Bank of England

Financial frictions and firms' capital composition: a structural estimation of firms' borrowing constraints for the UK

Staff Working Paper No. 1,132
June 2025

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Abstract

Is it more challenging to obtain external debt financing for firms with more intangible assets? We analyse how intangible capital matters for firm-level financial frictions in the debt market and propose a novel strategy to identify them. Our empirical strategy builds on a theoretical framework and combines a standard collateral constraint with a no-arbitrage condition on firm debt. Specifically, the model predicts that the sensitivity of the firm interest rate spread to the firm capital-to-debt ratio should be decreasing in firm intangible intensity if intangibles are less effective in mitigating financial frictions. Intuitively, increasing the capital-to-debt ratio has a smaller effect on the interest rate spread for firms with more intangible assets, if the liquidation recovery value of intangible assets lower relative to that of tangible assets. Using a large panel of UK firms, we estimate the structural parameters of firms' collateral constraint conditional on their capital composition. We find that interest rate spreads are indeed less sensitive to changes in the capital-to-debt ratio for firms with higher intangible intensity. Furthermore, a higher tangible stock lowers the firm interest rate spread, whilst a higher intangible capital stock is associated with a higher spread. Our findings are robust to controls for debt maturity and other firm characteristics commonly associated with financing frictions.

Key words: Intangible capital, financial frictions, borrowing constraint.

JEL classification: C58, D22, G32.

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The views expressed in this paper are those of the authors, and not necessarily those of the Bank of England or its committees. We would like to thank Steve Bond, Ambrogio Cesa-Bianchi, Andrea Chiavari, Andrea Ferrero, Irem Guceri, Jonathan Haskel, Rebecca Mari, Muhammad Meki, Simon Quinn, Federica Romei, Petr Sedlacek, Tatjana Schultze, Hannah Zillesen and an anonymous referee for helpful discussions and suggestions. We are grateful to seminar participants at the University of Oxford macro workshop and the Bank of England MA-SED S&T seminar for useful comments and conversations. We remain solely responsible for the content of this paper and any errors or omissions that could remain.

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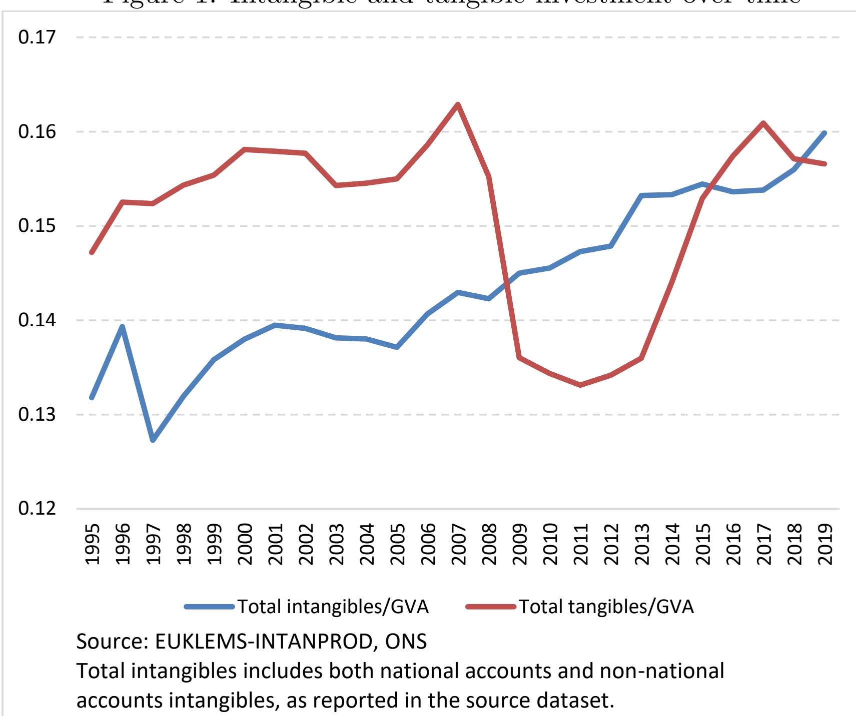
ISSN 1749-9135 (on-line)

1 Introduction

During the last few decades, intangible assets such as patents, brands, software, organisational design and distribution networks have become increasingly important inputs in the production processes of many firms. Figure 1 depicts UK intangible and tangible business investment relative to business sector gross value added over time. Whilst the tangible investment rate in 2019 is comparable to the investment rates of the early 2000s, investment in intangibles as a share of gross value added has been steadily growing. In fact, investment in intangibles exceeded investment in tangible assets between 2008 and 2015, and again in the final year of the sample (2019). The rising importance of intangibles in advanced economies has been well documented in the literature (Demmou et al. (2020); Corrado & Hulten (2010); Corrado et al. (2012); Corrado et al. (2013); Corrado et al. (2016); Andrews & Serres (2012)).

Figure 1: Intangible and tangible investment over time



One significant dimension in which intangible capital is often argued to differ from tangible capital is its pledgeability as loan collateral. Firms may be able to pledge tangible capital such as property, equipment or machinery as collateral; however, it may be more difficult to pledge intangible assets if they are very firm specific or have a more uncertain liquidation value (Williamson (1988); Shleifer & Vishny (1992); Hart & Moore (1994)). Moreover, intangible investment may be inherently riskier than investment in tangible assets, reducing the willingness of financial institutions and investors to lend to firms undertaking intangible investment (Barth et al. (2001); Himmelberg & Petersen

(1994)). The rise of intangibles may therefore have resulted in a tightening of firm financing constraints.

However, intangible assets also have the potential to loosen firm financial frictions. Very tangible assets are easier to sell, which may worsen some of the moral hazard problems associated with lending. For example, if assets are very liquid, managers may be tempted to sell off firm assets and walk away with the profits (Myers & Rajan (1998); Morellec (2001)). On the other hand, pledging collateral that is more valuable to the firm than the lender may ease credit market frictions, by aligning incentives or by signalling the quality of the borrower (Bester (1985); Bester (1987); Boot & Thakor (1994)). Finally, recent evidence by Kermani & Ma (2023) shows that the recovery rates of tangible assets and certain (reported) intangible assets may not be very different. Therefore, it is not ex ante obvious whether intangible intensive firms find it harder to obtain debt financing.

In this paper, we ask if intangible intensive firms face a tighter borrowing constraint. To answer this question, we propose a novel way of identifying firm borrowing constraints from the relationship between the firm interest rate spread and capital-to-debt ratio. To derive our empirical specification, we use a standard collateral constraint together with a no-arbitrage condition on firm debt. Specifically, the lender can recover a fraction of the firm capital stock in the event of default. The risk of default is priced competitively, such that the return on a loan equals the risk-free rate. These conditions result in a relationship between the firm interest rate spread (the difference between the interest rate faced by the firm and the risk-free rate), the firm capital-to-debt ratio and default probability. This relationship characterises the borrowing constraint. If a firm has enough recoverable capital to cover its debt in the event of default, it can borrow at a favourable interest rate. Increasing the amount of debt beyond the amount of recoverable capital increases the firm financing costs, as the lender needs to be compensated for incurring a risk of losses in the event of default. Hence, the more recoverable capital the firm has, the more it can borrow at a favourable interest rate. On the other hand, if a firm has very little recoverable capital, financing costs increase more quickly with the amount of debt.

Estimating the relationship between the firm interest rate spread and capital-to-debt ratio allows us to identify the structural parameters that govern the tightness of the firm borrowing constraint: how much firms can borrow against different types of capital, intangible and tangible, before incurring higher financing costs. Specifically, the model predicts that the sensitivity of the firm interest rate spread to their capital-to-debt ratio should be decreasing in firm intangible intensity, if intangibles do not loosen financial frictions as effectively as tangible assets do. Intuitively, this is because increasing the capital-to-debt ratio relaxes the borrowing constraint less for firms whose capital is more intangible, if lenders find it harder to liquidate intangible assets (or are less willing to lend to intangible intensive firms for some other reason).

Our identification strategy is attractive for four main reasons. Firstly, it does not rely on ex ante classification of firms into constrained or unconstrained groups, which is a challenge for many strategies proposed by previous literature. Secondly, our identification is robust to the presence of equity and other types of financing, as well as possible capital adjustment costs. Thirdly, no assumptions regarding the firm production function are necessary. Finally, our estimation can be performed using balance sheet data for private companies, as we do not need to control for market-to-book ratios or other proxies for investment opportunities that are often only available for public firms.

We use firm-level balance sheet data for a large sample of UK limited companies. Our dataset consists largely of private SMEs, for which borrowing constraints are likely to be particularly relevant. Before proceeding with the structural estimation, we conduct reduced form regressions to assess associations between firm intangible intensity (intangible capital over total capital), borrowing and loan terms. Our reduced form results indicate that high intangible intensity is associated with less borrowing and worse loan terms. Specifically, a one standard deviation increase in intangible intensity is associated with 49% lower debt volumes; an increase in firm financing costs by 62 basis points; and a 9 percentage point increase in the proportion of short term debt. Our estimated effects are of the same sign but larger in magnitude compared to previous studies. This could be because most previous analyses have been conducted by using data on large public corporations, which are likely to be less affected by financing frictions than private SMEs. Indeed, we find that the adverse associations between intangible intensity and debt volumes, leverage and financing costs are significantly less pronounced for large firms in our sample. Importantly, these associations represent general equilibrium outcomes rather than being driven solely by a credit supply friction.

Our structural estimates show that intangible intensive firms face a tighter borrowing constraint than tangible intensive firms, ceteris paribus. The estimates are statistically and economically significant: for the average firm in our sample, a one standard deviation increase in intangible intensity increases the firm interest rate by 126 basis points. We find that increasing the tangible capital stock is associated with a loosening of the borrowing constraint. In other words, the more tangible capital a firm has, the more it can borrow without incurring a significant increase in its financing costs. Alternatively, increasing tangible assets relative to debt reduces the firm financing costs. On the other hand, our results imply that increasing the intangible capital stock *worsens* the financial friction. The coefficient on intangible capital is not only lower than that of tangible capital (implying that intangible assets would relax the borrow constraint less), but *negative*. The negative coefficient on intangible capital prevails even when accounting for differences in debt maturity (as intangible intensive firms tend to use more short term borrowing) and other firm characteristics commonly associated with financing frictions (such as firm age, size and profitability).

Our results are consistent with the presence of indirect effects that amplify the direct impact of lower (liquidation) recovery rates of intangible capital. We cannot disentangle or quantify these indirect effects in our framework. They could include uncertainty about the valuation of intangibles from the lenders' side, contributing to lower use of collateralised loans by intangible intensive firms or segmented credit markets. We abstract from modelling specific features that might determine the design of debt contracts from the lender's perspective such as legal frameworks. Thus, our estimates of lower recovery rates may be affected by these unobserved effects. However, our framework considers these parameters as structural, capturing differences in the specificity of assets to the firm, rather than being determined by these indirect effects or financial policies.

Lastly, while our results are consistent with the view that tangible capital loosens the firm borrowing constraint more effectively than intangibles, this conclusion is based on firms' existing capital. We cannot infer whether intangible intensive firms would face tighter constraints to finance additional intangible investment than tangible intensive firms, all else equal. In addition, our results do not tell us whether or not intangible intensive firms are less likely to obtain the funds they need to reach their optimal levels of investment, i.e. the extent to which these firms behave as if they are financially constrained. It is therefore beyond the scope of our analysis to shed light on the macro-economic implications of these frictions and analyse optimal policy or regulatory responses, which are absent in our model. Hence, we abstract from these questions, and leave these for future research.

Related literature

Our work contributes to two strands of literature. Firstly, we contribute to a large literature on how to measure firm financial constraints, which are not directly observable. The most common ways to estimate financial constraints can be roughly divided into six categories. One of the most established approaches is to estimate the investment - cash-flow sensitivity for different groups of firms, as this relationship should vary with firm financial constraints (Fazzari et al. (1988); Himmelberg & Petersen (1994); Bond & Meghir (1994); Calomiris & Hubbard (1995); Gilchrist & Himmelberg (1995); Kaplan & Zingales (1997)). Others have used Euler-equation based identification (Whited (1992); Hubbard et al. (1995); Whited & Wu (2006)), or combined survey data with firm balance sheet information to construct indices relating to firm financial constraints (Lamont et al. (2001); Hadlock & Pierce (2010)). Identifying firms who behave in a financially constrained fashion following natural experiments has been another technique to gauge financial constraints (Blanchard et al. (1994); Lamont (1997); Rauh (2006); Banerjee & Duflo (2014); Farre-Mensa & Ljungqvist (2016)). Bau & Matray (2023) and others use firms' marginal revenue product of capital to determine how financially constrained a firm is. Finally, a recent strand of the literature (e.g. Cloyne et al. (2023), Ottonello & Winberry (2020), Jeenas (2023), Albrizio et al. (2024)) identifies financially constrained firms by examining their heterogeneous responses to monetary policy shocks. We contribute to this literature by proposing a novel way to identify firm financial constraints from a relationship between firm credit spread and capital-to-debt ratio.

Secondly, we contribute to the literature on the impact of intangible capital on firm financial constraints (Almeida & Campello (2007); Sibilkov (2009); Chen (2014); Falato et al. (2020); Lei et al. (2018); Demmou et al. (2019); Demmou et al. (2020); Kermani & Ma (2023), Boler et al. (2023), Dell'Ariccia et al. (2021), Holttinen (2025)). We make two main contributions related to this literature. Firstly, our sample includes private SMEs, for which financial constraints especially on the debt side are likely to be particularly relevant, while the existing literature is largely focused on public firms.[1] Secondly, to the best of our knowledge, we are first to provide estimates of structural parameters governing the severity of (debt) financing frictions specifically related to intangible capital. Holttinen (2025) builds on the framework developed in this paper by explicitly modelling the sorting of firms into collateralised and uncollateralised borrowers, which allows it to analyse the aggregate productivity effects of financing frictions related to intangibles which it finds can be potentially large.

The remainder of the paper is organised as follows. In section 2 we present our theoretical framework and derive the main empirical specification. Section 3 discusses identification challenges and proposed solutions. Section 4 reviews our data, and presents results from reduced form estimation. Section 5 outlines the results from our structural analysis. Section 6 concludes.

2 Theoretical Framework

We base our theoretical framework on a standard debt-financing friction used in the macro-finance literature, based on the seminal work of Kiyotaki & Moore (1997) and Bernanke et al. (1999). The financing friction arises from a "costly state verification" problem originally proposed by Townsend (1979): in the event of default, the lender recovers a fraction α of the value of firm's capital. Similar to Bernanke et al. (1999), Christiano et al. (2014) and Ottonello & Winberry (2020), firms can borrow more than the amount of collateral they have, exposing the lender to a loss in the event of default. A simpler (and more commonly used) borrowing constraint arises if firms can borrow at the risk-free rate up to a limit determined by the value of collateral. Allowing firms to go above this limit introduces heterogeneity in firm borrowing costs. For the purpose of our paper, we chose this framework over the simple borrowing limit, as it characterises a relationship between firm-specific

[1] There are some exceptions in recent work that are related to our paper but differ significantly in scope of their contribution. Dell'Ariccia et al. (2021) conduct some of their regressions for a sample of smaller firms, however, they are restricted to using data on government backed loans which may feature loan terms that are less sensitive to firm use of intangible or tangible assets. Demmou et al. (2020)'s data includes private and smaller firms, however, they do not specifically estimate the impact of intangibles on financing frictions, instead comparing the impact of financing frictions on productivity growth in intangible and tangible intensive sectors. Boler et al. (2023) covers the universe of Norwegian firms, however, the focus of the paper is on patenting activity rather than intangibles more broadly.

borrowing costs and firm assets.

The risk of losses to the lender is priced competitively: the expected return on firm debt equals the risk-free rate.[2] Building on Bernanke et al. (1999) and Ottonello & Winberry (2020), the expected payment from the borrower to the lender next period is given by

$$E_t \left[(1 - \chi_{it+1}) R_{it+1} b_{it} + \chi_{it+1} \left(min \left\{ \alpha k_{it+1}, R_{it+1} b_{it} \right\} - c R_{it+1} b_{it} \right) \right] \tag{1}$$

where χ is an indicator variable taking a value of one if a firm defaults and zero otherwise; R is the nominal gross interest rate on the loan; b is firm debt; and k is the firm capital stock. We allow for small fixed bankruptcy costs captured by c, which are assumed to be proportional to the amount of debt and interest for simplicity. This results in a strictly positive interest rate spread for firms with enough recoverable capital to cover debt and interest expenses in the event of default.

Equation (1) states that if the firm does not default ($\chi = 0$), the lender gets paid the loan amount (b) times the gross interest rate (R). If the firm defaults, χ is equal to 1, and the lender recovers a fraction α of firm assets, up to the value of debt times interest. The *min* operator ensures that the lender does not have a claim on the firm's assets beyond what is needed to cover debt and interest.

The parameter α governs the severity of the financial friction, determining the fraction of firm capital that can be recovered by the lender in the event of default.[3] For the analysis in this paper, this is the main parameter of interest, and the parameter we later estimate using firm-level data. If α is equal to 1, capital has the same value outside the firm as inside the firm (it is not firm-specific), and it can be reallocated to other firms costlessly. Hence, $\alpha < 1$ reflects frictions in liquidating firm assets in the event of default, caused by asset specificity (assets are more valuable inside the firm than outside the firm) and other costs associated with asset liquidation not included in the fixed cost c.

Next, we derive the empirical specification that allows us to estimate the financial friction parameter, α, from equation (1). The expected return on the loan is given by dividing equation (1) by b. Setting the expected return equal to the risk-free rate R^f results in

$$E_t \left[(1 - \chi_{it+1}) R_{it+1} + \chi_{it+1} \left(min \left\{ \frac{\alpha k_{it+1}}{b_{it}}, R_{it+1} \right\} - c R_{it+1} \right) \right] = E_t \left[R^f_{t+1} \right]. \tag{2}$$

Regarding the timing of decisions in the framework, interest paid (R_{it+1}) and the debt repayment due (b_{it}) next period are negotiated at time t, and hence known at time t. Abstracting from aggregate uncertainty, the risk-free rate R^f_{t+1} is also known at time t. Finally, a standard time-to-

[2]We later discuss the implications of assuming a perfectly competitive financial sector.

[3]The parameter α can also be a vector of parameters associated with different types of capital, as we will assume later when we expand the framework to differentiate between tangible and intangible capital.

build assumption implies that firm capital stock next period is given by

$$k_{it+1} = (1-\delta)k_{it} + i_{it}.$$

where δ is the depreciation rate and i is investment. Hence, the amount of capital next period is also known at time t. No aggregate uncertainty also implies no uncertainty regarding the price of the firm capital stock next period (normalised to 1). As a result, the only variable in equation (2) that is not known at time t is the firm default decision, χ.

Re-arranging and passing through the expectation operator therefore results in

$$\frac{R_{it+1} - R^f_{t+1}}{R_{it+1}} = E_t\left(\chi_{it+1}\right)\left(1 - min\left\{\frac{\alpha k_{it+1}}{R_{it+1} b_{it}}, 1\right\} + c\right). \tag{3}$$

The left-hand side term of equation (3) is the firm's interest rate spread $(R_i - R^f)$ as a percentage of the gross interest rate (R_i). On the right-hand side, the first term $(E(\chi_i))$ is the firm's default probability, and the second term equals expected losses in the event of default: 1 minus the loan recovery rate. Equation (3) states that the firm interest rate spread (the premium the firm pays on its debt over the risk-free rate) equals expected losses in the event of default times the probability of default. If the probability of default is zero $(E(\chi_i) = 0)$, the firm can borrow at the risk-free rate, and the left-hand side is also zero. If the firm has enough recoverable assets to cover debt and the interest payment, losses in the event of default simply reflect the fixed bankruptcy cost c, and the spread is given by

$$\frac{R_{it+1} - R^f_{t+1}}{R_{it+1}} = E_t\left(\chi_{it+1}\right) c.$$

If the firm has less recoverable assets than debt, the loan recovery rate is given by $\alpha k_i / R_i b_i - c$. Finally, if the firm has no recoverable capital, the recovery rate is zero, and the spread is given by the default probability times $(1 + c)$.

We allow for some measurement error in the interest rate spread, as we use the firm interest expenses over total debt as proxy for the firm interest rate. This is because the dataset used for estimation does not contain loan-level information. We therefore add an error term (ν) into equation (3), which results in:

$$\frac{R_{it+1} - R^f_{t+1}}{R_{it+1}} = E_t\left(\chi_{it+1}\right)\left(1 - min\left\{\frac{\alpha k_{it+1}}{R_{it+1} b_{it}}, 1\right\} + c\right)\nu_{it+1}. \tag{4}$$

Finally, we add intangible capital to the standard framework. If lenders can recover a fraction α^T of firm tangible capital k^T, and a potentially different fraction α^I of firm intangible capital k^I, equation (3) becomes:

$$\frac{R_{it+1}-R^f_{t+1}}{R_{it+1}} = \left(1 - min\left\{\frac{\alpha^T k^T_{it+1} + \alpha^I k^I_{it+1}}{R_{it+1}b_{it}}, 1\right\} + c\right) E_t\left(\chi_{it+1}\right)\nu_{it+1}.$$

Rearranging results in

$$\frac{R_{it+1}-R^f_{t+1}}{R_{it+1}} = \left(1 - min\left\{\left(\alpha^T - \left(\alpha^T - \alpha^I\right)\frac{k^I_{it+1}}{k_{it+1}}\right)\frac{k_{it+1}}{R_{it+1}b_{it}}, 1\right\} + c\right) E_t\left(\chi_{it+1}\right)\nu_{it+1} \tag{5}$$

where k_{it+1} is the total capital stock of the firm (intangible plus tangible).

This leads us to our main empirical specification. Writing equation (5) in terms of objects that can be measured using our firm level data, and for period t instead of $t+1$ we get

$$spread_{it} = \left(1 - min\left\{\left(\alpha^T - \left(\alpha^T - \alpha^I\right) II_{it}\right)\frac{k_{it}}{b_{it-1}\left(1+r_{it}\right)}, 1\right\} + c\right) PD_{it}\nu_{it} \tag{6}$$

where $spread = \frac{R_i - R^f}{R_i}$ is the firm interest rate spread in percentage terms; PD is the firm's probability of default (equal to $E(\chi)$); II denotes intangible intensity (intangible capital over total capital); k is total capital; b is total debt and r is the interest rate on firm debt. To help understand the intuition behind equation (6), we next consider the equation in cases, based on how much debt and recoverable capital the firm has (as the ratio of firm recoverable capital to debt determines the quantity inside the *min* operator):

$$spread_{it} = \begin{cases} \left(1 - \left(\alpha^T - \left(\alpha^T - \alpha^I\right) II_{it}\right)\frac{k_{it}}{b_{it-1}\left(1+r_{it}\right)} + c\right) PD_{it}\nu_{it} & \text{if } \frac{\left(\alpha^T - \left(\alpha^T - \alpha^I\right) II_{it}\right) k_{it}}{b_{it-1}\left(1+r_{it}\right)} < 1 \\ cPD_{it}\nu_{it} & \text{otherwise} \end{cases}$$

For firms with less recoverable capital than debt, the interest rate spread is determined by the top line. For these firms, increasing the capital-to-debt ratio should reduce the spread, as losses faced by the lender in the event of default get smaller. However, this effect will differ with intangible intensity if α^T and α^I are not equal. For instance, if α^I is smaller, increasing capital-to-debt will have a smaller effect on the spread for intangible intensive firms, as lenders can recover a smaller fraction of their capital in the event of default. Thus, the sensitivity of firm spread to capital-to-debt is decreasing in firm intangible intensity, if intangible assets loosen the financial constraint less than tangible assets do. However, for firms with enough recoverable capital to cover debt and interest expenses, the interest rate spread is only affected by the fixed bankruptcy cost, default probability, and the error term. When the firm has enough capital to cover debt and interest in the event of default, increasing the capital-to-debt ratio has no impact on the spread, as the lender can only claim up to the value of debt plus interest.

2.1 Empirical specification

Finally, to estimate equation (6), we take logs. This is for two reasons: firstly, the distribution of the interest rate spread is highly skewed, and thus a log-transformation will facilitate estimation. Secondly, taking logs will separate the default probability from the other variables of interest. Our baseline specification is therefore given by

$$\begin{aligned} ln(spread_{it}) =& ln\left(1 - min\left\{\left(\alpha^T - \left(\alpha^T - \alpha^I\right) II_{it}\right) \frac{k_{it}}{b_{it-1}\left(1 + r_{it}\right)}, 1\right\} + c\right) \\ &+ ln(PD_{it}) + ln(\nu_{it}). \end{aligned} \tag{7}$$

We estimate equation (7) by non-linear GMM. This is because the α parameters appear inside the logarithm, and the equation also contains a min-operator. We therefore cannot use linear estimators. GMM estimators are obtained by minimising the GMM criterion function, which is given by the appropriately weighted sample moment conditions. The population moment conditions in our case are given by

$$E_t\left[ln(\nu_{it})X_{it}\right] = 0$$

where $ln(\nu_{it})$ is the error term from equation (7) and X_{it} are the appropriate instruments (discussed in the next section). These are regular orthogonality conditions between the error term and the instruments, similar to those that underpin standard linear regression and linear GMM estimators. However, in linear models, the error term is a linear function of the parameters to be estimated. Our estimator is a non-linear GMM estimator, because the error term in the moment conditions $ln(\nu_{it})$ is not a linear function of the parameters.

We note that the equation in levels could also be estimated by OLS if the presence of the min-operator is ignored. We show in Appendix A.7 that running such linear regressions on the entire sample results in insignificant results. This could be because without the min-operator, some firms with more recoverable capital than debt are included in the estimation of the α parameters, which according to the model will bias the estimates towards zero. This is because for these firms, the interest rate spread should not depend on their capital-to-debt ratio. We show that excluding firms with a high capital-to-debt ratio (for which, according to the model, the sensitivity of the interest rate spread to capital-to-debt should be zero) results in significant results, and the signs of the estimated parameters are consistent with the model. This exercise illustrates the need to use the GMM estimator. This is because the correct cut-off for including firms in the data to estimate the parameters is not observable, and as we show, ignoring the cut-off is likely to result in a downward bias in the estimates.

Furthermore, with the use of the GMM estimator, it is possible to estimate the log-transformation of the equation, which separates the default probability from the other right-hand side variables. This is desirable as we do not observe default probability directly, and have to rely on proxies for this variable.

2.2 Benefits of the estimation strategy

There are several benefits of identifying financial constraints from the relationship given by equation (7). Firstly, one of the main issues related to many of the approaches proposed in the literature (for instance investment - cash-flow regressions; differences in marginal revenue products; or some natural experiment frameworks) is the need to ex-ante classify firms into constrained and unconstrained groups. However, equation (7) should hold for **all** firms, regardless of whether they are constrained or not. In addition, the cut-offs for using collateralised or uncollateralised lending, and having enough recoverable capital to cover debt, are determined by the α parameters as well as observed variables. Therefore, estimating equation (7) is equivalent to estimating the parameters and cut-offs jointly. There is therefore no need to split the sample in any way before estimating the parameters.

Secondly, equation (7) is not an investment regression, which means that the estimation is robust to potentially different adjustment costs on intangible and tangible capital stocks; availability of alternative sources of financing (for instance equity finance); and different investment opportunities which are particularly hard to control for for private companies. Finally, in order to derive equation (7), no assumptions are needed regarding the functional forms of the firm's production function or marginal product of capital.

We note that the estimation strategy identifies the parameters of the firm's borrowing constraint, or more specifically, the parameters of the firm-specific interest rate schedule. It therefore tells us whether or not intangible and tangible intensive firms face a different interest rate schedule, and hence a different borrowing constraint, everything else equal. Facing a tighter constraint would suggest that intangible intensive firms are *likely to be* more constrained than tangible intensive firms (everything else equal). However, the estimation cannot reveal whether or not intangible or tangible intensive firms *are* more constrained. Even if they face a tighter constraint than tangible intensive firms and all else equal, a larger cost to raise external funds, this does not necessarily imply that they *cannot* raise the funds they require to finance their desired, optimal levels of investment.

3 Main Hypothesis, Identification Challenges and Solutions

3.1 Hypothesis

We want to test if intangible intensive firms face a tighter borrowing constraint than firms using relatively more tangible capital. The α parameters govern the tightness of the borrowing constraint in our framework: the larger α, the more firms can borrow against their capital without incurring an increase in their borrowing costs. Our main hypothesis in terms of model parameters is therefore:

Hypothesis: $\alpha^T > \alpha^I$.

If this is true, the coefficient on capital-to-debt in equation (7), given by $\alpha^T - \left(\alpha^T - \alpha^I\right) II_{it}$, declines with intangible intensity. This would imply that intangible intensive firms face a tighter borrowing constraint: an intangible intensive firm would have a higher interest rate than a tangible intensive firm with the same amount of debt and total capital, and the same level of default risk. Moreover, for firms with very tangible capital, increasing the capital-to-debt ratio would lower borrowing costs. This effect would be subdued for intangible intensive firms, if the hypothesis is true. We note that we place no restrictions on the signs and magnitudes of the α parameters when estimating equation (7). We therefore allow for the α parameters to be equal, or for the possibility that α^I is *larger* than α^T, which would result in tangible intensive firms facing a tighter constraint.

3.2 Identification challenges and solutions

Contemporaneous values of capital, debt and default probability are unlikely to be exogenous. For instance, if there is a shock to the firm interest rate (spread) in the current period, this would directly feed into firm capital and debt decisions, as well as their default probability. However, previous values of these variables should not be correlated with (unexpected) current shocks to the interest rate. We allow for this form of endogeneity by using lags of capital, debt and default probability as instruments in the GMM estimation.

The main concern for identification stems from factors outside of the model that could affect the relationship between firm assets and the interest rate spread. In particular, these factors are a concern if they influence the estimated difference between the α parameters for intangible and tangible capital. For instance, if there is uncertainty about capital prices and quantities, this would result in additional terms in equation (6), reflecting the covariance between the loan recovery rate and the default probability. The presence of uncertainty would therefore influence the estimates of α parameters. For example, if there is more uncertainty about the intangible capital stock price, this could result in a lower estimated α. In addition, if states of the world in which the value of intangibles is low and firm defaults are high are more prevalent than for tangible capital, this lowers the α parameter estimate for intangible capital more than for tangible capital, resulting in a larger difference. However, the uncertainty about intangibles prices, as well as the potential case that intangible assets could have low value when default probability is high, would reflect additional reasons why intangible assets are not suitable to be used as loan collateral. Hence, if we interpret α more broadly as governing the severity of the financial friction in the debt market, these concerns are mitigated. We therefore conclude that these challenges mainly affect our ability to differentiate between the different channels through which intangible intensity affects firm financing constraints in the debt market. However, they should not alter our conclusions on whether intangible intensive firms face a tighter constraint when seeking out external debt financing.

Another factor outside of the model is the presence of lender mark-ups, as equation (6) is derived under the assumption of a perfectly competitive lender. Including industry- and time-fixed effects should mitigate some of the impact that lender mark-ups and potential time-varying risk premia have on the firm-level interest rate spread. However, the main concern for identification would be systematic differences (within industries) in the types of lenders that intangible- and tangible intensive firms borrow from. For example, if having less collateral (or assets that are more difficult to value) results in intangible intensive firms borrowing from more specialised lenders that charge a higher mark-up, this could result in a lower estimated α for intangible assets. Similar to the impact of uncertainty on the estimates discussed above, we conclude that borrowing from different types of lenders can be interpreted as an additional source of financing friction, which our estimation method would thus capture.

4 Data

Our dataset covers all UK limited companies annually, from 2000 to 2020, provided by Moody's Bureau van Dijk - FAME (BvD). Table 1 demonstrates the coverage of our sample, and how it is affected by missing data on key variables (intangible intensity, debt and interest expenses). Missing intangible intensity reduces our sample size from over 5 million firms in the full dataset to just over 1 million firms. This number is further reduced to almost 260 thousand firms, once observations with missing debt and interest expenses are removed.

Finally, the sample used to obtain the baseline structural estimates is an order of magnitude smaller, and contains just over 30 thousand firms. This is mainly because observations with interest expenses (and debt) at zero drop out, as the estimation is based on a relationship between a firm-level interest rate spread and firm capital-to-debt ratio. The interest rate proxy is also cleaned more heavily, with the top and bottom 5% of observations discarded, resulting in a further reduction in the sample size. Moreover, we need to compute Altman Z-scores, which we use as a proxy for default probability in the estimation. This requires non-missing values for more firm financials. We also need non-missing SIC codes in order to include industry fixed effects. Finally, we lose two time periods in the estimating sample. This is because the interest rate in the current period reflects firm fundamentals at the end of last period, and we use further lags of the independent variables as instruments.

Table 1: Sample of firms

	Full Sample	Intangible intensity not missing	Intangible intensity, debt & interest expenses	Sample for structural estimation
Nr of obs	30,278,295	9,681,298	915,814	108,308
Nr of firms	5,158,167	1,043,847	257,267	31,159
Median total assets (000s)	42	82	504	6231
Median turnover (000s)	91	103	476	9116
Median employees	2	4	62	108
Median age	5	8	9	17
Prop SMEs (%)	99.6	98.8	92.7	89.8
Private firms (%)	99.8	99.3	97.6	92.0

Source: BvD data, author calculations

Even though the number of firms is dramatically reduced, and the median firm in the estimating sample is larger and older than in the full dataset, our estimating sample consists mainly of private SMEs: the proportion of SMEs is approximately 90%, and the proportion of private companies is 92% in the final sample.[4]

4.1 Variables needed

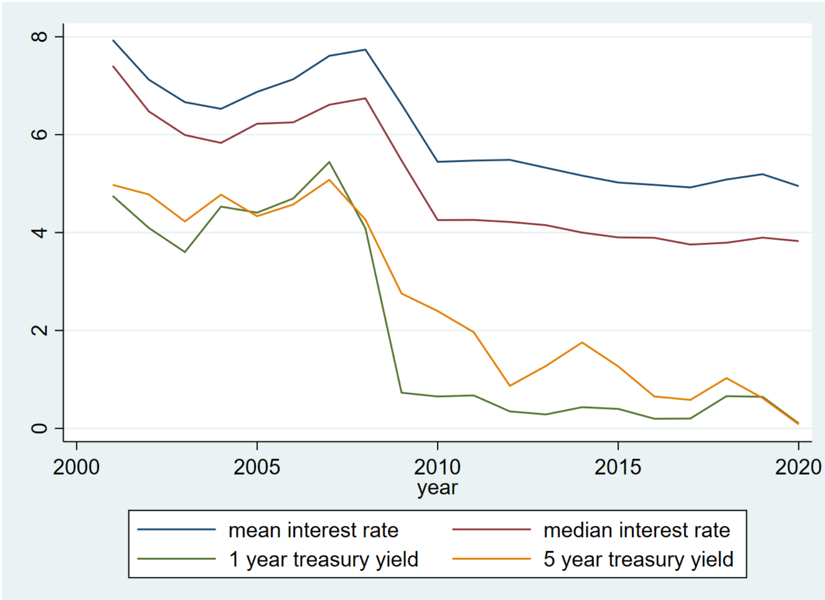
For our analysis, we need the following variables at the firm level: interest rate spread, default probability, intangible capital stock, tangible capital stock and total debt. The latter two are relatively straightforward to measure from firm balance sheet data, whilst the former three present some challenges. See Appendix A for a more detailed description of the variables. Firstly, we do not have loan level data, and hence use a proxy for the firm interest rate in order to construct the firm interest rate spread. The proxy is obtained by dividing interest expenses by total debt. For the risk-free rate, we use one year and five year UK government bond yields, and construct a weighted average of these to reflect the proportion of short term and long term debt at the firm level.[5] The interest rate proxy is quite noisy; we proceed by discarding the top and bottom 5% of observations in order to exclude large outliers. The resulting variable looks sensible: Figure 2 plots the average interest rate (mean and median) against one year and five year UK government bond (gilt) yields.

It is not straightforward to measure the intangible capital stock at the firms level, as most of intangible capital is not reported on the firm balance sheet. A proxy for the replacement value

[4]We use the UK SME definition: firms with less than 250 employees are considered to be SMEs.

[5]UK government bond yields are available from the Bank of England's Yield Curve Database and based on an estimated yield curve for the UK. Documentation and description can be obtained from the Bank of England's website.

Figure 2: Interest rate trends



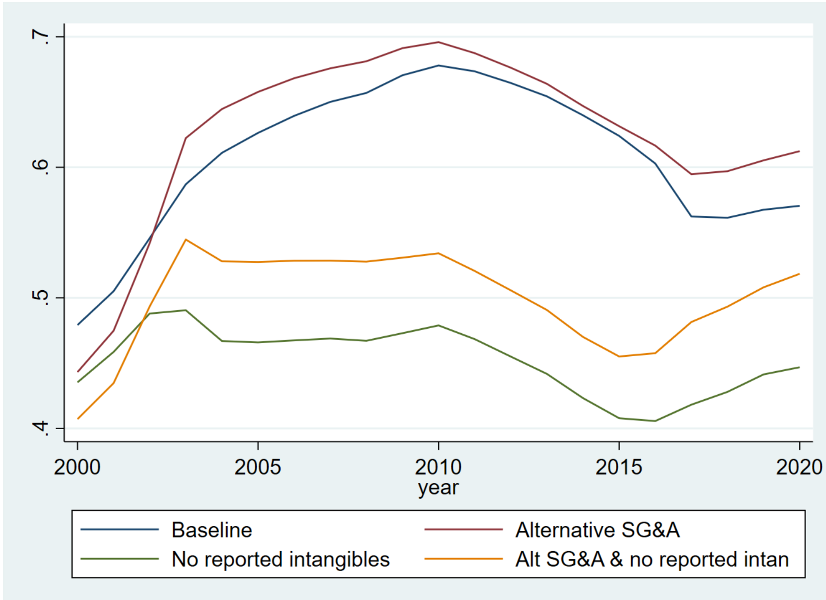
Average firm level interest rate and government bond yields (UK) over time. Sources: Interest rate proxies: BvD data. Treasury Yields: Bank of England Yield Curve Database (Bloomberg L.P., Tradeweb and Bank calculations). Author calculations.

of intangible capital can be obtained by capitalising research and development (R&D) and selling, general and administrative (SG&A) expenses, as in Peters & Taylor (2017) and Falato et al. (2020), and adding reported intangibles. Our dataset does not report SG&A expenses directly, and hence we use the following formula for SG&A: SG&A = gross profit − operating profit − depreciation. For robustness, we also use reported administrative expenses as a second SG&A proxy. Our baseline intangible capital stock measure includes externally purchased intangible capital (reported on the firm balance sheet), however, we also conduct robustness checks using an intangible capital stock measure that excludes reported intangibles.[6]

Figure 3 plots the mean intangible intensity over our sample period, defined as the intangble capital stock over total capital (intangible plus tangible), for our baseline intangible capital measure and three alternative proxies (with the alternative SG&A proxy, and with and without externally purchased intangibles). The different approaches to estimate SG&A do not result in significantly different trends; there seems to be mainly a level effect. Excluding externally purchased intangibles (mainly goodwill), on the other hand, has a bigger impact. We can see that most of the hump in intangible intensity prior to 2010, and the following decline, were largely driven by externally purchased intangible assets.

[6]Reported intangible assets consist of externally purchased intangible capital, which is mainly goodwill. In our dataset, we cannot separate goodwill from other externally purchased intangible assets. Hence, as a robustness exercise, we use an intangible capital stock measure that excludes all reported intangible assets.

Figure 3: Intangible intensity trends



Mean firm level intangible intensity over time. Intangible intensity is defined as firm intangible capital over total capital (intangible capital + tangible capital).
Source: BvD data, author calculations.

We compare our interest rate proxy and spread measure, as well as intangible intensity, with data on publicly listed UK companies from the (LSEG) Worldscope Fundamentals dataset (Worldscope). Even though our dataset consists mainly of private firms that are smaller and younger than the average publicly listed company, trends in the interest rate proxy are similar. The correlation between the average interest rate proxy for firms in BvD and Worldscope is 0.97; the correlation between the interest rate spread for the whole BvD sample and Worldscope is 0.36. This increases to 0.85 if the BvD sample is restricted to public companies only. Trends in intangible intensity are also similar for public firms in both datasets; the correlation in annual means is over 0.83. More detail on the Worldscope-BvD comparison can be found in Appendix A.6.

Firm specific default probabilities (PD) are also not straightforward to obtain. We use two different PD proxies in our analysis. The first is based on credit scores by CRIF Decision Solution Limited and Jordans, included in the BvD data used to construct our other variables. For this variable, we only have good coverage of firms for a limited number of years (2016 to 2020). These years have nevertheless good coverage, with approximately 85% of firm-year observations having non-missing values. The PD values are also of sensible magnitudes: the mean default probability for all firms is 6.86%; 6.9% for SMEs and 2% for large corporations.

We use Altman Z-scores as our second default probability proxy. Altman Z-scores are widely used to gauge firm financial health and the likelihood of bankruptcy. The framework was developed in the seminal work of Altman (1968), and is based on five financial ratios (profitability, leverage, liquidity, solvency, and activity) to predict whether a company has a high probability of becoming insolvent. There are separate formulas for public and private companies, as well as firms in manufacturing and other industries. The resulting score is interpreted against specific reference values. Firms with Z-scores below the high-risk cut-off have a heightened likelihood of default, whereas Z-scores above the low-risk mark signal good financial health. Firms with a Z-score falling between the high- and low-risk reference figures, or cut-offs, are judged to be medium risk. More detail on the methodology is outlined in Appendix A.3. In our baseline estimation, we use a capped Altman Z-score, with a lower bound of zero (the high-risk cut-off), and an upper bound given by the appropriate low risk cut-off depending on company type.

4.2 Associations between firm intangible intensity, borrowing and loan terms

Before proceeding with the structural estimation, we briefly explore whether firm characteristics and financial behaviour vary with intangible intensity, and run reduced form regressions on firm borrowing and loan terms against intangible intensity. Firm characteristics for different quartiles of intangible intensity are reported in Appendix A.4. Previous studies have found that intangible intensive firms tend to be younger and smaller. Consistent with previous work, we find that the most tangible intensive quartile is older, and larger in terms of total assets, than the other quartiles. However, the rest of the quartiles do not display any obvious relationship between intangible intensity and firm age and size.

We also assess how firm financing behaviour varies with intangible intensity. The results are outlined in Appendix A.5. Consistent with previous literature, intangible intensive firms in our sample have lower leverage and higher cash ratios. We find no raw trends in the share of public companies, or firms that have publicly issued shares.[7]

Next, we conduct reduced form regressions to asses whether the association between higher intangible intensity, less borrowing and worse loan terms is statistically and economically significant. We regress the logarithm of total debt, leverage (adjusted for intangible capital), proportion of short term debt, firm interest rate and interest rate spread on intangible intensity. We include common control variables: return on assets (ROA), cash ratio, firm age, as well as large firm and public firm dummies. Table 2 shows the results. Consistent with the descriptive analysis, high intangible intensity is associated with less borrowing and worse loan terms. Specifically, a one standard deviation increase in intangible intensity (0.4) is associated with 49% lower debt volumes and lower leverage (by 7.7 percentage points); an increase in firm financing costs by 62 basis points; as well as a 9 percentage point increase in the proportion of short term debt.

[7] We note that the dataset does not offer information of potential private equity or other types of venture capital financing, and hence it is possible that this type of non-debt financing is more common among intangibles firms.

Table 2: Intangible intensity, debt and loan terms

	(1) Total debt	(2) Leverage	(3) Interest rate	(4) Spread	(5) Prop ST debt
II	-1.233***	-0.193***	154.9***	189.9***	0.222***
	(0.0173)	(0.00344)	(4.407)	(4.451)	(0.00263)
Large	3.147***	0.000170	36.25***	11.56*	-0.130***
	(0.0306)	(0.00382)	(5.955)	(5.715)	(0.00508)
ROA	-0.211***	-0.0822***	47.26***	35.26***	0.00881***
	(0.0113)	(0.00432)	(4.843)	(4.694)	(0.000562)
Cash ratio	-2.804***	-0.0732***	173.2***	202.5***	0.255***
	(0.0189)	(0.00481)	(9.911)	(9.969)	(0.00230)
Age	0.0146***	-0.00323***	-0.811***	-0.944***	-0.000363***
	(0.000392)	(0.0000607)	(0.0785)	(0.0781)	(0.0000580)
Public	1.651***	-0.0661***	11.09*	-8.180	-0.146***
	(0.0286)	(0.00394)	(5.468)	(5.313)	(0.00456)
N	591047	623464	274632	219639	552588
adj. R^2	0.407	0.099	0.099	0.055	0.170

Notes: This table shows reduced form estimates of the association between intangible intensity and firm borrowing. The dependent variables are as follows: debt volume (the logarithm of total debt) in column 1; firm leverage (debt over total assets, including intangibles) in column 2; firm interest rate in column 3; firm interest rate spread (defined as firm interest rate minus a risk-free rate proxy) in column 4; and proportion of short term debt in column 5. All independent variables are lagged by one year due to potential endogeneity. All regressions include industry-year fixed effects. Standard errors are given in parentheses and are clustered at the firm level. Stars indicate significance at standard levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

The results are both statistically and economically significant. The coefficient on intangible intensity is significant at the 0.1% level in all regressions, and the magnitudes are large. In fact, the magnitudes are larger than those in Dell'Ariccia et al. (2021), who run similar regressions using data on US public firms.[8] A potential explanation for the larger effects found in our analysis is that our sample consists primarily of private SMEs, which are likely to be more constrained by debt financing frictions.

We proceed by including an interaction term (intangible intensity times the large firm dummy) in the reduced form regressions, in order to test whether the association between firm borrowing, loan terms and intangible intensity is less pronounced for large firms. Our results support for this hypothesis: Table 3 show that the interaction terms are positive and significant in the regressions with debt volumes and leverage as dependent variables. This implies that the associations between intangibles, debt volumes and leverage are less negative for large firms. The positive association between intangibles and loan interest rates is also significantly less pronounced for large firms in our

[8]Dell'Ariccia et al. (2021) find that a 1 standard deviation increase in intangibles is associated with 10% lower debt volumes (compared to 49% in our analysis) and 6.6 basis points higher interest rates (compared to 62 basis points in our regressions).

sample. We find, however, no significant difference in the association between intangible intensity and debt maturity for SMEs and large firms.

Table 3: Regressions including an interaction term for intangibles and firm size

	(1) Total debt	(2) Leverage	(3) Interest rate	(4) Spread	(5) Prop ST debt
II	-1.247***	-0.195***	157.6***	194.6***	0.222***
	(0.0176)	(0.00350)	(4.473)	(4.524)	(0.00264)
II x Large	0.489***	0.0561***	-46.29*	-70.33***	-0.00971
	(0.0905)	(0.0131)	(18.38)	(17.64)	(0.0170)
N	591047	623464	274632	219639	552588
adj. R^2	0.408	0.099	0.099	0.055	0.170

Notes: This table shows reduced form estimates of the association between intangible intensity and firm borrowing, allowing for differences between SMEs and larger firms. The dependent variables are as follows: debt volume (the logarithm of total debt) in column 1; firm leverage (debt over total assets, including intangibles) in column 2; firm interest rate in column 3; firm interest rate spread (defined as firm interest rate minus a risk-free rate proxy) in column 4; and proportion of short term debt in column 5. All independent variables are lagged by one year due to potential endogeneity. All regressions include industry-year fixed effects, as well as the following controls: large firm dummy, ROA, Cash ratio, public dummy. Standard errors are given in parentheses and are clustered at the firm level. Stars indicate significance at standard levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Although some of the literature examining intangible capital and firm financing constraints has also used datasets including private and/or smaller firms, the analysis in this paper is not directly comparable to these studies. Dell'Ariccia et al. (2021) conduct similar analysis on loan-level data for smaller, younger firms and find, if anything, *smaller* results than for the large firms in the syndicated loans data. This is likely to be because their small firm data consists of government backed loans. For these loans, loan volumes and terms are less likely to reflect differences in the composition of firm assets, as the government backing mitigates the need for collateral. The dataset in Demmou et al. (2020) also includes private and smaller firms, however, they do not specifically estimate the impact of intangibles on debt volumes and/or loan terms, instead comparing the impact of financing frictions on productivity growth in intangible and tangible intensive sectors. Finally, the dataset in Boler et al. (2023) covers the universe of Norwegian firms, however, the focus of the paper is on patenting activity rather than intangibles more broadly. In particular, they examine the impact of a legislative change allowing firms to pledge patents as collateral on credit access of patenting versus non-patenting firms. As such, the paper does not report associations between firm intangible intensity, debt volumes and loan terms.

Overall, the reduced form evidence is consistent with the view that intangible intensive firms may face a tighter borrowing constraint than tangible intensive firms: higher intangible intensity is associated with significantly less debt financing (both in terms of loan volumes and leverage), higher financing costs, and more short term borrowing.

5 Structural estimation

Table 4 outlines the parameter estimates for equation (7). The first column shows the estimates obtained using the default probability data by CRIF/Jordans to control for the probability of default. As this variable has good coverage from 2016 onwards only, the sample is shorter. The second column shows estimates obtained using (the logarithm of) the Altman Z-score as a proxy for default probability, for the same sample of firms. As can be seen, the estimated α parameters are very similar. We therefore proceed by estimating equation (7) for all the available years (2000-2020), using Altman Z-scores as our default probability proxy. The third column shows the parameter estimates obtained for the full sample. All regressions include industry and time dummies.[9]

Table 4: Structural parameter estimates, baseline

	(1)	(2)	(3)
$-\alpha^T$	-0.0297***	-0.0341***	-0.0533***
	(0.00552)	(0.00502)	(0.00281)
$\alpha^T - \alpha^I$	0.0525***	0.0579***	0.105***
	(0.00822)	(0.00777)	(0.00444)
PD	0.209***	-0.0108***	-0.00950***
	(0.0368)	(0.00253)	(0.00134)
constant	-2.815***	-3.770***	-3.810***
	(0.173)	(0.0526)	(0.0333)
Observations	9,390	9,390	108,307
Industry & Year FE	Yes	Yes	Yes

Notes: This table shows structural parameter estimates obtained by non-linear GMM estimation of equation (7). The dependent variable in all regressions is the firm interest rate spread. Estimates in column 1 are obtained using the CRIF PD measure, which has good coverage for years 2016-2020. In column 2, the Altman Z-score is used as a default probability proxy, for the same sample as in column 1 (years 2016-2020). Estimates in column 3 reflect the full sample (years 2000-2020), using Altman Z-scores as the PD variable. All regressions include industry and year fixed effects. Standard errors are given in parentheses and are clustered at the firm level. Stars indicate significance at standard levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

All parameter estimates have expected signs, and are significant at the 0.1% level. The first row displays the estimated (negative of) α^T, the parameter governing the degree to which tangible capital eases the borrowing constraint. As expected, α^T is positive and between 0 and 1, meaning that a higher ratio of tangible capital to debt is associated with lower financing costs. The second row shows our main coefficient of interest; the difference in the α parameters associated with tangible and intangible capital, $\alpha^T - \alpha^I$. It is positive and significant, meaning that the estimated α^I is significatly lower than α^T. This implies that intangible intensive firms face a tighter borrowing

[9] We do not control for firm fixed effects. This is because in our sample, there is very little within-firm variation in intangible intensity.

constraint, ceteris paribus. In other words, intangible capital does not relax the firm borrowing constraint as effectively as tangible capital does.

The estimated difference in the α parameters is also economically significant. A one standard deviation increase in intangible intensity (0.283 for the estimating sample) is associated with an increase in the firm interest rate by 1.26 percentage points. This is significant compared to the mean firm interest rate for our sample, approximately 4.8%, with a standard deviation of 4.3 percentage points. Moreover, based on our estimates, a firm at the 90th percentile in intangible intensity (II=0.93) would pay an interest rate of 3.53 percentage points higher than a firm with an identical capital-to-debt ratio and default probability, whose intangible intensity is at the 10th decile (II=0.138).[10] It is important to emphasise that our structural estimates of the borrowing constraint apply to the firm's existing capital stock, rather than additional investments. Thus, while our results suggest that intangible intensive firms face tighter borrowing constraints, we cannot infer whether additional investments in either type of capital would be subject to interest rate differentials, conditional on intangible intensity.

Why is the association between intangible intensity and the firm spread so much higher (126 basis points) using the structural estimates when compared to the reduced form estimates (62 basis points)? There are two key reasons why this is likely to be the case. Firstly, the reduced form regressions capture a simple association between the spread and intangible intensity with limited controls. Crucially, the spread regression, following Dell'Ariccia et al. (2021), does not include a control for leverage or default probability, which are included in the structural estimation. As intangible intensive firms have a lower leverage ratio, this is likely to lower their interest rate spread, reducing the association between intangibles and the interest rates in the reduced form regressions. This effect is accounted for in the structural estimation, which is likely to increase the impact of intangibles on the spread.

Secondly, in the model, the impact of intangibles on the spread is not linear: it differs with default probability and capital-to-debt, and it is calculated at the mean values for these variables. Estimating a linear effect, as is the case in the reduced form associations, can therefore lead to a different result.

The α^T estimates (around 0.03 to 0.05) are an order of magnitude lower than previous estimates of liquidation rates for tangible capital in the literature; typical values range from around 0.3 to over 0.5 (Berger et al. (1996); Kermani & Ma (2023)). We next outline some of the reasons why this is likely to be the case. Firstly, our estimates capture frictions related to asset pledgeability beyond liquidation values being less than one. For instance, any uncertainty related to future capital prices

[10] These values are computed for the mean intangible intensity (0.539), mean capital-to-debt ratio (5.77) and mean default probability (6.86%).

may reduce the willingness of lenders to accept firm assets as collateral, resulting in a lower α parameter. It should also be noted that α may also capture other costs the lender faces in the event of default, such as broader legal and monitoring costs related to bankruptcy. Secondly, a large share of debt in our dataset is short term debt, which is likely to be uncollateralised. It is reasonable to assume that the interest rate on uncollateralised debt is less sensitive to changes in firm assets than for collateralised loans, resulting in a lower average α^T. This implies that although tangible capital does relax the firm borrowing constraint, the impact is smaller for firms in our dataset than what would be predicted based on previous estimates of liquidation values of tangible assets.

Column (1) gives an estimate of the coefficient on default probability. It is positive and statistically significant, consistent with the model, as higher values relate to a higher default probability.[11] Columns (2) and (3) use the Altman Z-score as a default probability proxy. The coefficient is negative and significant, as expected, given that *lower* scores are associated with *higher* default risk.[12]

We note that we do not directly estimate the fixed cost parameter, c. This is because including a constant inside the logarithm in the non-linear GMM estimation results in problems with convergence. We therefore fix c at 0.01 (implying that 1% of debt is paid in expenses if the firm defaults), and allow for a constant term outside the logarithm. For robustness, we try other values of c (0.005, 0.02 and 0.05). The results are reported in Appendix B1. We find that changing the fixed cost mainly affects the estimate of the constant term and does not significantly alter the α parameter or PD coefficient estimates.

Section B2 of the Appendix provides results of estimating equation (7) using alternative proxies for intangible capital. Our results are robust to the choice of intangibles proxy: using different measures does not alter the signs or magnitudes of the parameter estimates in a meaningful way. Appendix B3 reports estimates for the baseline specification, controlling for firm characteristics that are often associated with differences in borrowing costs (including firm size, firm age, ROA and firm cash ratio). Including these controls has a negligible effect on the estimates of the parameters of interest. Our results are also robust to using alternative Altman Z-scores (logarithm or levels; capped or uncapped; and dummies for high-, low- and medium risk scores) as the default probability variable.

[11] Our framework predicts a coefficient of 1; the estimate is lower, around 0.21. We expect this to be due to different definitions of default: in our framework, the default indicator refers to events of full default leading to insolvency and liquidation of firm assets. Most probability models used to assess default probability in the data, however, would classify default as a "default event", including significant delays in loan repayment or partial default, both of which result in smaller losses to the lender than the case of full default and firm liquidation. Alternatively, some estimate the likelihood of firm exit for any reason; not the likelihood of insolvency and asset liquidation. Hence, we would expect the coefficient on default probability to not necessarily be equal to one, given the likely differences in definitions of default in the theoretical framework and the methodologies used to estimate default probabilities in the data.

[12] We do not have a prior on the magnitude of the coefficient on the Altman Z-score, as it is not a 0-1 default probability measure as in the model.

The results are available upon request.

We include the logarithm of the lag of the ratio of intangible investment to total investment as an additional instrument in our regressions. Results are provided in Appendix B4. Again, the results are very similar. With the additional instrument, we can also conduct the Hansen test of overidentifying restrictions (a test gauging instrument validity).[13] We do not reject the null that the instruments are valid. In the baseline specification, we use logarithms of all independent variables as instruments. We also estimate equation (7) by using levels of the capital-to-debt ratio and intangible intensity times capital-to-debt as instruments. Our results (reported in Appendix B4) are similar, though quantitatively slightly smaller, than in the baseline estimation.

Finally, we report convergence robustness checks for the GMM estimator in Appendix B.5. The estimation routine results in the same estimates for all coefficients of interest regardless of the starting values. The starting values for the coefficients tried are 0 (baseline), 0.1, 0.25, 0.5, 0.75, 0.9 and 1.

Next, we turn our attention to the sign and magnitude of α^I. This will inform us on the impact of intangible capital on the firm borrowing constraint. If α^I is positive and significant, investing in intangibles loosens the financing constraint, though less than investing in tangible assets, as α^T is larger. If α^I is not significantly different from zero, investment in intangibles does not loosen the borrowing constraint. Finally, we have placed no restrictions on the signs of the parameters in our estimation. Therefore, it is also possible that the α^I estimate is *negative*. This would imply that investing in intangibles results in a *tighter* borrowing constraint. As mentioned in Section 3.2, we cannot interpret the α parameters as reflecting pure liquidation rates of different types of assets, as our estimation is likely to capture additional financing frictions beyond recovery rates being less than one. Given that recovery rates on assets have a lower bound of zero, a negative coefficient would be consistent with additional financing frictions affecting intangible intensive firms.

In order to estimate the α parameters separately (rather than estimating their difference), we estimate the following equation:

$$\begin{aligned} ln(spread_{it}) =& ln\left(1 - min\left\{\left(\alpha^T \frac{k_{it}^T}{b_{it-1}\left(1+r_{it}\right)} + \alpha^I \frac{k_{it}^I}{b_{it-1}\left(1+r_{it}\right)}\right), 1\right\} + c\right) \\ &+ ln(PD_{it}) + ln(\nu_{it}). \end{aligned} \tag{8}$$

Table 5 shows the results. Similar to Table 4, results in the first column are obtained using the CRIF PD measure, whilst column 2 shows the results obtained using Altman Z-scores as a proxy

[13]In our baseline specification, the number of instruments is equal to the number of parameters, and hence we cannot conduct the Hansen test.

for default probability. Interestingly, the estimated α^I is negative and significant, around -0.02 for the shorter time series and -0.05 for the full sample. This implies that an increase in intangible capital relative to debt is associated with *higher* financing costs. As discussed above, the negative coefficient is consistent with further frictions, arising from indirect effects of low recovery rates, or other channels. An example of the former would be a case in which intangible intensive firms are less able to access collateralised borrowing, or have to borrow from lenders charging higher mark-ups, due to the lack of collateral. The latter could include other channels such as intangible investment being riskier.

Table 5: Structural parameter estimates (separately)

	(1)	(2)	(3)
α^T	0.0310***	0.0359***	0.0512***
	(0.00574)	(0.00510)	(0.00279)
α^I	-0.0231***	-0.0245***	-0.0513***
	(0.00379)	(0.00383)	(0.00221)
PD	0.208***	-0.0106***	-0.00978***
	(0.0369)	(0.00255)	(0.00135)
constant	-2.816***	-3.762***	-3.819***
	(0.173)	(0.0540)	(0.0329)
Observations	9,390	9,390	108,308
Industry & Year FE	Yes	Yes	Yes

Notes: This table shows structural parameter estimates obtained by non-linear GMM estimation of equation (8). The dependent variable in all regressions is the firm interest rate spread. Estimates in column 1 are obtained using the CRIF PD measure, which has good coverage for years 2016-2020. In column 2, the Altman Z-score is used a default probability proxy, for the same sample as in column 1 (years 2016-2020). Estimates in column 3 reflect the full sample (years 2000-2020), using Altman Z-scores as the PD variable. All regressions include industry and year fixed effects. Standard errors are given in parentheses and are clustered at the firm level. Stars indicate significance at standard levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

We proceed by investigating the negative α^I coefficient further. We add controls, similar to the robustness check performed for the baseline specification. The results are reported in Appendix C1. We find that this has a very limited effect on our estimates. If anything, the coefficient on intangible capital is *more* negative, though the difference is small. We also perform the same estimation using an intangible capital measure that excludes externally purchased intangibles, as these consist mainly of goodwill which may have particularly low pledgeability. The coefficients remain very similar.

We know from the reduced form regressions conducted in Section 4.2 that intangible intensity is associated with a larger fraction of short term debt. Next, we investigate if the parameters in

Table 6: Impact of debt maturity on estimates

	(1)	(2)
$\frac{k^T}{Rb}$	0.0310***	0.0638***
	(0.00574)	(0.00999)
$\frac{k^T}{Rb}$ x ST		-0.0446*
		(0.0221)
$\frac{k^I}{Rb}$	-0.0231***	-0.0303**
	(0.00379)	(0.00977)
$\frac{k^I}{Rb}$ x ST		-0.00177
		(0.0177)
PD	0.208***	0.206*
	(0.0369)	(0.0870)
PD x ST		0.0225
		(0.165)
ST		-0.395
		0.746
constant	-2.816***	-2.568***
	(0.173)	(0.400)
Observations	9,390	9,390
Industry & Year FE	Yes	Yes

Notes: This table shows structural parameter estimates obtained by non-linear GMM estimation of equation (8), allowing for different coefficients (α parameters, default probability coefficients and constant term) for short-term and long-term debt. The dependent variable in all regressions is the firm interest rate spread. Estimates are obtained for the shorter sample (2016-2020) for which the CRIF default probability variable is available. Column 1 reports estimates for the baseline specification, column 2 reports estimates including interaction terms with the proportion of short term debt and the independent variables. Both regressions include industry and year fixed effects. Standard errors are given in parentheses and are clustered at the firm level. Stars indicate significance at standard levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

equation (8) (α^T, α^I, PD coefficient and/or constant) are different for short term and long term debt. We do this by interacting the proportion of short term debt with tangible capital-to-debt, intangible capital-to-debt and default probability, and adding the proportion of short term debt as a control. The results are shown in Table 6. We find that the α^T parameter is significantly larger for long-term debt than for short-term debt. This is consistent with the hypothesis that long-term debt is more likely to be collateralised, and lenders might expect to recover a larger proportion of (tangible) assets in the event of default. The remainder of the interaction terms are not statistically significant, hence we we do not reject the hypothesis that the α^I parameters, PD coefficients and the constant term are the same for short and long term debt. We find that α^I is negative and significant for both types of debt. Hence, differences in loan maturity between intangible and tangible intensive firms does not seem to explain the negative coefficient on intangibles.

The negative coefficient could, however, capture other differences in the type of debt used by intangible and tangible intensive firms beyond loan maturity. As mentioned above, intangible intensive firms may be relying more on uncollateralised loans, resulting in a lower estimated α^I. Our dataset does not include information on loan collateralisation, and hence we cannot directly control for the proportion of collateralised and uncollateralised debt. The split into short term and long term debt above may not be sufficient to capture the impact of differences in the use of collateralised and uncollateralised loans. For example, our dataset is likely to also include long term loans that are not collateralised; and if the long-term debt held by intangible intensive firms is less often collateralised than the long-term debt of tangible intensive firms, this could again result in a negative α^I coefficient.

Indeed, Holttinen (2025) shows that explicitly allowing for differences in loan terms for uncollateralised and collateralised loans in the model results in estimated α^T and α^I parameters that are both positive. Importantly, the estimated α^T is still significantly larger than the estimated α^I. This is consistent with the hypothesis that the negative coefficient estimated here could capture differences in the use of collateralised loans between intangible and tangible intensive firms.[14]

Apart from the presence of these potentially amplifying mechanisms, the low collateral value of intangibles - or the pure collateral channel - can also be an important driver of our results. There are several reasons why the estimated recovery rate for intangible capital is a lot lower than what the findings in Kermani & Ma (2023) suggest, owing to differences in the definition of intangible capital as well as differences in methodologies and the sample. Firstly, our measure of intangibles includes internally generated intangible capital (and goodwill in the baseline specification), which are likely to be much less pledgeable than externally purchased intangible assets included in the analysis of Kermani and Ma. Secondly, our dataset is for the UK, whereas Kermani and Ma analyse US companies. Kermani and Ma find a large industry dispersion in the liquidation values of firm assets; part of the differences in the results obtained here could also reflect a different industry composition of UK firms compared to the US. Therefore, even if our estimates reflect 'pure' recovery rates, it is likely that our estimates would differ from those of Kermani and Ma.

Finally, in addition to other mechanisms beyond the collateral channel mentioned earlier, our estimates can capture additional reasons why intangibles may be less suitable to use as collateral than tangible assets, irrespective of differences in pure liquidation rates. For example, there could

[14] Lastly, beyond reflecting 'pure' recovery rates, the α coefficients could capture additional legal or monitoring costs that occur to the lender.

be higher uncertainty regarding the valuation of intangibles. Additionally, legal frameworks could affect lending terms to different types of capital differently. Our estimation method would pick up these additional effects influencing the relative pledgeability of intangibles. However, our modelling approach reflects that we do not view the underlying structural parameters as being directly determined by these indirect mechanisms which will contribute to financing conditions more generally and are outside the scope of our model.

6 Concluding remarks

We investigate if it is harder for firms to borrow against intangible capital. We propose a novel way of identifying firm credit constraints in the debt market. Our theoretical framework combines a standard collateral constraint with a no-arbitrage condition on firm debt. In the event of default, the lender recovers a fraction of the firm capital stock. The risk of default is priced competitively, such that the return on a loan equals the risk-free rate. These conditions result in a relationship between the firm credit spread and capital-to-debt ratio, which varies with intangible intensity. Specifically, the model predicts that the sensitivity of firm financing costs to firm capital-to-debt ratio should be decreasing in firm intangible intensity, if intangible intensive firms face worse financial frictions. Intuitively, this is because increasing the capital-to-debt ratio relaxes the borrowing constraint less for firms whose capital is more intangible.

We estimate the structural parameters that govern the impact of tangible and intangible capital on the firm borrowing constraint, using a large panel of UK firms. We find that increasing the tangible capital stock loosens the firm borrowing constraint more effectively than increasing intangible capital. The difference is statistically and economically significant: a one standard deviation increase in intangible intensity increases the firm interest rate by 126 basis points for the average firm in our sample. This implies that it is indeed harder to borrow against intangible assets. Importantly, our results identify borrowing constraints conditional on firms' existing capital stock and its composition. We cannot infer whether firms would also face different interest rate schedules for new investment, conditional on intangible intensity, so this remains an important question to address.

Moreover, our estimates show that whilst increasing the tangible capital stock loosens the borrowing constraint, a higher intangible capital stock is associated with a *tighter* borrowing constraint. If the parameter estimates reflected pure recovery rates on different types of capital, we would expect the lower bound for the parameters to be zero. The negative and significant coefficient on intangible capital is therefore likely to reflect indirect, amplifying effects resulting from the lack of collateral, including intangible intensive firms relying more heavily on uncollateralised lending. In addition, our estimates could capture additional channels beyond the differences in recovery rates on different types of assets. For instance, if intangible assets are harder to value; there is more uncertainty regarding the quantity or price of intangible capital; or intangible investment is associated with higher risk, these effects would make the parameter estimate smaller, possibly even negative. Disentangling the contribution of these channels in future work will help us refine the borrowing constraint related to intangible capital.

Our results are consistent with the view that tangible capital loosens the firm borrowing constraint more effectively than intangibles. Holttinen (2025), building on our results, shows that financing frictions related to intangibles can result in sizeable output, investment and productivity losses. However, while our empirical findings suggest that the friction faced by most firms in the economy may be larger than what other studies have suggested when taking into account SMEs, due to the partial equilibrium framework used in this paper, we cannot quantify the macroeconomic implications arising from the estimated financial friction directly. It is therefore beyond the scope of our analysis to shed light on macroeconomic effects or any optimal policy or regulatory responses to these frictions. In particular, our results do not tell us whether or not intangible intensive firms can obtain the funds they need to reach their optimal levels of investment. If they cannot, there could be multiple tools through which policymakers could address these frictions, which are not present in our model. Hence, we abstract from these questions, and leave these for future research.

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A Data

A.1 Intangible capital

It is not straightforward to measure the firm intangible capital stock, as most of intangible capital is not reported on the firm balance sheet. A proxy for the replacement value of intangible capital can be obtained by capitalising research and development (R&D) and selling, general and administrative (SG&A) expenses, as in Peters & Taylor (2017) and Falato et al. (2020), and adding reported intangibles. Our dataset does not report SG&A expenses directly, and hence we use the following formula for SG&A: SG&A = gross profit − operating profit − depreciation. For robustness, we also use reported administrative expenses as a second SG&A proxy. Our baseline intangible capital stock measure includes externally purchased intangible capital (reported on the firm balance sheet), however, we also conduct robustness checks using an intangible capital stock measure that excludes reported intangibles.[15]

Figure 3 in the main text plots the mean intangible intensity over our sample period, defined as the intangible capital stock over total capital (intangible plus tangible), for our baseline intangible capital measure and three alternative proxies (with the alternative SG&A proxy, and with and without externally purchased intangibles). The different approaches to estimate SG&A do not result in significantly different trends; there seems to be mainly a level effect. Excluding externally purchased intangibles (mainly goodwill), on the other hand, has a bigger impact. We can see that most of the hump in intangible intensity prior to 2010, and the following decline, were largely driven by externally purchased intangible assets.

A.2 Interest rate proxy

We do not have loan level data, and hence use a proxy for the firm interest rate in order to construct the firm interest rate spread. The proxy is obtained by dividing interest expenses by total debt. For this period's interest rate, we use interest expenses for the current reporting period, divided by an average of total debt at the end of last period and debt at the end of the current period. This is because interest expenses this period are likely to reflect interest payments made on existing debt as well as new debt. For the risk-free rate, we use one year and five year UK government bond yields, and construct a weighted average of these to reflect the proportion of short term and long term debt at the firm level. The interest rate proxy is quite noisy; we proceed by discarding the top and bottom 5% of observations in order to exclude large outliers. The resulting variable looks sensible: Figure 2 in the main text plots the average interest rate (mean and median) against the one year and five year government bond yields.

[15] Reported intangible assets consist of externally purchased intangible capital, which is mainly goodwill. In our dataset, we cannot separate goodwill from other externally purchased intangible assets. Hence, as a robustness exercise, we use an intangible capital stock measure that excludes all reported intangible assets.

A.3 Default probability measures

Firm specific default probabilities (PD) are also not straightforward to obtain. We use two different PD proxies in our analysis. The first is based on credit scores by CRIF Decision Solution Limited and Jordans, included in the BvD data used to construct our other variables. For this variable, we only have good coverage of firms for a limited number of years (2016 to 2020). These years have nevertheless good coverage, with approximately 85% of firm-year observations having non-missing values. The PD values are also of sensible magnitudes: mean default probability for all firms is 6.86%; 6.9% for SMEs and 2% for large corporations.

We use Altman Z-scores as our second default probability proxy. Altman Z-scores are widely used to gauge firm financial health and the likelihood of bankruptcy. The framework was developed in the seminal work of Altman (1968), and is based on five financial ratios (profitability, leverage, liquidity, solvency, and activity) to predict whether a company has a high probability of becoming insolvent. There are separate formulas for public and private companies, as well as firms in manufacturing and other industries. The resulting score is interpreted against specific reference values. Firms with Z-scores below the high-risk cut-off have a heightened likelihood of default, whereas Z-scores above the low-risk mark signall good financial health. Firms with a Z-score falling between the high- and low-risk reference figures, or cut-offs, are judged to be medium risk. In our baseline estimation, we use a capped Altman Z-score, with a lower bound of zero (the high-risk cut-off), and an upper bound given by the approriate low risk cut-off depending on company type.

A.4 Firm characteristics by intangible intensity

We explore if intangible and tangible intensive firms differ in terms of their characteristics, specifically by their size and age. Previous studies have found that intangible intensive firms tend to be younger and smaller. Table A.1 shows how firm age, number of employees and total assets (with and without estimated intangible capital) vary with firm intangible intensity. Consistent with previous work, we find that the most tangible intensive quartile is older, and larger in terms of total assets, than the other quartiles. However, these firms are slightly smaller in terms of number of employees. The rest of the quartiles do not display any obvious relationship between intangible intensity and firm age and size.

Table A.1: Firm characteristics by intangible intensity

Quartile	Intangible Intensity	Age	Employees	Total Assets	Total Assets Inc Intan
1	0.14	10	8	387	399
2	0.57	6	17	121	135
3	0.84	5	14	88	109
4	0.97	6	11	109	153

Source: BvD data, author calculations.

A.5 Firm finance by intangible intensity

Previous studies have found that higher levels of intangible capital are associated with less debt financing and higher cash holdings. This is also the case in our sample. Table A.2 shows how the following variables differ by intangible intensity, with quartile 1 being most tangible intensive and quartile 4 being most intangible intensive: firm leverage (debt-to-capital); intangibles adjusted leverage (debt to total capital including intangibles); interest rate on firm debt (interest expenses over debt), short term debt ratio (short term debt to total debt), cash ratio (cash to total assets), percentage of privately owned firms, and the percentage of firms that have publicly sold some shares at least once in their lifetime.

Table A.2: Finance by intangible intensity

Quartile	Leverage	Leverage Inc Intan	Interest rate (%)	ST Debt ratio	Cash ratio	Privately owned (%)	Equity Finance, % Firms
1	0.28	0.27	4.65	0.60	0.07	99.61	0.32
2	0.25	0.20	5.01	0.92	0.14	99.38	0.25
3	0.21	0.14	4.93	1.00	0.17	99.27	0.22
4	0.19	0.11	4.47	1.00	0.18	98.91	0.23

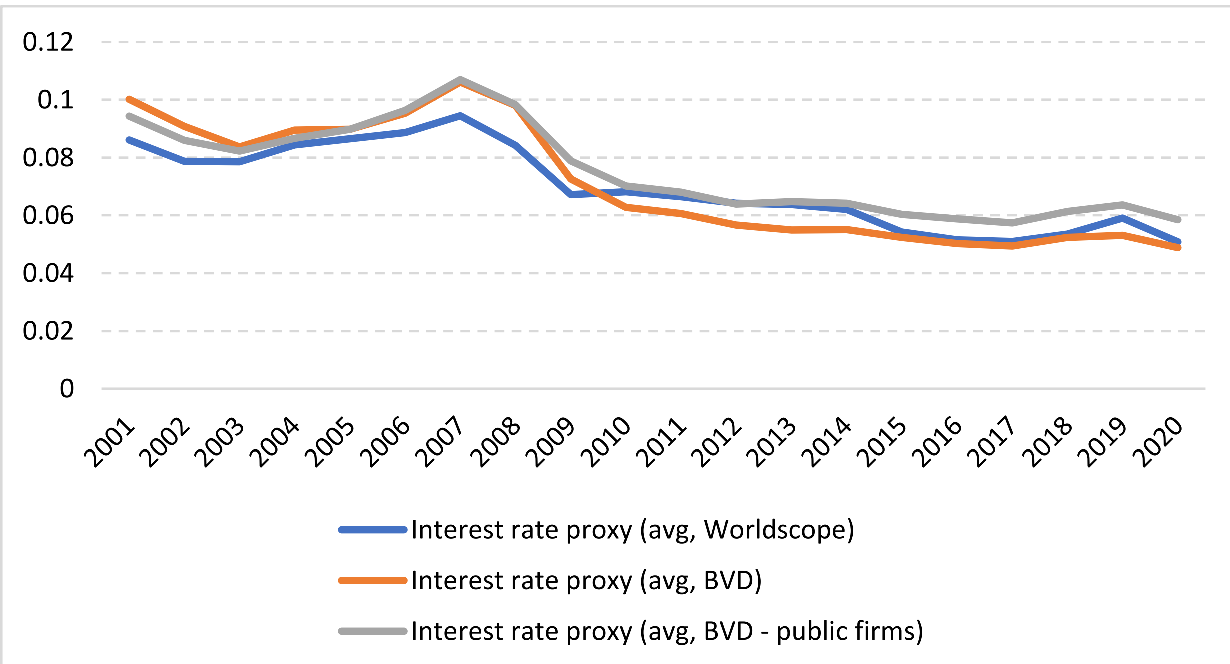
Source: BvD data, author calculations.

Consistent with previous literature, intangible intensive firms in our sample have lower leverage and higher cash ratios. They also tend to borrow shorter term. There are, however, no raw trends in the interest rates paid. We also explore whether intangible intensive firms compensate for less debt financing by selling shares publicly, and find no raw trends in the share of public companies or the proportion of firms who have issued shares. It should be noted that this is only a superficial glance; our data does not capture private equity, financing through mergers and acquisitions, or forms of venture capital that do not include equity sales.

A.6 Comparisons with Worldscope data

We compare our interest rate proxy and spread measure, as well as intangible intensity, with data on publicly listed UK companies from the (LSEG) Worldscope Fundamentals (Worldscope) dataset . Even though our dataset consists mainly of private firms that are smaller and younger than the average publicly listed company, trends in the interest rate proxy are similar. The correlation between the average interest rate proxy for firms in BvD and Worldscope is 0.97; the correlation between the interest rate spread for the whole BvD sample and Worlscope is 0.36. This increases to 0.85 if the BvD sample is restricted to public companies only.

Figure A.1: BvD - Worldscope data comparison: interest rate trends



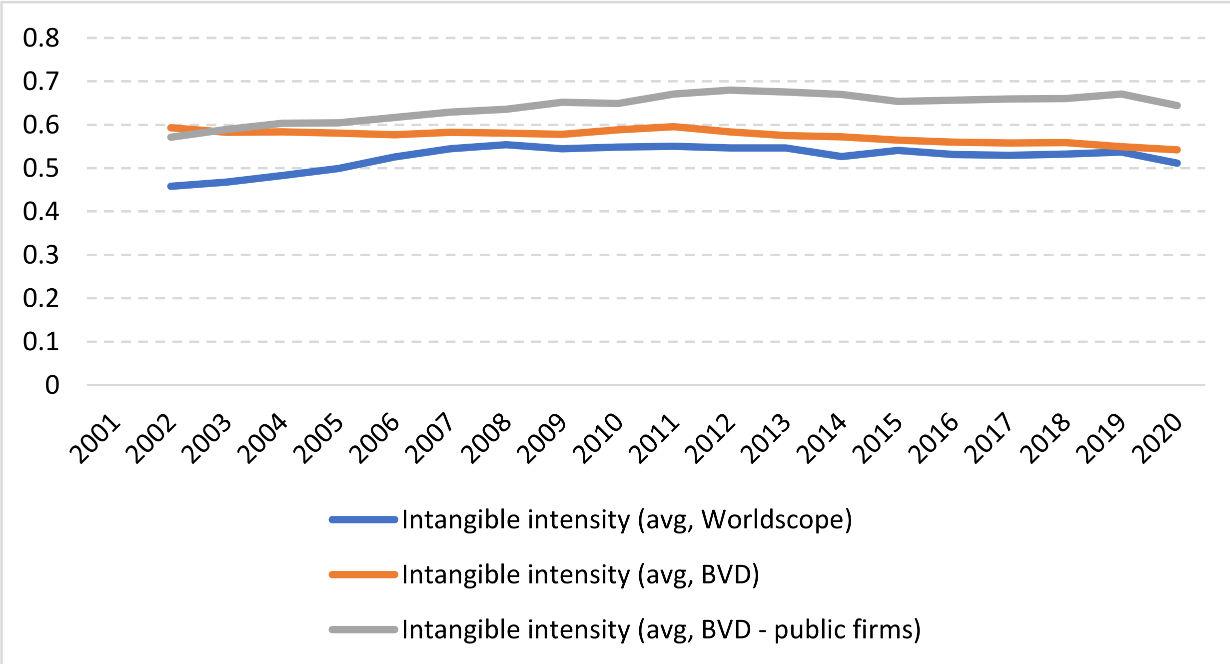
Sources: *BvD data, LSEG Worldscope Fundamentals, author calculations.*

Trends in intangible intensity (intagible capital over total capital) are also similar for public firms in both datasets; the correlation in annual means is over 0.83. There seems to be a difference in the level of intangible intensity between public firms in BvD and the Worldscope dataset. This is likely to be due to the fact that Worldscope reports SG&A expenditures directly, whereas BvD does not (we use the following formula to compute our baseline SG&A proxy: SG&A = gross profit – operating profit – depreciation).

A.7 Estimating the structural equation using OLS

We obtain preliminary estimates of the structural α parameters by using OLS with lagged dependent variables to estimate the following equation:

Figure A.2: BvD - Worldscope data comparison: intangible intensity trends



Sources: *BvD data, LSEG Worldscope Fundamentals, author calculations.*

$$spread_{it} = \gamma PD_{it} - \alpha^T \frac{capital_{it}}{debt_{it}\left(1+r_{it}\right)} PD_{it} + \left(\alpha^T - \alpha^I\right) II_{it} \frac{capital_{it}}{debt_{it}\left(1+r_{it}\right)} PD_{it} + \nu_{it}. \tag{9}$$

This is simply equation (6) without the min-operator, and allowing the coefficient on PD (γ) to be different from 1. The results are outlined in Figure A.3.

When we winsorize capital-to-debt at the standard 1%, the α parameters are insignificant, as can be seen in the first column. However, we have estimated the equation without the min operator; the model predicts that for firms with enough recoverable capital to cover debt, the coefficients should be zero, as the interest rate spread should not respond to changes in capital-to-debt. When we exclude firms with high capital-to-debt ratio (top 5%, 20% and 50% in columns 2, 3, and 4, respectively), α^T and the difference between the α parameters becomes significant. The coefficients also have expected signs. The estimate of the difference between α^T and α^I is positive, supporting the hypothesis that α^I is less than α^T. This means that intangible assets do not loosen financial constraints as effectively as tangible assets do.

This exercise motivates the use of the GMM estimator, as it illustrates the downward bias in the coefficients that is likely to be present if the min-operator in equation(6) is ignored.

	Exclude capital-to-debt in top 1%	Exclude capital-to-debt in top 5%	Exclude capital-to-debt in top 20%	Exclude capital-to-debt in top 50%
PD	0.0881***	0.0533**	0.0836***	0.114***
$-\alpha^T$	0.00337	-0.00717	-0.0558***	-0.0744**
$(\alpha^T - \alpha^I)$	0.00347	0.0377***	0.110***	0.132***
N	13441	13037	11097	6629
adj. R^2	0.037	0.047	0.055	0.075

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
All regressions include industry x year fixed effects
Independent variables are lagged by one period

Figure A.3: Table: Preliminary results using OLS with lagged dependent variables

B Robustness checks

B.1 Robustness of results: changing the fixed cost

Table B1 reports the structural parameter estimates for different values of the fixed bankruptcy cost. The estimates are obtained using the CRIF PD proxy, and hence the shorter time series (for which the PD measure is available). In the baseline specification (column 1), c is set to 0.01 implying that fixed bankruptcy costs are 1% of debt. In columns 2 to 4, we investigate whether our results are robust to changing the fixed cost parameter. We find very similar results when setting $c = 0.02$, $c = 0.05$ and $c = 0.005$ compared to the baseline specification.

B.2 Robustness of results: alternative intangibles measures

Table B2 reports parameter estimates for the baseline specification, for different measures of intangible capital. The estimates are obtained using the CRIF PD proxy, and hence the shorter time series (for which the PD measure is available). Column (1) reports the estimates obtained using the baseline intangibles stock measure, obtained using the SG&A formula[16], and including externally purchased intangibles. Column (2) reports results obtained using the same SG&A measure as in the baseline measure, however, excluding externally purchased intangibles (which consist mainly of goodwill). Estimates reported in Column (3) are ontained using reported Adiministrative expenses as a proxy for SG&A, including externally purchased intangibles. Finally, the fourth column also uses Administrative expenses for SG&A, but excludes reported (externally purchased) intangibles. The signs and magnitudes of all parameters are similar in all columns, illustrating that using alternative measures for intangible capital does not have a significant effect on the results obtained.

[16]SG&A = gross profit – operating profit – depreciation

Table B1: Structural parameter estimates,
Changing the fixed bankruptcy cost

	(1) $c = 0.01$	(2) $c = 0.02$	(3) $c = 0.05$	(4) $c = 0.005$
$-\alpha^T$	-0.0297***	-0.0300***	-0.0309***	-0.0296***
	(0.00552)	(0.00557)	(0.00574)	(0.00549)
$\alpha^T - \alpha^I$	0.0525***	0.0530***	0.0546***	0.0522***
	(0.00822)	(0.00831)	(0.00855)	(0.00818)
PD	0.209***	0.209***	0.209***	0.209***
	(0.0368)	(0.0368)	(0.0368)	(0.0368)
constant	-2.815***	-2.825***	-2.854 ***	-2.810***
	(0.173)	(0.173)	(0.173)	(0.173)
N	9,390	9,390	9,390	9,390

Dependent variable: firm interest rate spread
Column 1: fixed cost set at 1% of debt (baseline)
Column 2: fixed cost set at 2% of debt
Column 3: fixed cost set at 5% of debt
Column 4: fixed cost set at 0.5% of debt
Standard errors in parentheses, clustered at firm level
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
All regressions include industry and time fixed effects

B.3 Robustness checks, extra controls

Table B3 compares our baseline results to those obtained by using additional controls in the GMM estimation. Column (1) reports the baseline estimates, without controls. The estimates are obtained using the CRIF PD proxy, and hence the shorter time series. We first add controls for the following firm characteristics: proxies for firm size (total assets (in logs), and two large firm dummies: Large 1 equals 1 if the firm is in the top decile in terms of total assets; Large 2 equals 1 if the firm has more than 250 employees); firm age (two dummies for old firms: Old 1 equals 1 if the firm is more than 10 years old; Old 2 equals 1 if the firm is in the top decile by age); and a dummy for firms that only have short term debt. Estimates including these controls are reported in Column (2). Finally, we add a dummy for public companies; ROA (return on assets, defined as operating profit to total assets); and the cash ratio (bank deposits over total assets). Estimates for this specification are reported in Column (3). All controls (apart from firm age and being a public company) are lagged to account for potential endogeneity.

It is clear that the parameter estimates of interest (the difference in α parameters, as well as the

Table B2: Structural parameter estimates,
Alternative intan stocks

	(1)	(2)	(3)	(4)
$-\alpha^T$	-0.0297***	-0.0271***	-0.0286***	-0.0280***
	(0.00552)	(0.00625)	(0.00574)	(0.00597)
$\alpha^T - \alpha^I$	0.0525***	0.0451***	0.0471***	0.0439***
	(0.00822)	(0.00952)	(0.00803)	(0.00848)
PD	0.209***	0.206***	0.214***	0.204***
	(0.0368)	(0.0368)	(0.0354)	(0.0350)
constant	-2.815***	-2.831***	-2.814***	-2.858***
	(0.173)	(0.173)	(0.168)	(0.166)
N	9,390	9,383	9,752	9,815

Dependent variable: firm interest rate spread
Column 1: Baseline intan measure
Column 2: Intan measure exlcudes reported intangibles
Column 3: Intan constructed with admin expenses
Column 4: Intan with admin expenses, excluding reported intangibles
Standard errors in parentheses, clustered at firm level
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
All regressions include industry and time fixed effects

PD coefficient and estimated α^T) are robust to controlling for a broad range of firm characteristics. The signs and magnitudes of these parameters are very similar accross the different specifications. We conclude that controlling for firm characteristics does not affect our the estimation of the parameters of interest in a meaningful way.

B.4 Robustness to alternative instruments

Table B4 shows the results of the structural parameter estimates using different instruments. The first column reports the baseline estimates, which use the lags of the logarithm of capital-to-debt as well as intangible intensity times capital-to-debt as instruments. In the second column, the logarithm of the share of intangible investment to total investment (lagged by one period) is added as an extra instrument, which allows us to test for instrument validity by using Hansen's J-test of overidentifying restrictions. The p-value is high, meaning that the null hypothesis of instrument validity is not rejected.

Column (3) and Column (4) use the levels of (lagged) capital-to-debt and intangible intensity times capital-to-debt as instruments instead of the logarithm. The resulting coefficient estimates are qualitatively similar, though slightly smaller. In Column (4), the intangible investment share is again added as an extra instrument. The test of overidentifying restrictions does not reject the null of instrument validity.

B.5 Convergence: robustness of GMM estimates to using different starting values

Table B5 shows the results of the GMM-estimation routine, using different starting values. The first column uses starting values of 0 for all coefficients; in Column (2) estimation starts at 0.1 for all main coefficients (α^T, $\alpha^T - \alpha^I$, and the default probability coefficient). The rest of the columns (3 to 7) have starting values of 0.25, 0.5, 0.75 and 0.9 and 1 respectively, for all main coefficients. The table illustrates that the GMM-estimator converges to the same results, regardless of the starting values selected.

C Drivers of the negative coefficient on intangibles

C.1 Adding controls

Table B3: Structural parameter estimates, controls

	(1)	(2)	(3)
$-\alpha^T$	-0.0297***	-0.0302***	-0.0297***
	(0.00552)	(0.00557)	(0.00569)
$\alpha^T - \alpha^I$	0.0525***	0.0585***	0.0581***
	(0.00822)	(0.00845)	(0.00881)
PD	0.209***	0.216***	0.209***
	(0.0368)	(0.0426)	(0.0453)
Total assets (log)		-0.000391	-0.0106
		(0.0113)	(0.0122)
Large 1		0.190***	0.179***
		(0.0439)	(0.0445)
Large 2		-0.0334	-0.0368
		(0.0285)	(0.0287)
Old 1		-0.0978***	-0.107***
		(0.0258)	(0.0261)
Old 2		-0.0212	-0.0322
		(0.0274)	(0.0277)
ST debt		-0.158 ***	-0.155***
		(0.0386)	(0.0390)
Public			0.137***
			(0.0399)
ROA			-0.0755
			(0.159)
Cash ratio			-0.204
			(0.109)
constant	-2.815***	-2.705***	-2.599***
	(0.173)	(0.178)	(0.183)
N	9,390	9,280	9,140

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

All regressions include industry and time fixed effects

Standard errors clustered at firm level

Table B4: Structural parameter estimates,
Alternative instruments

	(1)	(2)	(3)	(4)
$-\alpha^T$	-0.0297***	-.0273***	-.0168***	-.0165***
	(0.00552)	(0.00572)	(0.00459)	(0.00443)
$\alpha^T - \alpha^I$	0.0525***	0.0476***	0.0299***	0.0296***
	(0.00822)	(0.00814)	(0.00637)	(0.00620)
PD	0.209***	0.198***	0.216***	0.214***
	(0.0368)	(0.0394)	(0.0364)	(0.0372)
constant	-2.815***	-2.854***	-2.812***	-2.814***
	(0.173)	(0.183)	(0.172)	(0.175)
N	9,390	8,554	9,390	9,212
Hansen's J-test	-	0.000123	-	2.687
J-test p-value	-	0.991	-	0.101

Dependent variable: firm interest rate spread
Column 1: Baseline instruments
Column 2: Extra instrument: intangible investment share (lagged by one period)
Column 3: Instruments in levels instead of logs
Column 4: Instruments in levels, including extra instrument
(lagged intangible investment share)
Standard errors in parentheses, clustered at firm level
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
All regressions include industry and time fixed effects

Table B5: Convergence of GMM estimator

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$-\alpha^T$	-0.0297***	-0.0297***	-0.0297***	-0.0297***	-0.0297***	-0.0297***	-0.0297***
	(0.00552)	(0.00552)	(0.00552)	(0.00552)	(0.00552)	(0.00552)	(0.00552)
$\alpha^T - \alpha^I$	0.0525***	0.0525***	0.0525***	0.0525***	0.0525***	0.0525***	0.0525***
	(0.00822)	(0.00822)	(0.00822)	(0.00822)	(0.00822)	(0.00822)	(0.00822)
PD	0.209***	0.209***	0.209***	0.209***	0.209***	0.209***	0.209***
	(0.0368)	(0.0368)	(0.0368)	(0.0368)	(0.0368)	(0.0368)	(0.0368)
constant	-2.815***	-2.815***	-2.815***	-2.815***	-2.815***	-2.815***	-2.815***
	(0.173)	(0.173)	(0.173)	(0.173)	(0.173)	(0.173)	(0.173)
N	9390	9390	9390	9390	9390	9390	9390

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
All regressions include industry and time fixed effects
Standard errors clustered at firm level

Table C1: Structural parameters separately, controls

	(1)	(2)	(3)
α^T	0.0310***	0.0326***	0.0311***
	(0.00574)	(0.00574)	(0.00598)
α^I	-0.0231***	-0.0290***	-0.0288***
	(0.00379)	(0.00423)	(0.00460)
PD	0.208***	0.214***	0.208***
	(0.0369)	(0.0428)	(0.0455)
Total assets (log)		-0.000241	-0.0104
		(0.0112)	(0.0122)
Large 1		0.190***	0.179***
		(0.0439)	(0.0445)
Large 2		-0.0351	-0.0378
		(0.0284)	(0.0285)
Old 1		-0.0969***	-0.106***
		(0.0258)	(0.0262)
Old 2		-0.0192	-0.0309
		(0.0385)	(0.0278)
ST debt		-0.157 ***	-0.154***
		(0.0385)	(0.0389)
Public			0.136***
			(0.0397)
ROA			-0.0757
			(0.159)
Cash ratio			-0.201
			(0.110)
constant	-2.816***	-2.708 ***	-2.601***
	(0.173)	(0.178)	(0.183)
N	9,390	9,280	9,140

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

All regressions include industry and time fixed effects

Standard errors clustered at firm level