Beck et al., 2004; Chong et al., 2013, Ryan et al., 2014). Hence, as encouraging anti-competitive policy and market power in the banking industry could overall introduce loss outweighing the gain, policymakers should consider the balance between the pros and cons of different competition promoting strategies and the consequences to different types of microeconomic agents. Policymakers must also pay attentions to the measures of reducing information barriers between SMEs and creditors to enable financial institutions to allocate their funds more efficiently, and at a bank risk-taking level. Attentions should also be paid on striking unfair lending prices. In 2014, SMEs' average borrowing costs were 140 basis points higher than those of large enterprises in the Eurozone[33], and this figure went up to 210 for micro firms (Kaya, 2014). Although high credit cost may reflect higher risk, it could also be one of the hindrances impairing SME borrowers' survival and development. Moreover, high credit cost could result in severer consequences damaging the financial stability than credit rationing as the Moral Hazard dilemma (Holmstrom and Tirole, 1998) has suggested that borrowers may be incentivized to exercise less effort or take on higher business risk after the issuance of a loan to compensate the high interest cost, therefore putting the banking industry at risk.

However, there have been several solutions[34] on reducing the information asymmetries between creditors and SME borrowers, reducing the risk of creditors and SME borrowing costs, and facilitating credit supply to SMEs.

One of the solutions would be the governments' development of sustainable Credit Guarantee Schemes (CGSs). A CGS is a tool that facilitates lending to smaller businesses that are less able to directly obtain finance from their commercial creditors (e.g. banks) due to having difficulties meeting their creditors' security requirements, for example, collateral requirements.

[33] All 19 Eurozone countries are members of the European Union.
[34] We thank an anonymous referee for providing us the ideas on this matter.

Such a government-backed guarantee is a form of loan collateral that would allow borrowers to apply for loan funds beyond its own collateral limits, and transfer the credit risk of creditors to the government guarantors. Hence, reducing creditors' risk and increasing the flow of funds into businesses that have difficulties raising funds, including the SME sector (Yoshino and Taghizadeh-Hesary, 2018). For example, the Enterprise Finance Guarantee (EFG) Scheme launched in 2009 in the UK has been providing loan guarantees to facilitate lending to viable businesses that have been turned down for a normal commercial loan due to a lack of security or a proven track record. The EFG provides the lender with a government-backed guarantee of up to 75%, and the creditors (banks) are fully delegated to lending decisions. Until the end of 2017, it has supported the provision of over GBP £3.3 billion of finance to more than 35,000 smaller businesses in the UK. However, there are still two concerns of the EFG, or any other CGSs[35]. Firstly, the government's coverage ratio. A high credit guarantee policy may introduce moral hazard problem, where lending institutions (e.g. banks) would decrease their effort input level in monitoring and analyzing the healthiness of borrowers, resulting in an increase in the number of nonperforming loans and a decrease in the productivity of public reserve (Yoshino and Taghizadeh-Hesary, 2016)[36]. Secondly, for SME borrowers, a CSG comes at a cost. Using the UK's EFG as an example, small business borrowers supported via EFG are required to pay a 2% annual fee to the government, as a contribution towards the cost of the scheme. Hence, such a scheme may not necessarily reduce the lending costs, although it promotes a better credit supply to SMEs.

Another solution of the aforementioned problems would be the development of SME credit risk databases and SME credit rating models. SMEs' financial and non-financial accounts are often difficult to assess, but Japan's Credit Risk Database (CRD) of the CRD Association as a nationwide financial infrastructure provides an example that is worth addressing. The Japan's CRD is a membership system (with 180 CGS and financial institution members in 2015) whose members maintain the database by offering SME financial statements (Kuwahara et al., 2015).

[35] For a more detailed review of the general principles and adoption of CGSs, please see Yoshino and Taghizadeh-Hesary (2018) and Yoshino and Taghizadeh-Hesary (2016). And for the UK's EFG, please see https://www.british-business-bank.co.uk/ourpartners/supporting-business-loans-enterprise-finance-guarantee/about-efg/

[36] See Yoshino and Taghizadeh-Hesary (2019) for a research on the determinants of an optimal credit guarantee ratio for SMEs.

As of 31st of March 2015, the Japan's CRD includes data on 3.309 million incorporated and sole-proprietor SMEs, which was around 95% of the total SME population, and the database for enterprises in default covered 500,000 SMEs (Yoshino and Taghizadeh-Hesary, 2015). The purpose of the CRD is to reduce information asymmetries and to provide a credit rating service on SMEs for lending agencies, therefore improving the efficiency of credit supply to SMEs (Kuwahara et al., 2015). With such a large-scale SME financial database, the CRD Association has been able to introduce a reliable statistical method into evaluating SMEs' credit risk through "the law of large numbers". In fact, the CRD Association has built several credit ratings models (scoring systems) for the assessment of the credit risk of incorporated SMEs and sole-proprietor SMEs, and both have been in use in the Credit Insurance System. Essentially speaking, the scoring models produce an estimated probability of default for each SME by adopting logistic regression techniques on a large number of financial indexes that correlate with defaults, such as profitability, coverage, leverage, liquidity, etc., with accumulated qualitative data (Kuwahara et al., 2019). Such scoring systems present a universal standard for the assessment of business risk and are an effective remedy for asymmetric information that can also be used for the development of the member's own internal rating system (Kuwahara et al., 2015)[37]. In the EU countries, using the UK as an example, the CRIF Decision Solutions Limited provides a QuiScore that uses a proprietary model that utilizes both financial and non-financial information (e.g. directors' history, County Court Judgements) to estimate the likelihood of company default for the coming 12 months, which is evidenced to be an effective indicator of the economic resilience of firms (Soroka et al., 2019). This QuiScore covers a large percentage of the population of UK SMEs that have published annual accounts, and its score is classified into five rating groups: secure, stable, normal, caution and high risk. However, there is still a concern that the score is prone to unaudited financial statements' outliers and less precise data, and therefore less effective for the assessment of micro firms, which could also result in borrower discouragement.

One solution that can have a favorable impact on reducing bank credit cost of SMEs would be the launch of a funding scheme where the government can conditionally supply funding to commercial lenders (e.g. Banks) at a lower deposit rate requirement for the purpose of

[37] For a comprehensive review of the Japan's CRD, their Statistical Scoring Model, and practicality, please see Kuwahara et al. (2015) and Kuwahara et al. (2019).

a boost of cheaper credit supply to SMEs. The UK's Funding for Lending Scheme (FLS) is a strong representative of the idea. The FLS was launched by the Bank of England (the Bank) and HM Treasury in 2012, with the aim of encouraging lending to UK households and private non-financial corporations by making more cheaper funding available to banks and building societies[38], conditional on their lending to the real economy. Cheaper credit should boost consumption and investment and results in increased economic activity and incomes (Bank of England, 2012). However, there have been undesirable figures and views on the Scheme since its introduction. Early evidence (Milligan, 2013) has shown that the scheme only has a small impact on business lending, despite the reduced cost of loans to businesses claimed by participating banks of the scheme. In addition, the real effect of FLS is difficult to quantify, noted by the Bank's chief economist Martin Ellis (Milligan, 2013). Data has also shown that the lending to small businesses under FLS falls continuously two years after the introduction of the scheme, with a drop by £723m, followed by a drop of £435m in the next quarter (Source: Bank of England). One concern of FLS, or a similar scheme to SMEs is that, it does not necessarily help to reduce information barriers between informationally opaque or risker borrowers and banks, although it can provide cheaper credit to firms that are more transparent and have a better credit history.

We address the limitations of this research and the recommendations for future studies as follows. First, our sample covers 17 economies but the other 11 EU countries could not be included due to the absence of required information (e.g. interest payment data), making the result less persuasive for an EU study. Future studies could benefit from a larger sample coverage. Second, since all the 17 EU countries in our study are developed countries, the tests on country level heterogeneity effects of bank market power are less persuasive compared with Love and Peria (2014) and Beck et al. (2004). Third, our cost of debt is implicitly measured and the numerical interpretations would be more accurate if loan level data was available. In the end, we call for future research to further explore the solutions to reduce information barriers between commercial lenders (e.g. banks) and SMEs, and the effectiveness of relevant lending schemes that aim at increasing credit supply to SME lenders, and reducing their bank credit costs, in the EU countries.

[38] Since January 2014, the FLS is no longer available to support mortgage lending.

Appendix A: Bank market power measures

We follow Fosu et al. (2018), Love and Peria (2014) and Anginer et al. (2014) to generate the Lerner index as a proxy of disaggregate level bank market power. The Lerner index is defined as the difference between banking output prices and marginal costs (relative to prices) as follows:

$$\text{Lerner Index} = \frac{\text{P} - \text{MC}}{\text{P}} \qquad \text{(A1)}$$

where P is the output price and MC denotes the marginal cost. Price is measured as the (gross income plus dividend income) / total assets, or alternatively, total earning assets replaces total assets. The marginal cost is the first-order derivative of the following trans-log cost function with respect to output.

$$\begin{aligned} \ln(TC) = {} & \alpha + \beta_1 \ln(Q) + \beta_2\,(\ln(Q))^2 + \beta_3 \ln(W_1) + \beta_4 \ln(W_2) + \beta_5 \ln(W_3) + \beta_6 \ln(Q)\ln(W_1) \\ & + \beta_7 \ln(Q)\ln(W_2) + \beta_8 \ln(Q)\ln(W_3) + \beta_9 (\ln(W_1))^2 + \beta_{10} (\ln(W_2))^2 + \beta_{11} (\ln(W_3))^2 \\ & + \beta_{12} \ln(W_1)\ln(W_2) + \beta_{12} \ln(W_1)\ln(W_3) + \beta_{12} \ln(W_2)\ln(W_3) + \delta \ln(\text{controls}) + \text{FE} \\ & + \text{year effects} + \varepsilon \qquad \text{(A2)} \end{aligned}$$

In Equation A2, total cost (TC) is the total expenses of a bank and output (Q) is proxied by bank total assets (or total earning assets). They change to gross loan or total deposits, money market and short-term funding when estimating lending market Lerner Index. W_1 is the cost of labor, measured by personnel expenses to total assets (or total earning assets). W_2 is the cost of fund measured by total interest expenses over total deposit money market and short-term funding, or alternatively interest expenses to average interest-bearing liabilities. W_3 is the cost of physical capital measured by total non-interest expenses (excluding personnel expenses) to fixed assets. Controls are bank leverage ratio (equity to total assets), liquidity ratio (loans to assets) and net interest margin. Subscripts i and t denote bank i at time t and it is removed in Equation A2 for simplicity. In the trans-log function, the symmetry condition is imposed and estimation is done under the restriction of linear homogeneity of degree on in input prices. We use alternative measures for Lerner index variables in our robustness check with different combinations allowed. Using the full 3,319 bank data as discussed in Section 3.1, models are estimated with two-way fixed effects or alternatively, we estimate the Equation A2 separately in each country for robustness check. Results do not change if estimations are done using random-effect and pooled OLS estimators.

We then use the coefficients estimated from equation (A2) to calculate marginal cost for each bank as in below equation:

$$MC = \partial TC / \partial Q \qquad \text{(A3)}$$

Lerner index is then calculated taking the MC derived from Equation A3 to Equation A1.

For calculating the Lerner index at lending market as discussed in Section 3.2.2. We use the exact same method by following Forssbeck and Shehzad (2015). In brief, as shown in Equation A4, similar to the above steps of generating Lerner index, we now introduce two outputs into the trans-log total cost function at both deposit market and lending market. Hence, the marginal cost on lending market is the first-order derivative of total cost regarding to outputs at the lending market.

$$\text{Lending market Lerner Index} = \frac{\text{RL} - \text{RM} - \text{MCL}}{\text{RL}} \qquad \text{(A4)}$$

The lending market Lerner index is calculated as Equation A4, where RL is calculated by a bank's ratio of interest income to loans, as a reverse proxy of bank lending price. RM is the market rate measured by the mean of country level nominal short-term and long-term interest rates. MCL is the marginal cost derived from the trans-log cost function at the lending market. Detailed procedures of calculating the lending market Lerner index (and depositing market Lerner index) are available from Forssbeck and Shehzad (2015).

Variables	Definition	Original source
Dependent variables		
Cost of Debt (COD)	Ratio of SME financial expenses to average short-term & long-term debt	BVD Amadeus
COD. Robustness	Other robustness check measures derived from COD, see details in Section 4.2	BVD Amadeus
Main variables		
Lerner index	Measure(s) of individual bank market power, see details in Appendix A	Fitch Connect and BankFocus
Lending market Lerner index	Measure(s) of individual bank lending market power, see details in Appendix A	Fitch Connect and BankFocus
HHI Index	Herfindahl-Hirschman index, sum of the squared values of each bank's market share (total assets) in a banking market	ECB Data Warehouse
Concentration	Sum of total assets of three largest banks in a banking market as a share of total banking industry assets.	Global Financial Development
Firm variables		
Firm size	Natural logarithm of SME's total assets in dollars	BVD Amadeus
Firm age	Natural logarithm of SME's age plus 10	BVD Amadeus
Cash-richness	Cash and cash equivalent divided by total assets (without cash)	BVD Amadeus
Tangibility	Fixed tangibile assets scaled by total assets.	BVD Amadeus
Liquidity	(Current assets - stock) / Current liabilities.	BvD Amadeus
Trade credit	Net trade credit scaled by total assts.	BvD Amadeus
Growth opportunity	Industry-level median sales growth rate or for robustness, industry's intangible assets to total assets.	BvD Amadeus
Depreciation	Ratio of depreciation to total assets	BvD Amadeus
Working capital	Ratio of working capital divided by total assets	BvD Amadeus
Short-term	Ratio of short-term debt to total debt	BvD Amadeus
No long-term	Binary variable equals to one if the SME has no long-term debt	BvD Amadeus
Innovation	Time invariant binary variable equals to one if a SME has ever had a patent or trademark	BvD Amadeus
Bank-level controls		
Bank size	Natural logarithm of bank's total assets in thousands of dollars	Fitch Connect
Bank NIM	Net interest margin	Fitch Connect
Country variabes		
GDP growth rate	Annual growth rate of GDP	World Development Indicators
Inflation	Annual percentage inflation rate, GDP deflator or consumer prices	World Development Indicators
Bank development	Domestic credit to private sector by banks (% of GDP)	World Development Indicators
Credit info. Depth	Depth of credit information index (0-8)	World Bank Job database
Business disclosure	Business extent of disclosure index (0-10)	World Development Indicators

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Table 1: Statistics of main variables by country

	Cost of debt (COD)			Lerner index			Lending market Lerner index			HHI	
	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.	Mean	Std. Dev.
Austria	0.072	0.045	0.081	0.211	0.205	0.088	0.719	0.775	0.189	0.042	0.004
Cyprus	0.090	0.074	0.058	0.253	0.260	0.126	0.796	0.848	0.164	0.121	0.022
Germany	0.086	0.059	0.081	0.212	0.208	0.082	0.734	0.807	0.206	0.026	0.005
Spain	0.072	0.051	0.071	0.258	0.248	0.111	0.634	0.717	0.267	0.063	0.015
France	0.093	0.059	0.093	0.230	0.225	0.098	0.697	0.778	0.251	0.061	0.004
UK	0.058	0.042	0.062	0.252	0.240	0.137	0.750	0.809	0.199	0.048	0.004
Greece	0.075	0.066	0.052	0.203	0.210	0.086	0.700	0.778	0.224	0.156	0.046
Croatia	0.102	0.077	0.087	0.192	0.173	0.099	0.603	0.629	0.149	0.138	0.001
Hungary	0.153	0.122	0.109	0.216	0.218	0.124	0.462	0.475	0.252	0.086	0.003
Ireland	0.051	0.037	0.055	0.220	0.208	0.115	0.669	0.727	0.251	0.068	0.002
Lithuania	0.085	0.062	0.071	0.228	0.208	0.121	0.566	0.633	0.271	0.178	0.011
Latvia	0.072	0.050	0.074	0.319	0.312	0.143	0.672	0.759	0.286	0.106	0.009
Malta	0.061	0.047	0.059	0.322	0.301	0.169	0.737	0.787	0.194	0.134	0.018
Netherland	0.098	0.065	0.092	0.209	0.203	0.099	0.707	0.774	0.248	0.207	0.007
Poland	0.123	0.092	0.096	0.208	0.186	0.107	0.490	0.504	0.139	0.060	0.004
Portugal	0.067	0.050	0.061	0.220	0.214	0.112	0.779	0.814	0.147	0.117	0.004
Slovenia	0.070	0.053	0.064	0.231	0.218	0.114	0.691	0.767	0.237	0.115	0.009

Table 2: Descriptive statistics

Variables	Obs.	Mean	Median	Std.Dev.	P1	P99	Skew.	Min.	Max.
Dependent variable									
COD	316568	0.079	0.054	0.080	0.004	0.422	2.526	0.002	0.500
COD. CV	315415	0.061	0.037	0.081	-0.026	0.416	2.617	-0.036	0.500
RCOD	303504	0.063	0.036	0.082	-0.010	0.418	2.599	-0.013	0.500
COD. GR	292975	-0.001	0.000	0.549	-1.306	1.318	0.015	-1.412	1.425
COD. Delta	316568	0.000	-2.369	7.862	-8.218	33.919	2.547	-10.693	44.518
Main bank variables									
Lerner index	651261	0.230	0.234	0.117	-0.161	0.441	-1.720	-0.930	0.706
LM. Lerner index	648493	0.775	0.875	0.283	-0.024	1.126	-1.403	-1.491	1.213
HHI Index	688841	0.064	0.055	0.039	0.018	0.220	2.712	0.018	0.341
Concentration	608028	67.398	66.016	11.218	42.445	98.604	0.567	38.562	100.000
Firm variables									
Firm size	579051	16.429	16.345	1.255	13.189	19.926	0.083	8.525	25.276
Firm age	677369	3.444	3.434	0.489	2.485	4.736	0.342	2.398	6.474
Cash	551320	0.168	0.053	0.312	0.000	1.646	3.980	0.000	3.000
Tangibility	566652	0.218	0.120	0.247	0.000	0.952	1.373	0.000	1.000
Liquidity	553107	1.999	1.058	4.891	0.042	22.681	9.236	0.001	85.000
Trade credit	537325	-0.068	-0.034	0.191	-0.605	0.438	-0.240	-0.717	0.552
Growth Opp.	694332	0.011	0.000	0.089	-0.095	0.243	1.171	-0.167	0.254
Depreciation	472592	0.031	0.022	0.029	0.000	0.134	1.614	0.000	0.169
Working capital	535815	0.239	0.210	0.234	-0.202	0.823	0.494	-0.295	0.893
Innovation	694368	0.213	0.000	0.410	0.000	1.000	1.400	0.000	1.000
Bank & Country controls									
Bank size	663088	18.964	19.313	2.144	14.109	21.810	-0.534	8.400	21.843
NIM	656120	0.017	0.015	0.008	0.004	0.040	1.149	0.000	0.069
GDP growth rate	694368	0.738	1.313	2.668	-6.564	6.045	-0.377	-14.814	26.276
Inflation (CPI)	694368	1.422	1.530	1.348	-1.044	5.185	2.343	-9.753	20.149
Bank develop.	693458	122.89	114.77	42.01	43.20	196.15	0.18	36.12	253.57
Credit info. Depth	614043	5.607	6.000	1.299	3.000	8.000	-0.284	0.000	8.000
Business disclosure	693377	6.848	7.000	2.350	1.000	10.000	-0.116	1.000	10.000

Table 3: Baseline results

Dependent variable: Cost of debt (COD)	Model 1	Model 1'	Model 2	Model 2'	Model 3	Model 3'	Model 4	Model 4'	Model 5	Model 5'	Model 6	Model 6'	Model 7	Model 7'
Main regressors														
Lerner index	**-2.495*** **		**-2.353*** **		**-1.918*** **		**-2.608*** **		**-2.487*** **		**-2.882*** **		**-0.951*** **	
	(0.144)		(0.156)		(0.154)		(0.161)		(0.160)		(0.162)		(0.158)	
Lending market Lerner		**-2.718*** **		**-2.811*** **		**-3.139*** **		**-2.963*** **		**-3.126*** **		**-3.653*** **		**-0.252* **
		(0.087)		(0.102)		(0.105)		(0.105)		(0.108)		(0.087)		(0.146)
HHI					**0.377*** **	**0.360*** **			**0.407*** **	**0.354*** **	**0.364*** **	**0.374*** **	**0.322*** **	**0.319*** **
					(0.015)	(0.014)			(0.015)	(0.015)	(0.015)	(0.015)	(0.013)	(0.013)
Firm & industry controls														
Firm size	-0.768***	-0.816***	-0.966***	-0.997***	-0.868***	-0.912***	-0.997***	-1.013***	-0.901***	-0.937***	-1.319***	-1.021***	-0.562***	-0.560***
	(0.065)	(0.065)	(0.077)	(0.077)	(0.078)	(0.078)	(0.077)	(0.077)	(0.078)	(0.078)	(0.077)	(0.077)	(0.029)	(0.029)
Firm age	-8.771***	-3.783***	-8.058***	-3.473***	-9.747***	-5.076***	-7.806***	-3.172***	-9.249***	-4.905***				
	(0.214)	(0.272)	(0.252)	(0.307)	(0.324)	(0.365)	(0.257)	(0.313)	(0.329)	(0.370)				
Cash			-0.244	-0.259	-0.166	-0.162	-0.204	-0.204	-0.140	-0.132	-0.263	-0.238	-0.053	-0.055
			(0.166)	(0.166)	(0.167)	(0.167)	(0.167)	(0.167)	(0.168)	(0.167)	(0.166)	(0.166)	(0.088)	(0.088)
Liquidity			-0.038***	-0.036***	-0.039***	-0.038***	-0.039***	-0.036***	-0.039***	-0.038***	-0.043***	-0.039***	-0.020***	-0.020***
			(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.005)	(0.005)
Tangibility			-2.859***	-3.080***	-2.776***	-2.956***	-2.811***	-3.035***	-2.731***	-2.903***	-2.481***	-3.137***	-4.155***	-4.164***
			(0.206)	(0.206)	(0.207)	(0.206)	(0.206)	(0.206)	(0.207)	(0.206)	(0.205)	(0.205)	(0.119)	(0.119)
Trade credit			2.249***	2.151***	2.286***	2.126***	2.187***	2.096***	2.226***	2.087***				
			(0.344)	(0.345)	(0.345)	-0.345	(0.346)	(0.347)	(0.347)	(0.347)				
Depreciation			2.175*	1.417	3.897***	3.274**	1.746	1.192	3.428***	2.947**	2.286*	2.404*	-3.467***	-3.467***
			(1.307)	(1.317)	(1.323)	(1.323)	(1.305)	(1.314)	(1.321)	(1.322)	(1.326)	(1.322)	(0.816)	(0.816)
Growth opportunity			2.575***	2.353***	2.487***	2.300***	2.581***	2.116***	2.718***	2.335***	5.139***	2.766***	-0.806	-0.795
			(0.170)	(0.169)	(0.172)	(0.171)	(0.174)	(0.173)	(0.176)	(0.175)	(0.167)	(0.168)	(0.609)	(0.609)
Working capital			-0.595*	-0.769**	-0.479	-0.622*	-0.604*	-0.767**	-0.495	-0.619*	-2.352***	-2.342***	-2.220***	-2.219***
			(0.341)	(0.342)	(0.343)	(0.342)	(0.343)	(0.344)	(0.344)	(0.344)	(0.208)	(0.207)	(0.108)	(0.108)
Innovation			N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	0.886***	0.881***
			N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	(0.072)	(0.072)
Bank & Country controls														
Bank size							0.780***	0.956***	0.266**	0.483***	0.447***	0.528***	0.221***	0.221***
							(0.107)	(0.109)	(0.110)	(0.111)	(0.110)	(0.110)	(0.018)	(0.019)
Bank NIM							0.382***	-0.070	0.682***	0.218***	1.030***	0.273***	0.201***	0.123***
							(0.062)	(0.061)	(0.064)	(0.062)	(0.063)	(0.062)	(0.039)	(0.037)
GDP growth rate					-0.107***	-0.152***			-0.115***	-0.147***	-0.157***	-0.130***	-0.036***	-0.031***
					(0.007)	(0.007)			(0.007)	(0.007)	(0.006)	(0.006)	(0.010)	(0.010)
Inflation	0.214***	0.142***	0.253***	0.105***	0.438***	0.248***	0.261***	0.118***	0.447***	0.250***	0.712***	0.351***	0.155***	0.149***
	(0.012)	(0.012)	(0.016)	(0.017)	(0.019)	(0.019)	(0.016)	(0.017)	(0.019)	(0.019)	(0.020)	(0.019)	(0.020)	(0.020)
Bank development					-0.012***	-0.020***			-0.011***	-0.020***				
					(0.001)	(0.001)			(0.001)	(0.001)				
Observations	296,369	294,851	257,908	256,616	255,435	255,505	255,374	254,103	252,983	253,053	255,201	255,271	255,201	255,271
Groups	55,748	55,701	50,629	50,577	50,466	50,469	50,468	50,417	50,309	50,313	50,628	50,632	50,628	50,632
Estimator	F.E.	F.E.	F.E.	F.E.	F.E.	F.E.	F.E.	F.E.	F.E.	F.E.	F.E.	F.E.	RE MLE	RE MLE
R^2	48.99%	49.31%	49.55%	49.84%	49.91%	51.07%	49.61%	49.91%	49.97%	50.19%	49.52%	50.06%	N/A	N/A

*, ** and *** respectively represents significance at 10%, 5% and 1% level. Standard errors are reported in parentheses. Constants are added but not reported. F.E. and RE MLE respectively stand for fixed-effect and random-effect maximum likelihood estimator. The R-squared (adjusted-R^2) for F.E. models include variations captured by firm fixed-effects. In the RE MLE Model 7 we allow for firm's country, industry and legal-form dummies being inserted, but results do not vary if dummies are removed. Standard errors are clustered at firm level and results do not change if they are clustered at industry or country level. For all these fixed-effect models, results are robust with White cross-section coefficient covariance method with number of degree of freedom correctio.

Table 4: Robustness tests - Sample regrouping

	Model 1	Model 1'	Model 2	Model 2'	Model 3	Model 3'	Model 3''	Model 4	Model 4'
Dependetnt variable	COD	COD	COD	COD	COD	COD	COD	COD	COD
Grouping	*By Country*		*By Year*			*By Industry*		*By "total debt ratio"*	
Sample	Big 4	Non-Big 4	07-09	10-15	Manu.	Wholesale	Others	Less	More
Main regressors									
Lerner index	**-2.521*****	**-3.455*****	**-2.099*****	**-1.042*****	**-2.754*****	**-3.865*****	**-2.037*****	**-3.180*****	**-2.426*****
	(0.198)	(0.306)	(0.321)	(0.188)	(0.280)	(0.299)	(0.264)	(0.331)	(0.135)
HHI	**0.353*****	**0.256*****	**1.139*****	**0.268*****	**0.425*****	**0.504*****	**0.157*****	**0.551*****	**0.213*****
	(0.026)	(0.019)	(0.090)	(0.018)	(0.027)	(0.027)	(0.026)	(0.034)	(0.012)
Firm & industry controls									
Firm size	-1.204***	-1.648***	-0.097	-1.008***	-1.843***	-1.490***	-0.853***	-1.126***	-0.789***
	(0.085)	(0.184)	(0.176)	(0.101)	(0.149)	(0.140)	(0.117)	(0.143)	(0.074)
Cash	-0.175	-1.554***	-0.223	0.057	-0.473	-0.516	-0.010	-0.323	-0.799***
	(0.175)	(0.514)	(0.318)	(0.213)	(0.348)	(0.324)	(0.232)	(0.231)	(0.185)
Liquidity	-0.043***	-0.002	-0.036*	-0.036***	-0.060*	-0.030	-0.041***	-0.019	-0.025***
	(0.009)	(0.026)	(0.020)	(0.011)	(0.032)	(0.034)	(0.010)	(0.018)	(0.008)
Tangibility	-2.445***	-3.668***	-1.636***	-3.833***	-4.482***	-4.622***	-0.867***	-4.117***	-0.122
	(0.227)	(0.501)	(0.359)	(0.311)	(0.507)	(0.483)	(0.245)	(0.531)	(0.152)
Depreciation	-0.966	14.482***	18.507***	2.512	3.502	2.925	2.433	0.212	6.662***
	(1.476)	(2.972)	(2.859)	(1.576)	(2.314)	(2.719)	(2.014)	(2.647)	(1.137)
Growth opportunity	3.848***	5.935***	1.575***	4.149***	5.656***	5.818***	4.309***	5.055***	4.151***
	(0.199)	(0.358)	(0.407)	(0.301)	(0.293)	(0.306)	(0.276)	(0.311)	(0.139)
Working capital	-2.123***	-3.973***	-0.495	-2.130***	-2.699***	-4.068***	-0.605*	-1.718***	-1.318***
	(0.231)	(0.485)	(0.404)	(0.251)	(0.400)	(0.360)	(0.337)	(0.350)	(0.183)
Bank & Country									
Bank size	-0.311**	2.988***	0.088	0.024	0.580***	0.381*	0.505***	0.405*	0.620***
	(0.124)	(0.268)	(0.199)	(0.143)	(0.202)	(0.197)	(0.175)	(0.214)	(0.097)
Bank NIM	0.583***	1.789***	0.494***	0.774***	1.126***	1.145***	0.816***	1.117***	0.952***
	(0.076)	(0.130)	(0.099)	(0.086)	(0.119)	(0.108)	(0.103)	(0.116)	(0.056)
GDP growth rate	-0.164***	-0.146***	0.119***	-0.060***	-0.197***	-0.214***	-0.083***	-0.202***	-0.115***
	(0.008)	(0.012)	(0.020)	(0.012)	(0.012)	(0.012)	(0.010)	(0.013)	(0.005)
Inflation	0.929***	0.386***	0.336***	0.255***	0.817***	0.928***	0.381***	0.902***	0.496***
	(0.026)	(0.028)	(0.026)	(0.018)	(0.036)	(0.034)	(0.030)	(0.037)	(0.017)
Ovservations	214,849	40,352	76,132	179,069	75,863	86,218	93,120	130,960	124,241
Groups	42,401	8,227	33,478	47,359	14,091	16,413	20,124	35,241	31,478
Estimator	F.E.	F.E.	F.E.	F.E.	F.E.	F.E.	F.E.	F.E.	F.E.
R^2	48.60%	55.14%	61.29%	57.52%	50.16%	51.44%	46.93%	47.38%	54.23%

*, ** and *** respectively represents significance at 10%, 5% and 1% level. Standard errors are reported in parentheses. F.E. stands for fixed-effect estimator. The R-squared (adjusted-R^2) for F.E. models include variations captured by firm fixed-effects. Standard errors are clustered at firm level and results do not change if they are clustered at industry or country level. In Model 3, SMEs are grouped by industry and, from left to right they are industries of Manufacturing, Wholesale and retail trade (including repair of motor vehicles and motorcycles) and other industries.

Table 5: Robustness tests - Dependent variable substitutions

	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14
Dependetnt variable:	COD1P	COD2	COD1NA	COD1NAL	COD.CV	RCOD	COD. LDVM	COD.GR	COD.delta	COD.CV.adj
Sample:	Full	Full	Full	Full	Full	Full	Full	Full	Full	Full
Main regressors										
Lerner index	**-2.645*** **	**-0.970*** **	**-2.974*** **	**-3.371*** **	**-1.008*** **	**-1.163*** **	**-0.409*** **	**-0.354*** **	**-3.175*** **	**-1.618*** **
	(0.166)	(0.053)	(0.186)	(0.199)	(0.156)	(0.163)	(0.027)	(0.017)	(0.164)	(0.171)
HHI	**0.374*** **	**0.066*** **	**0.341*** **	**0.340*** **	**0.362*** **	**0.402*** **	**0.004*** **	-0.002	**0.358*** **	0.012
	(0.016)	(0.005)	(0.018)	(0.019)	(0.013)	(0.014)	(0.001)	(0.001)	(0.016)	(0.015)
Firm & industry controls										
Firm size	-1.309***	-0.179***	-2.480***	-0.279***	-0.871***	-1.482***	0.018***	-0.057***	-1.234***	-1.292***
	(0.079)	(0.023)	(0.087)	(0.094)	(0.078)	(0.081)	(0.003)	(0.006)	(0.077)	(0.089)
Cash	0.198	-0.122***	0.277	-0.564***	-0.281*	-0.067	0.001	-0.024*	-0.291*	0.166
	(0.181)	(0.042)	(0.197)	(0.199)	(0.170)	(0.181)	(0.014)	(0.014)	(0.166)	(0.206)
Liquidity	-0.047***	0.008**	-0.064***	-0.024**	-0.038***	-0.037***	-0.002*	-0.003***	-0.045***	-0.053***
	(0.008)	(0.004)	(0.011)	(0.012)	(0.009)	(0.010)	(0.001)	(0.001)	(0.009)	(0.011)
Tangibility	-2.141***	0.660***	-4.131***	-0.938***	-4.006***	-2.540***	-0.104***	-0.068***	-2.456***	-3.107***
	(0.209)	(0.073)	(0.233)	(0.243)	(0.206)	(0.215)	(0.015)	(0.017)	(0.206)	(0.232)
Depreciation	1.903	4.256***	16.776***	-20.648***	1.818	0.282	0.281**	1.991***	2.826**	-0.581
	(1.417)	(0.400)	(1.509)	(1.656)	(1.369)	(1.406)	(0.112)	(0.114)	(1.329)	(1.525)
Growth opportunity	5.915***	1.212***	2.395***	7.590***	2.201***	3.888***	3.140***	0.410***		2.154***
	(0.170)	(0.051)	(0.199)	(0.216)	(0.173)	(0.171)	(0.055)	(0.018)		(0.192)
Working capital	-2.289***	0.147***	-3.915***	-1.433***	-2.487***	-2.515***	-0.045***	0.018	-2.388***	-2.762***
	(0.220)	(0.054)	(0.240)	(0.243)	(0.213)	(0.219)	(0.014)	(0.027)	(0.209)	(0.245)
Bank & Country										
Bank size	0.095	0.412***	0.206	0.482***	0.427***	-0.669***	0.011***	-0.032***	0.783***	0.410***
	(0.109)	(0.037)	(0.125)	(0.133)	(0.111)	(0.112)	(0.002)	(0.009)	(0.110)	(0.123)
Bank NIM	0.819***	0.341***	0.884***	1.239***			0.037***	0.005	0.950***	
	(0.064)	(0.020)	(0.072)	(0.078)			(0.005)	(0.005)	(0.064)	
GDP growth rate	-0.160***	-0.061***	-0.141***	-0.150***	0.054***	0.043***	0.003***	0.011***	-0.138***	0.161***
	(0.007)	(0.002)	(0.007)	(0.008)	(0.006)	(0.006)	(0.001)	(0.001)	(0.006)	(0.007)
Inflation	0.722***	0.237***	0.567***	0.886***			-0.012***	0.016***	0.917***	
	(0.021)	(0.006)	(0.022)	(0.025)			(0.003)	(0.002)	(0.020)	
Ovservations	256,648	334,100	265,723	252,209	258,476	247,858	208,829	235,009	255,201	251,031
Groups	50,232	59,891	52,064	50,899	50,967	50,072	45,498	48,562	50,628	49,539
Estimator	F.E.	F.E.	F.E.	F.E.	F.E.	F.E.	Panel probit	F.E.	F.E.	F.E.
R^2	49.53%	52.89%	43.86%	42.25%	48.47%	48.51%	N/A	20.31%	49.26%	48.92%

*, ** and *** respectively represents significance at 10%, 5% and 1% level. Standard errors are reported in parentheses. F.E. stands for fixed-effect estimator. The R-squared (adjusted-R^2) for F.E. models include variations captured by firm fixed-effects. Standard errors are clustered at firm level and results do not change if they are clustered at industry or country level.

Table 6: Robustness tests - endogeneity, non-linearity, and others

	Model 15	Model 16	Model 17	Model 18	Model 19	Model 20		Model 21		Model 22
Dependetnt variable:	COD	COD	COD	COD	COD	COD		COD		COD
Sample	Full	Full	Full	Full	Full	Full		Full		Full
Main regressors										
Lerner index		**-2.825*****		**-2.734*****	**-6.274*****	**-4.770*****	**l.Lerner**	**-1.184*****	**Lerner**	**-2.600*****
		(0.162)		(0.157)	(1.447)	(0.682)		(0.172)		(0.171)
Lending market Lerner			**-3.606*****						**Lerner^2**	**-1.807*****
			(0.087)							(0.339)
HHI	**0.373*****			**0.353*****	**0.404*****	**0.337*****	**l.HHI**	**0.262*****	**HHI**	**0.360*****
	(0.015)			(0.013)	(0.015)	(0.014)		(0.016)		(0.015)
Firm variables										
Firm size	-1.296***	-1.389***	-1.123***	-0.654***	-0.912***	-1.338***		-1.368***		-1.328***
	(0.076)	(0.076)	(0.077)	(0.027)	(0.063)	(0.059)		(0.083)		(0.077)
Cash	-0.275*	-0.316*	-0.296*	-0.018	-0.072	-0.177		-0.215		-0.260
	(0.164)	(0.165)	(0.166)	(0.088)	(0.122)	(0.120)		(0.180)		(0.166)
Liquidity	-0.043***	-0.043***	-0.039***	-0.023***	-0.039***	-0.040***		-0.040***		-0.043***
	(0.009)	(0.009)	(0.009)	(0.005)	(0.007)	(0.007)		(0.009)		(0.009)
Tangibility	-2.541***	-2.560***	-3.207***	-4.066***	-3.291***	-2.848***		-2.817***		-2.479***
	(0.205)	(0.204)	(0.205)	(0.115)	(0.205)	(0.199)		(0.241)		(0.205)
Depreciation	2.142	0.681	0.618	-0.682	2.614**	1.689		1.406		2.349*
	(1.316)	(1.311)	(1.317)	(0.798)	(1.167)	(1.147)		(1.379)		(1.326)
Growth opportunity	5.326***	5.029***	2.735***	5.127***	1.532***	2.311***		3.692***		5.060***
	(0.165)	(0.166)	(0.169)	(0.163)	(0.485)	(0.288)		(0.250)		(0.168)
Working capital	-2.318***	-2.406***	-2.453***	-1.995***	-0.708***	-2.462***		-2.464***		-2.356***
	(0.207)	(0.208)	(0.208)	(0.106)	(0.274)	(0.162)		(0.220)		(0.208)
Bank & Country										
Bank size	0.237**	0.799***	0.894***	0.456***	0.405***	0.721***		0.775***		0.443***
	(0.099)	(0.109)	(0.109)	(0.089)	(0.119)	(0.100)		(0.118)		(0.110)
NIM	0.765***	0.741***	-0.010	1.019***	1.002***	1.242***		0.737***		1.040***
	(0.059)	(0.062)	(0.061)	(0.050)	(0.139)	(0.082)		(0.065)		(0.063)
GDP growth rate	-0.164***	-0.104***	-0.072***	-0.159***	-0.100***	-0.173***		-0.128***		-0.156***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)		(0.007)		(0.006)
Inflation	0.757***	0.532***	0.180***	0.725***	0.401***	0.644***		0.629***		0.703***
	(0.020)	(0.017)	(0.017)	(0.016)	(0.020)	(0.019)		(0.018)		(0.020)
Notes				***BFE***	***IV1***	***IV2***				
Ovservations	259,708	257,602	256,322	255,201	215,578	223,421		229,472		255,201
Groups	51,198	50,786	50,735	50,628	42,530	43,266		49,473		50,628
Estimator	F.E.	F.E.	F.E.	RE MLE	2SLS IV FE	2SLS IV FE		F.E.		F.E.
R^2	49.41%	49.27%	49.89%	N/A	2.90%	2.21%		51.43%		49.52%

*, ** and *** respectively represents significance at 10%, 5% and 1% level. Standard errors are reported in parentheses. F.E. stands for fixed-effect estimator. The R-squared (adjusted-R^2) for F.E. models include variations captured by firm fixed-effects. Standard errors of F.E. models are clustered at firm level and results do not change if they are clustered at industry or country level. Model 18 includes bank fixed-effects (BFE). Instrumental variables for Model 19 and 20 respectively are bank growth of gross loan and lagged Lerner index. RE MLE stands for random-effect maximum likelihood estimator. 2SLS IV FE stands for two-stage least-square instrumental variable fixed-effect estimator. R^2 in Models 19 and 20 are the centered R^2. l.Lerner and l.HHI in Model 21 are respectively one-year lagged Lerner index and one-year lagged HHI.

Table 7: Heterogeneity tests (firm characteristics)

	Model 1	Model 1'	Model 1''	Model 1'''	Model 2	Model 2'	Model 2''	Model 2'''	Model 2''''	Model 3	Model 3'	Model 3''	Model 3'''	Model 3''''
Dependetnt variable:	COD	COD	COD	COD	COD	COD	COD	COD	COD	COD	COD	COD	COD	COD
Sample		**Innovation**					**Firm size**					**Opacity (information)**		
	non-innovative	Innovative	Full	Full	Micro	Small	Medium	Full	Full	1st third	2nd third	3rd third	Full	Full
Regressors														
Lerner index	**-2.894*** **	**-2.743*** **	**-2.482*** **		**-4.693*** **	**-3.211*** **	**-1.901*** **	**-5.354*** **		**-1.820*** **	**-2.562*** **	**-3.927*** **	**-2.503*** **	
	(0.182)	(0.358)	(0.166)		(0.813)	(0.317)	(0.208)	(0.731)		(0.264)	(0.277)	(0.367)	(0.198)	
Lending market Lerner				**-3.457*** **					**-6.366*** **					**-3.503*** **
				(0.088)					(0.341)					(0.100)
HHI	**0.372*** **	**0.303*** **	**0.179*** **	**0.202*** **	0.031	**0.375*** **	**0.299*** **	**0.311*** **	**0.358*** **	**0.164*** **	**0.415*** **	**0.625*** **	**0.401*** **	**0.398*** **
	(0.017)	(0.040)	(0.009)	(0.009)	(0.061)	(0.028)	(0.021)	(0.016)	(0.016)	(0.023)	(0.026)	(0.037)	(0.116)	(0.016)
Innovation			**1.469*** **	**1.019*** **										
			(0.114)	(0.155)										
Lerner & Innovation			-0.583											
			(0.354)											
LM. Lerner * Innovation				0.083										
				(0.176)										
Size								**-0.509*** **	**-0.901*** **					
								(0.103)	(0.125)					
Lerner * Size								**1.110*** **						
								(0.271)						
LM. Lerner * Size									**1.046*** **					
									(0.128)					
Opacity													**0.034*** **	**0.050*** **
													(0.007)	(0.009)
Lerner. Opacity													**-0.041** **	
													(0.021)	
LM. Lerner * Opacity														**-0.029*** **
														(0.009)
Constant & controls		CFBM					CFBM					CFBM		
Observations	194,199	61,002	255,201	255,271	17,538	72,350	125,337	213,546	213,607	75,531	83,235	82,446	241,212	241,277
Groups	38,638	11,990	50,628	50,632	5,691	19,553	29,735	47,419	47,422	19,704	23,563	22,292	48,784	48,787
Estimator	F.E.	F.E.	RE MLE	RE MLE	F.E.	F.E.	F.E.	F.E.	F.E.	F.E.	F.E.	F.E.	F.E.	F.E.
R^2	49.71%	48.64%	N/A	N/A	47.55%	52.72%	51.46%	50.86%	50.24%	51.56%	52.32%	51.13%	49.52%	50.24%

*, ** and *** respectively represents significance at 10%, 5% and 1% level. F.E. and RE MLE stand for fixed-effect and random-effect maximum likelihood estimator respectively. The R-squared (adjusted-R^2) for F.E. models include variations captured by firm fixed-effects. Standard errors are reported in parentheses and they are clustered at firm level, results do not change if they are clustered at industry or country level. CFBM stands for that the model has entered constant and firm, bank, and macroeconomic control variable. In Model 3, the grouping trisection is done in the full sample and thus observations are not necessarily evenly divided.

Table 8: Heterogeneity tests (macroeconomic characteristics)

	Model 4	Model 4'	Model 5	Model 5'	Model 6	Model 6'	Model 7	Model 7'	Model 8	Model 8'
Dependetnt variable:	COD	COD	COD	COD	COD	COD	COD	COD	COD	COD
Interaction term:	Banking Mkt. HHI		Economic growth		Financial development		Credit info. depth		Business disclosure	
Regressors										
Lerner	-0.235		**-2.904*** **		**-4.092*** **		**-2.151** **		**-4.323*** **	
	(0.355)		(0.161)		(0.842)		(1.042)		(0.673)	
LM. Lerner		**-0.574*** **		**-3.681*** **		**-6.349*** **		**-6.382*** **		**-6.244*** **
		(0.191)		(0.088)		(0.297)		(0.440)		(0.267)
HHI	**0.456*** **	**0.929*** **	**1.031*** **	**0.279*** **	**0.475*** **	**0.382*** **	**0.412*** **	**0.419*** **	**0.251*** **	**0.404*** **
	(0.019)	(0.038)	(0.064)	(0.062)	(0.016)	(0.016)	(0.018)	(0.018)	(0.021)	(0.023)
Lerner * HHI	**-0.375*** **									
	(0.043)									
LM. Lerner * HHI		**-0.581*** **								
		(0.033)								
GDP growth rate			**-0.171*** **	**-0.169*** **						
			(0.014)	(0.026)						
Lerner * GDPGR			0.053							
			(0.049)							
LM. Lerner * GDPGR				0.049						
				(0.031)						
Financial development					**0.004** **	**-0.027*** **				
					(0.002)	(0.002)				
Lerner * FD					**0.014*** **					
					(0.005)					
LM. Lerner & FD						**0.019*** **				
						(0.002)				
Credit info. Depth							**0.795*** **	**-0.656*** **		
							(0.100)	(0.072)		
Lerner * CID							**0.341** **			
							(0.168)			
LM. Lerner * CID								**0.579*** **		
								(0.078)		
Business disclosure									**0.343*** **	**-0.169*** **
									(0.045)	(0.048)
Lerner * BD									**0.142* **	
									(0.082)	
LM. Lerner * BD										**0.327*** **
										(0.032)
Constant & controls	CFBM		CFBM		CFBM		CFBM		CFBM	
Observations	255,201	255,271	255,201	255,271	235,261	235,331	231,948	234,540	249,801	251,744
Groups	50,628	50,632	50,628	50,632	49,530	49,535	49,442	49,467	50,388	50,476
Estimator	F.E.	F.E.	F.E.	F.E.	F.E.	F.E.	F.E.	F.E.	F.E.	F.E.
R^2	49.53%	50.19%	49.52%	50.06%	50.54%	51.10%	51.26%	50.99%	49.55%	49.95%

*, ** and *** respectively represents significance at 10%, 5% and 1% level. Standard errors are reported in parentheses. F.E. stands for fixed-effect estimator. The R-squared (adjusted-R^2) for F.E. models include variations captured by firm fixed-effects. Standard errors are clustered at firm level and results do not change if they are clustered at industry or country level. CFBM stands for that the model has entered constant and firm, bank, and macroeconomic control variable.

Highlights (6) (4-6 required)

- Few studies have questioned the banking impacts on SME cost of bank debt.

- High credit cost may impair the survival and development of an SME and incur high credit risk to banks.

- This paper studies how bank market power affects debt financing cost for SME borrowers.

- We show that bank market power reduces the cost of debt for EU SMEs at a disaggregate level.

- The effect is more pronounced for informationally opaque SMEs or those in an economy subject to less business transparency.

- We show supporting evidence to the Information-based hypothesis.