Capital Allocations in Closed and Open Economies

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Lincoln College

University of Oxford

Thesis submitted for the degree of

Doctor of Philosophy in Economics

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This thesis consists of three self-contained essays on the allocation of capital, applied in the context of closed and open economies. Chapter 1 explores whether the rising share of intangible capital leave firms with less loan collateral, hence tightening firm borrowing constraints. Using a large sample of UK firms, the structural parameters governing the pledgeability of intangible and tangible capital are estimated. The results suggest that the collateral value of intangibles is significantly lower than the collateral value of tangible assets, consistent with the view that it is harder to borrow against intangible capital. Building on these results, Chapter 2 investigates the impact of the low collateral value of intangibles on aggregate productivity and resource allocation. I construct a model with heterogeneous firms facing financial constraints and using tangible and intangible capital in production. In addition to reducing investment and employment, the low collateral value of intangibles amplifies opposing mechanisms that have previously been overlooked. On the one hand, the financing friction reduces productivity by limiting default and exit of less productive firms. On the other hand, the presence of intangibles leads to a tighter connection between firm financing costs and productivity. Quantitatively, the former effect dominates and financial constraints have a negative impact on the economy – much larger than when intangibles are ignored. Finally, Chapter 3 explores the allocation of capital in an open economy context. I examine the ability of frictionless open economy models to generate empirically consistent patterns in gross capital flows. Through the lens of a simple two-country model, I find that standard shocks change hedging properties of assets, resulting in positively correlated capital flows and the puzzling “retrenchment" of domestic capital following adverse domestic shocks.

Supervisors This thesis was supervised by Professor Andrea Ferrero, and by Professor Guido Ascari in the early stages of research.

Total words This thesis contains approximately 69,454 words. This corresponds to 574 words per 121 pages. The representative page used for counting the number of words is page number 3.

Statement of authoship The work in this thesis is based exclusively on research carried out during my time as a DPhil student at the University of Oxford between October 2018 and April 2025. No part of this thesis has been submitted for a degree at the University of Oxford or any other university. Chapter 1 is joint work with Marko Melolinna and Maren Froemel. Chapters 2 and 3 are single-authored and are fully my own work.

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Sara Holttinen
Oxfordshire, April 2025

Contents

CHAPTER 1

Impact of Intangible Capital on Firm Borrowing Constraints

with **Marko Melolinna** and **Maren Froemel***

Abstract Intangible assets have become increasingly important in modern economies. Does the rising share of intangibles leave firms with less loan collateral, hence tightening firm borrowing constraints? We study the impact of intangible capital on firm borrowing, and propose a novel way of identifying credit constraints in the debt market. Our empirical strategy builds on a theoretical framework combining a standard asset-based lending contract with a no-arbitrage condition on firm debt. 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 more difficult to pledge as collateral. Intuitively, increasing the capital-to-debt ratio relaxes the borrowing constraint less for firms whose capital is more intangible, if lenders are less able to liquidate intangible assets. Using a large sample of UK firms, we estimate the structural parameters governing the pledgeability of intangible and tangible capital. The results suggest that the collateral value of intangibles is significantly lower than the collateral value of tangible assets, consistent with the view that it is harder for firms to borrow against intangible capital.

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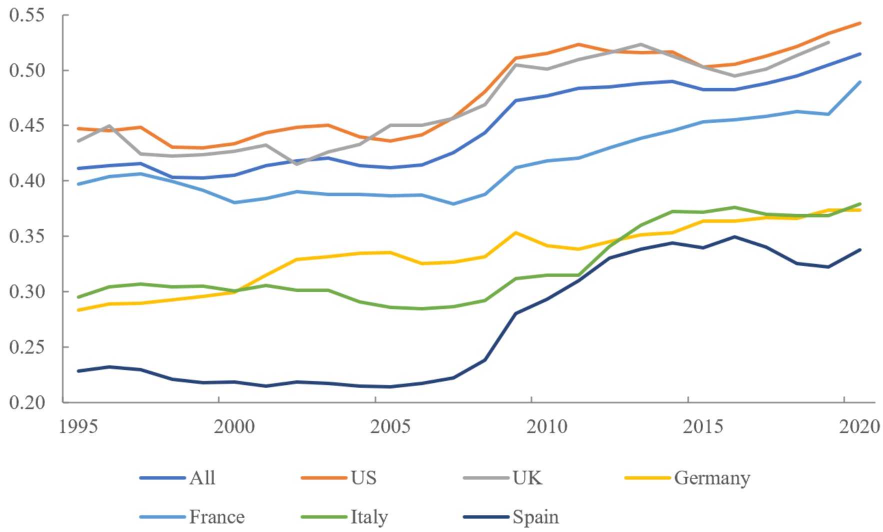
1.1 Introduction

Intangible assets, including patents, brands, software, organisational design and distribution networks, have become increasingly important in modern economies. Figure 1.1 illustrates the upward trend in the share of intangibles in total business investment for the US, UK, and the four largest EU countries.[1] Whilst tangible assets such as property, equipment or machinery can often be used as loan collateral, banks and investors could be more reluctant to lend against intangibles if they are very firm specific or have a more uncertain liquidation value (Williamson (1988); Shleifer and Vishny (1992); Hart and Moore (1994)). The rise of intangibles may therefore have resulted in a tightening of firm credit constraints by reducing the proportion of firm assets that are suitable to be used as loan collateral.

Figure 1.1: Rise of intangibles



Source: EUKLEMS & INTANProd data, author calculations. For more information on the database, see Bontadini et al. (2023). The graph shows the share of intangible business investment in total business investment (intangible + tangible) over time for the US, UK and the largest four EU countries (Germany, France, Italy and Spain), as well as the total for these countries.

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 and Rajan (1998); Morellec (2001)). On the other hand, pledging collateral that is more valuable to the firm than the lender may ease credit mar-

[1] Similar trends have been documented by Corrado and Hulten (2010), Corrado et al. (2012), Corrado et al. (2013), Corrado et al. (2016), Andrews and Serres (2012) and Demmou et al. (2020).

ket frictions, by aligning incentives or by signaling the quality of the borrower (Bester (1985); Bester (1987); Boot and Thakor (1994)). Finally, recent evidence by Kermani and Ma (2023) shows that the recovery rates of some intangible assets may not be very different to those of tangible assets. Therefore, it is not ex ante obvious whether it is significantly harder for firms to borrow against their intangible capital stock compared to their tangible capital.

In this paper, we propose a novel way of identifying firm borrowing constraints from a structural relationship between the firm interest rate, debt-to-capital ratio and default probability, derived by combining a standard asset-based lending contract with a no-arbitrage condition for the lender. Estimating this relationship using a large panel of UK companies allows us to identify the proportions of different types of firm assets that can be used as loan collateral. Our results show that the average firm level intangible capital stock, consisting of a broad range of intangibles, has a significantly lower collateral value (13%) than that of tangible capital (38%). The estimation circumvents multiple issues associated with identifying firm financing frictions, as it is robust to potentially different adjustment costs on intangible and tangible capital and different investment opportunities. In addition, no assumptions regarding the firm production function or the set of firms that are (un)constrained are required.

The firm borrowing constraint takes the form of a firm-specific interest rate schedule. The schedule is derived from a standard financing friction commonly used in the macro-finance literature: lenders can recover a fraction of firm capital, or the loan collateral, in the event of default. Allowing firms to borrow beyond the amount of collateral they have exposes the lender to a risk of losses. The risk is priced competitively, such that the expected return on the loan equals the risk free rate. This results in a relationship between the firm interest rate, capital-to-debt ratio and default probability, which characterises the borrowing constraint. The collateral values enter the borrowing constraint, as they dictate how much firms can borrow against different types of capital, intangible and tangible, before incurring higher financing costs. Building on our recent work (Holttinen et al. (2025)), we add a distinction between collateralised and uncollateralised lending. This helps to account for the large share of smaller loans in the dataset, which are likely to be uncollateralised.

Our estimation 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 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 balance sheet data for a large panel of UK companies to estimate the borrowing constraint. Financing frictions related to intangibles are likely to be particularly relevant in the UK, due to the high levels of intangible investment combined with the prevalence of asset-based lending.[2] We construct a firm-level intangible capital measure from balance sheet and income statement data, following the state-of-the-art in the literature (Peters and Taylor (2017); Falato et al. (2022)).

Our dataset consists largely of private SMEs, for which borrowing constraints are likely to be particularly relevant. Before proceeding with the structural estimation, we follow Holttinen et al. (2025) and 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.

We find that there is indeed a stark difference in the collateral values of intangible and tangible assets. The estimated proportion of tangible capital that can be pledged as collateral is 38.1%, which is within the range of previous estimates in

[2]The US has a similar share of intangible investment to the UK, however, cash-flow based lending is more common, partly due to the lower chance of asset liquidation in the event of bankruptcy (between 2019 and 2023, 49.5% of bankruptcies in the US resulted in liquidations, compared to 90% in the UK). On the other hand, many European countries also exhibit a higher share of asset-based lending than the US, however, the share of intangibles is also lower. *Data sources:* S&P Global Market Intelligence 2024; UK government statistics on company insolvencies; international comparison of intangible investment shares based on author calculations using EUKLEMS & INTANProd data.

the literature (Berger et al (1996); Kermani & Ma (2023)). On the other hand, the estimated proportion of intangibles that can be pledged is significantly lower at 13.4%. The results are robust to using alternative intangible capital measures, and are obtained controlling for differences in debt maturity[3] and other firm characteristics commonly associated with financing frictions (such as firm age, size, profitability and cash holdings). Our results imply that intangible intensive firms have significantly less loan collateral than a tangible intensive firm with a similar sized capital stock. Hence, an intangible intensive firm faces a tighter borrowing constraint than a tangible intensive firm, conditional on having the same default probability and total capital-to-debt ratio.

The estimated difference in the collateral value parameters is also economically significant. A one standard deviation increase in intangible intensity is associated with an increase in the firm interest rate by 2.97 percentage points for collateralised loans. This is effect is large compared to the mean firm interest rate for our sample, approximately 4.8%, with a standard deviation of 4.3 percentage points.

1.1.1 Related literature

Our work contributes to two strands of literature. Firstly, we contribute to the large literature on measuring firm financial constraints, which are not directly observable. The most common ways to estimate financial constraints can be roughly divided into five 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 and Petersen (1994); Bond and Meghir (1994); Calomiris and Hubbard (1995); Gilchrist and Himmelberg (1995); Kaplan and Zingales (1997)). Others have used Euler-equation based identification (Whited (1992); Hubbard et al. (1995); Whited and Wu (2006)), or combined survey data with firm balance sheet information to construct indices relating to firm financial constraints (Lamont et al. (2001); Hadlock and 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 and Duflo (2014); Farre-Mensa and Ljungqvist (2016)). Bau and Matray (2023) and others use firm marginal revenue product of capital to determine how financially constrained a firm is. Finally, a recent strand of the

[3] Intangible intensive firms tend to use more short term borrowing.

literature (e.g. Cloyne et al. (2023), Ottonello and 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 the firm interest rate spread and capital-to-debt ratio.

We also add to the literature on intangible capital and financing constraints. Most existing work supports the hypothesis that intangible intensive firms are more credit constrained (Almeida and Campello (2007), Sibilkov (2009), Chen (2014), Lei et al. (2018), Demmou et al. (2019), Demmou et al. (2020), Dell'Ariccia et al. (2021), Falato et al. (2022), Lee and Paluszynski (2022), Boler et al. (2023), Holttinen et al. (2025)). However, Kermani and Ma (2023) show that some intangibles have similar liquidation rates to tangible assets. In contrast to Kermani and Ma (2023), our results are consistent with the view that the collateral value of tangible capital is significantly higher than that of intangibles. One possible reason for the lower estimate of the collateral value of intangibles is the fact that our measure of intangible capital captures a much broader range of intangible assets, whereas the dataset of Kermani & Ma is restricted to a much narrower set of *separable* intangibles, included in the valuation of firm assets for the purpose bankruptcy proceedings. To the best of our knowledge, we are the first to provide estimates of the suitability of the intangible capital stock as loan collateral, including a broader range of intangible assets, as our analysis is not restricted to intangible assets reported on the firm balance sheet.

Holttinen et al. (2025) develop a novel way to estimate firm borrowing constraints from a structural relationship between the firm interest rate, capital-to-debt ratio and default probability. They find that whilst tangible capital loosens the constraint, intangible capital tightens it. We build on this framework by distinguishing between collateralised and uncollateralised lending in the model. This leads to a better identification of the collateral value parameters, as the potentially large share of uncollateralised debt is accounted for. Indeed, the collateral values estimated have expected signs and magnitudes, and do not reflect the impact of intangible intensive firms using more uncollateralised lending.

The rest of the paper is organised as follows. In section 1.2 we present our theoretical framework and derive the main empirical specification. Section 1.3 discusses identification challenges and proposed solutions. Section 1.4 reviews our data, and presents results from reduced form estimation. Section 1.5 outlines the results from our structural analysis. Section 1.6 concludes.

1.2 Theoretical framework: endogenous borrowing constraint

In this section, we derive the estimating equation from a firm borrowing constraint. Following Holttinen et al. (2025), the theoretical framework is based on a standard debt-financing friction commonly used in the macro-finance literature, related to the seminal work of Kiyotaki and 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 and Winberry (2020), firms can borrow more than the amount of collateral they have, exposing the lender to a loss in the event of default. The risk of losses to the lender is priced competitively: the expected return on firm debt equals the risk free rate.[4] A simpler, commonly used borrowing constraint arises if firms can borrow at the risk-free rate but only 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 this paper, we chose this framework over the simple borrowing limit, as it characterises a relationship between firm-specific borrowing costs and firm assets.

We build on the framework developed in Holttinen et al. (2025) by introducing a distinction between collateralised and uncollateralised loans. Specifically, we assume that the lender only recovers assets if the loan is collateralised. In order to collateralise a loan, the lender must pay a fixed upfront monitoring cost in order to value firm assets. For uncollateralised loans, there is no initial fixed cost; however, the lender cannot recover firm assets in the event of default. The distinction between uncollateralised and collateralised loans allows for small (often uncollateralised) loans to have different loan terms to larger loans. This enables us to identify the structural α parameters in a cleaner way, as the estimates will better reflect collateral values on different types of assets, instead of capturing potential differences in the use of collateralised lending between intangible and tangible intensive firms. See Appendix A6 for further motivation behind the inclusion of uncollateralised lending into the framework.

For a collateralised loan, the expected payment to the lender next period, minus the cost of providing the loan, is given by

$$E_t[(1-\chi_{it+1})R_{it}b_{it} + \chi_{it+1}min\{\alpha k_{it}, R_{it}b_{it}\} - C] \tag{1.1}$$

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

where χ is an indicator variable taking a value of one if a firm defaults and zero otherwise; R is the gross interest rate on the loan; b is firm debt; k is firm capital stock and C is the valuation cost. Equation (1.1) 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 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 used as loan collateral.[5] For the empirical 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 the entire capital stock is perfectly collateralisable. Hence, $\alpha < 1$ reflects frictions in liquidating firm assets in the event of default, caused by asset specifity (assets being more valuable inside the firm than outside the firm) and other frictions associated with asset liquidation.

For uncollateralised loans, the expected payment is simply

$$E_t[(1-\chi_{it+1})R_{it}b_{it}] \tag{1.2}$$

as the lender recovers nothing in the event of default.

Assuming a profit maximising lender, offering the contract with the higher expected payment, equations (1.1) and (1.2) can be combined into a single equation:[6]

$$E_t[(1-\chi_{it+1})R_{it}b_{it}] + max\{E_t[\chi_{it+1}min\{\alpha k_{it}, R_{it}b_{it}\}] - C, 0\}. \tag{1.3}$$

Next, we derive the empirical specification that allows us to identify the collateral value parameter, α, from equation (1.1). Dividing equation (1.3) by b results in the expected return on the loan. Assuming a perfectly competitive lender, the expected return on the loan equals the risk-free rate, R^f:

$$E_t\left[(1-\chi_{it+1})R_{it}\right] + max\left\{E_t\left[\chi_{it+1}min\left\{\frac{\alpha k_{it}}{b_{it}}, R_{it}\right\}\right] - \frac{C}{b_{it}}, 0\right\} = R_t^f \tag{1.4}$$

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

[6]The same equation would follow if the lender offers the firm both contracts and the firm choosing the contract that gives them a lower interest rate.

Regarding the timing of decisions in the framework, we note that the amount of debt to be repaid, b_{it}, as well as the gross interest rate to be paid the next period, R_{it}, are both negotiated at time t and hence known quantities. A standard time-to-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. We abstract from aggregate uncertainty; hence the risk-free rate next period is also known. No aggregate uncertainty also implies no uncertainty regarding the price of the firm capital stock next period (normalised to 1). The only source of uncertainty next period is the firm's default decision, χ_{it+1}. This means that the expectation operator can be passed through; re-arranging results in

$$\frac{R_{it} - R_t^f}{R_{it}} = PD_{it}\left(1 - max\left\{min\left\{\frac{\alpha k_{it}}{R_{it}b_{it}}, 1\right\} - \frac{C}{R_{it}b_{it}PD_{it}}, 0\right\}\right) \tag{1.5}$$

where $PD_{it} = E_t[\chi_{it+1}]$ is the firm's probability of default.

The left-hand side term of equation (1.5) is the firm interest rate spread ($R_i - R^f$) as a percentage of the firm gross interest rate (R_i). On the right-hand side, the first term (PD) is the firm default probability, and the second term equals expected losses in the event of default: 1 minus the loan recovery rate, adjusted for the fixed collateralisation cost for collateralised loans. Equation (1.5) states that the firm interest rate spread (the premium the firm pays on its debt over the risk free rate) equals losses in the event of default (adjusted for collateralisation costs) times the probability of default.

We allow for some measurement error in the interest rate spread, given that our dataset does not include loan-level information, and we use the firm interest expenses over total debt as proxy. This results in an error term (ν) in the equation:

$$\frac{R_{it} - R_t^f}{R_{it}} = \left(1 - max\left\{min\left\{\frac{\alpha k_{it}}{R_{it}b_{it}}, 1\right\} - \frac{C}{R_{it}b_{it}PD_{it}}, 0\right\}\right) PD_{it}\nu_{it}. \tag{1.6}$$

Finally, we introduce intangible capital by splitting the total capital stock into two components: k^T and k^I for tangible and intangible capital, respectively. We allow for potentially different collateral values on each type of capital: α^T on tangible capital and α^I on intangible capital. This results in

$$\frac{R_{it}-R^f_t}{R_{it}} = \left(1 - max\left\{min\left\{\frac{\alpha^T k^T_{it} + \alpha^I k^I_{it}}{R_{it}b_{it}}, 1\right\} - \frac{C}{R_{it}b_{it}PD_{it}}, 0\right\}\right) PD_{it}\nu_{it}. \tag{1.7}$$

To provide some intuition behind equation (1.7), which forms the basis for the empirical specification, it is worth considering the equation in cases instead of using the min and max operators:

$$\underbrace{\frac{R_{it}-R^f_t}{R_{it}}}_{\text{spread}} = \begin{cases} \frac{C}{R_{it}b_{it}}\nu_{it} & \text{if } \alpha k_{it} > R_{it}b_{it}; R_{it}b_{it} > \frac{C}{PD_{it}} \\ PD_{it}\left(1 - \frac{\alpha^T k^T_{it} + \alpha^I k^I_{it}}{R_{it}b_{it}} + \frac{C}{R_{it}b_{it}PD_{it}}\right)\nu_{it} & \text{if } \alpha k_{it} < R_{it}b_{it}; \alpha k_{it} > \frac{C}{PD_{it}} \\ PD_{it}\nu_{it} & \text{if } min\{\alpha k_{it}, R_{it}b_{it}\} < \frac{C}{PD_{it}} \end{cases}$$

where $\alpha k_{it} = \alpha^T k^T_{it} + \alpha^I k^I_{it}$. The top line holds for firms with enough recoverable capital to cover debt and interest expenses in the event of default; and large enough loans to be able to access collateralised lending. For these firms, the interest rate spread simply reflects the fixed collateralisation cost, as the payment received by the lender next period is the same regardless of whether the firm defaults or not. The bottom line holds for firms with too little debt or recoverable assets to access collateralised lending. These firms use uncollateralised loans, and hence their interest rate spread simply reflects their default probability.

Finally, the middle case holds for firms with a) enough recoverable capital to access collateralised lending; and b) not enough recoverable capital to cover debt and interest if the firm defaults. As can be seen, for these firms, there is a relationship between the firm interest rate spread and capital-to-debt ratio that depends on the α parameters. Specifically, the interest rate spread should decrease if capital-to-debt increases, as losses the lender faces in the event of default decline. Moreover, the interest rate spread will be less sensitive to changes in intangible capital, if intangibles are harder to pledge as collateral ($\alpha^I < \alpha^T$).

However, this relationship only holds up to the point at which the firm has enough recoverable capital to cover its debt and interest payment: the model predicts that increasing capital-to-debt beyond this point has not effect on the spread, as the lender can only claim up to the value of debt and interest. Similarly, for very low levels of debt or (recoverable) capital, the firm uses uncollateralised loans, and hence marginal changes in its debt-to-capital ratio have no impact on the spread. This is the role of the min and max operators in equation (1.7).

There are several benefits of identifying financial constraints from the relationship given by equation (1.7). 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 (1.7) 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 (1.7) is equivalent to estimating the parameters and cut-offs jointly. We therefore do not need to split the sample in any way before estimating the parameters.

Secondly, equation (1.7) is not an investment regression, which means that the estimation is robust to potentially different adjustment costs on intangible and tangible capital stocks; and different investment opportunities which are particularly hard to control for private companies. Finally, in order to derive equation (1.7), no assumptions were made regarding the functional forms of the firm production function or marginal product of capital.

We note that the estimation strategy identifies the parameters of the firm 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. However, the empirical estimates alone do not determine which firms are actually constrained: even if some firms face a tighter constraint, this does not necessarily imply that they cannot raise the funds they require to finance their desired, optimal levels of investment. Chapter 2 of this thesis uses the structural parameter estimates in a full heterogeneous firms model to assess which firms are constrained and which are not.

1.2.1 Empirical specification

We estimate the following two equations, based on equation (1.7). First, we take logs of both sides, which results in

$$ln\left(\frac{R_{it}-R_t^f}{R_{it}}\right) = ln\left[1 - max\left\{min\left\{\alpha^T \frac{k_{it}^T}{R_{it}b_{it}} + \alpha^I \frac{k_{it}^I}{R_{it}b_{it}}, 1\right\} - \frac{C}{R_{it}b_{it}PD_{it}}, 0\right\}\right] + \beta_3 ln\left(PD_{it}\right) + constant + ln(\nu_{it+1}) \tag{1.8}$$

This allows us to directly estimate the α parameters. The second estimating equation is obtained by re-arranging equation (1.7), and taking logs:

$$ln\left(\frac{R_{it}-R_t^f}{R_{it}}\right) = ln\left[1 - max\left\{min\left\{\beta_1 \frac{k_{it}}{R_{it}b_{it}} + \beta_2 \frac{k_{it}^I}{k_{it}} \frac{k_{it}}{R_{it}b_{it}}, 1\right\} - \frac{C}{R_{it}b_{it}PD_{it}}, 0\right\}\right] + \beta_3 ln\left(PD_{it}\right) + constant + ln(\nu_{it+1}) \tag{1.9}$$

where $\beta_1 = \alpha^T$; $\beta_2 = -(\alpha^T - \alpha^I)$; and $k_it = k_{it}^I + k_{it}^T$. This results in an estimate of the difference in the α parameters for intangible and tangible capital, and lends itself to a straight-forward hypothesis test on the significance of the potential difference.

There are two main reasons for estimating equation (1.7) in logs. Firstly, the distribution of the spread is skewed, meaning a log-transformation will improve the properties of the error term. Secondly, the log-transformation separates the default probability from other independent variables. As default probability is not observable, we will be relying on proxies for this variable. It is therefore an attractive option to separate default probability from the capital-to-debt ratios in order to improve the accuracy of the estimated collateral value parameters (α parameters).

Estimation is conducted by non-linear GMM. This is because some parameters are inside the logarithm and the equation contains non-linearities due to the presence of the min and max operators. Therefore, we 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 this case are given by

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

where $ln(\nu_{it})$ is the error term from equation (1.8) 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. The estimator used here 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 do not place any restrictions on the signs or magnitudes of the parameter values. Although not a formal test of model specification, estimates of the parameter values that fall within the expected range would be consistent with the model being correctly specified.

1.3 Main Hypothesis, Identification Challenges and Solutions

1.3.1 Hypothesis

We want to test if it is harder for firms to borrow against their intangible capital stock than tangible capital stock. 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: $\alpha^I < \alpha^T$.

If this is true, the coefficient on capital-to-debt in equation (1.9), 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 is 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 (1.8). 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.

1.3.2 Identification challenges

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, if the model assumptions hold, previous values of these variables should not be correlated with current shocks to the interest rate. We therefore use 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, for the purpose of this paper, 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 (1.7), reflecting the covariance between the loan recovery rate and firm 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 less suitable to be used as loan collateral. Hence, the presence of uncertainty mainly affects the ability of the estimation method to identify pure liquidation rates of different types of assets. Instead, if the parameter estimates are interpreted as reflecting the suitability of different types of assets as collateral, capturing unmodelled effects related to uncertainty or difficulty in valuing different types of assets is less of a concern.

Another factor that is outside of the model is the presence of lender markups, as equation (1.7) 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 collateral value for intangible assets. Future research could investigate whether controlling for lender fixed effects would have a significant impact on the parameter estimates.

1.4 Data

Our dataset covers all UK limited companies annually, from 2000 to 2020, provided by Bureau van Dijk (BvD). Table 1.1a demonstrates the coverage of the full 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 around 260 thousand firms, once observations with missing debt and interest expenses are removed.

Default probability data is only available for the 2016 to 2020 period, and hence the structural estimation is performed on the shorter time series. We also lose two additional 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 1.1b shows the coverage of our data for the three years included in the structural estimation (2018-2020).

In addition to missing intangible intangible intensity, debt and interest expenses, the sample for structural estimation is further reduced 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, the default probability proxy is only available for around 85% of the sample. We also need non-missing SIC codes in order to include industry fixed effects.

Even though the number of firms is reduced, and the resulting sample covers larger and older firms than the full dataset, we are still left with a dataset where close to 90% of companies are private SMEs. We use the UK SME definition: firms with less than 250 employees are considered to be SMEs.

Table 1.1a: Sample of firms			
	Full Sample	Intangible intensity not missing	Intangible intensity, debt & interest expenses
Nr of obs	30,278,295	9,681,298	915,814
Nr of firms	5,158,167	1,043,847	257,267
Median total assets (000s)	42	82	504
Median turnover (000s)	91	103	476
Median employees	2	4	62
Median age	5	8	9
Prop SMEs (%)	99.6	98.8	92.7
Private firms (%)	99.8	99.3	97.6

Source: BvD data

Table 1.1b: Sample of firms, 2018-2020				
	Full Sample	Intangible intensity not missing	Intangible intensity, debt & interest expenses	Sample for structural estimation
Nr of obs	5,732,880	1,339,869	41,222	9,896
Nr of firms	2,646,495	533,573	22,917	5,851
Median total assets (000s)	38	92	882	1,255
Median turnover (000s)	77	108	1,255	1,838
Median employees	2	3	83	115
Median age	6	13	14	20
Prop SMEs (%)	99.6	99.1	90.0	86.6
Private firms (%)	99.9	99.6	93.6	91.8

Source: BvD data

The empirical analysis is based on UK data for two reasons. Firstly, intangible investment in the UK is similar to the high levels of the US, whereas most other European economies have a lower intangibles share. On the other hand, collateral constraints are likely to be more relevant in the UK compared to the US. This is because the likelihood of asset liquidation in case of bankruptcy, as well as the economic importance of SMEs, are higher in the UK (and other European countries). For example, between 2019 and 2023, 49.5% of bankruptcies in the US were liquidations, compared to 90% in the UK.[7] In addition, the employment share of SMEs is larger (61%) in the UK than in the US (46%).[8] Asset-based lending, for

[7]These figures are based on data from S&P Global Market Intelligence 2024 for the US, and UK government statistics on company insolvencies.

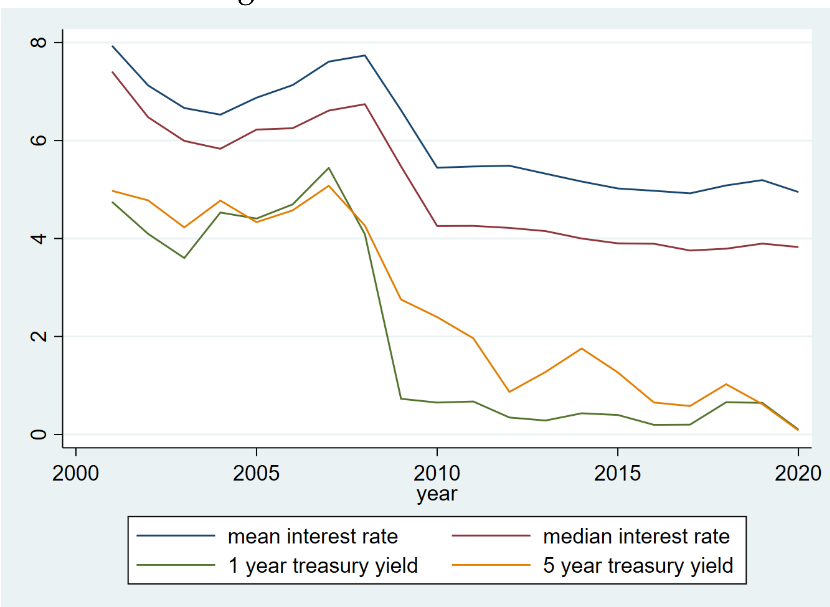
[8]Sources: US small business administration, office of advocacy; Business population estimates for the UK and regions 2023 by the UK government.

which the liquidation value of firm assets is most relevant, is prevalent amongst smaller firms as well as in countries where liquidations are more likely (Lian & Ma (2021)). For these reasons, financing frictions related to intangible assets are likely to be particularly relevant in the UK.

1.4.1 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 1.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. 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 1.2 plots the average interest rate (mean and median) against the one year and five year government bond yields.

Figure 1.2: Interest rate trends



Average firm level iterest rate and government bond yields (UK) over time.
Source: BvD data, author calculations.

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 and 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.[9]

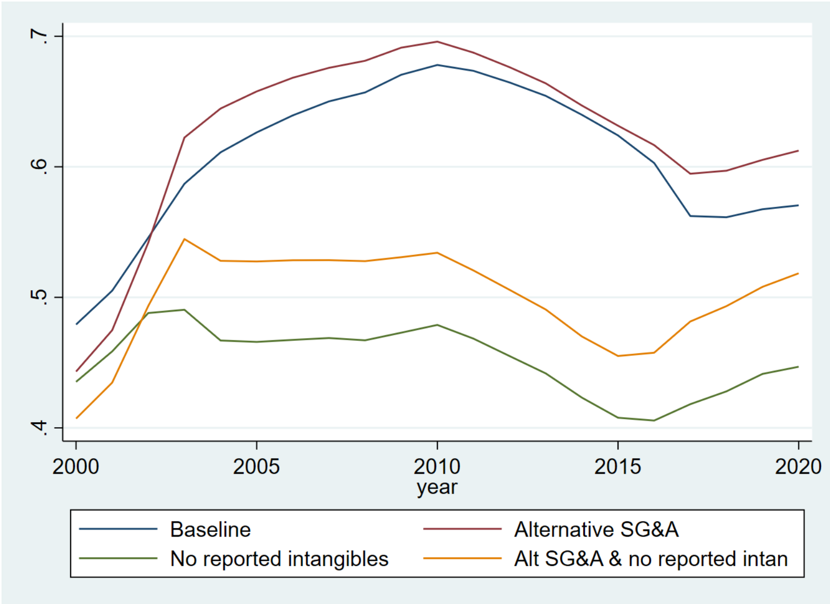
Figure 1.3 plots the mean intangible intensity over our sample period, defined as the intangble capital stock over total capital (intangible plus tangible), for our baseline intangible capital measure and three alternative proxies (with the alternative SG&A proxy, and with and without externally purchased 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.

We compare our interest rate proxy and spread measure, as well intangible intensity, with data on publicly listed UK companies from the 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 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 1.A5.

We also need to control for firm-specific default probabilities (PD) in the estimation. We use PDs based on credit scores by CRIF Decision Solution Limited and Jordans, included in the BvD data used to construct the other variables.

[9]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 1.3: 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.

However, the time series dimension of the PD variable is limited. It has good coverage only from 2016 to 2020. For these years, 85% of firm-year observations have non-missing values. The mean default probability for all firms is 6.86%; 6.9% for SMEs and 2% for large corporations. Due to the availability of the PD measure, the structural estimation results are based on data from 2016 to 2020.

The sample is restricted to the pre-Covid 19 period. During and after Covid restrictions there was significant government support to businesses, including government backed loans. Firm debt during this period is therefore likely to be less related to firm fundamentals than before Covid.

1.4.2 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 1.A3. 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 financial behaviour varies with intangible intensity. The results are outlined in Appendix 1.A4. 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.[10]

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 1.2 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.

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.[11] 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 this hypothesis: Table 1.3 shows 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

[10]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.

[11]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).

Table 1.2: 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: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

rates is also significantly less pronounced for large firms in our sample. We find, however, no significant difference in the association between intangible intensity and debt maturity for SMEs and large firms.

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

Table 1.3: 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: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

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.

1.5 Structural estimation

Table 1.4 presents the results of the two estimation equations, equations (1.8) and (1.9), using the baseline intangible capital measure. The dependent variable in all regressions is the firm interest rate spread. Columns 1 and 3 reflect the specification where the difference in the collateral proportions is estimated. In Columns 2 and 4, the collateral values are estimated separately for both types of capital. All regressions include industry and year fixed effects. Columns 3 and 4 also include the following controls: two large firm dummies, one taking a value of 1 if a firm has more than 250 employees, the other if a firm has a turnover of over £50 million; dummies for firms that are older than 10 years and in the 90th

Table 1.4: Collateral value estimates

ln(spread)	(1)	(2)	(3)	(4)
α^T	0.418***	0.418***	0.381***	0.381***
	(0.0634)	(0.0634)	(0.0545)	(0.0543)
$-(\alpha^T - \alpha^I)$	-0.354***		-0.247**	
	(0.0873)		(0.0858)	
α^I		0.0646		0.134***
		(0.0340)		(0.0399)
C	11.63***	11.63***	7.314***	7.314***
	(3.063)	(3.033)	(1.830)	(1.832)
PD	0.0979*	0.0979*	0.187**	0.187**
	(0.0489)	(0.0489)	(0.0698)	(0.0698)
Observations	10261	10261	9896	9896
Industry & Year FE	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes

Notes: This table shows the estimated proportions of tangible (α^T) and intangible capital (α^I) that can be used as loan collateral. The dependent variable in all regressions is the firm interest rate spread. Columns 1 and 3 reflect the specification where the difference in the collateral proportions is estimated. In Columns 2 and 4, the collateral values are estimated separately for both types of capital. All regressions include industry and year fixed effects. Columns 3 and 4 also include the following controls: two large firm dummies, one taking a value of 1 if a firm has more than 250 employees, the other if a firm has a turnover of over £50 million; dummies for firms that are older than 10 years and in the 90th percentile in age; public firm dummy; dummy for firms using mainly (over 99%) short term debt; ROA (operating profit over total assets) and cash ratio (bank deposits over total assets). All controls are lagged by one period. Standard errors are given in parentheses and are clustered at the firm level. Stars indicate significance at standard levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

percentile in age; public firm dummy; dummy for firms using mainly short term debt (over 99% of total debt); ROA (operating profit over total assets) and cash ratio (bank deposits over total assets). All controls are lagged by one period.

The signs and magnitudes of all parameters are in the expected range. Although this is not a formal test of model specification, it provides some reassurance on the validity of the estimates. The estimated α^T in the specification without controls (columns 1 and 2) is 0.418, and falls slightly to 0.381 when the controls are included (columns 3 and 4). This is our baseline estimate, and implies that the proportion of tangible assets that can be pledged as collateral is 38.1%. The estimate is lower than older estimates (the value commonly used in the macro-finance literature is over 0.5), but close to the average recovery rate of 0.35 estimated by Kermani and Ma (2023).

The coefficient on default probability is positive and significant, as predicted by the theoretical framework.[12] The fixed monitoring cost for loan collateralisation is estimated to be around £7300, once the controls are added. It is positive as expected, and significant at the 1% level. We have no strong prior on the magnitude of the loan collateralisation cost. This coefficient may also capture additional costs the lender expects to face in the event of default, going through bankruptcy proceedings and asset liquidation.

Moving onto the main parameters of interest, the first and third columns provide an estimate of the difference in the proportions of intangible and tangible capital that can be used as collateral. It is negative and significant, implying that the collateral value of intangible capital is estimated to be significantly lower than the collateral value of tangible capital. Hence, our results are consistent with the view that it is harder for firms to borrow against intangible capital.

The difference is also economically large: the baseline estimate implies that the collateral value of intangibles is 24.7 percentage points lower than that of the tangible capital stock. In addition, using the parameter estimates in the model shows that 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 2.97 percentage points for collateralised loans. This is a large effect compared to the mean firm interest rate for our sample, approximately 4.8%, with a standard deviation of 4.3 percentage points.[13]

The second and fourth columns provide estimates of the individual coefficients. The estimated collateral value of intangible capital is positive, and becomes larger and statistically significant when the controls are added in column (4). The baseline estimate, given in column (4), implies that 13.4% of the firm intangible capital stock can be used as collateral. This is higher than the 0% that has been used in some previous work. For instance, Falato et al. (2022) argue that the collateral value of intangible assets that are not patents or brands is zero. However, our estimate is lower than the average liquidation recovery rate of 24.8% for book intangibles obtained in Kermani and Ma (2023). The range of estimates for different industries in Kermani and Ma (2023) is very large: the 25th percentile is

[12] In the theoretical framework, the coefficient on default probability is 1. In the estimation, I allow for a coefficient that is different from unity. This is because there is no partial default in the model, however, many empirical default probability models consider a "default event" to also cover cases of partial payment or significant payment delays. The definition of default probability in the model is therefore unlikely to perfectly match empirical proxies used in estimation. Consistent with different definitions between the model and data, the coefficient is below 1, around 0.175.

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

2.14% and 75th percentile is 31.46%; we note that our baseline estimate of 13.4% falls well within this range.

Section B1 of the Appendix 1 provides results of estimating equation (1.8) using the alternative intangible capital measures described in the data section (based on different definitions of the SG&A variable, as well as including and excluding externally purchased intangibles, mainly consisting of goodwill). Our results are robust to the choice of intangibles proxy: using different measures results in similar estimates. Using the alternative SG&A measure results in slightly lower α^T and α^I estimates, whilst excluding externally purchased intangibles increases the estimated α^I by a couple of percentage points. We also find that excluding firms with intangible intensity of 0 or 1 has almost no effect on the estimated parameters, meaning that our results are not driven by firms who only use tangible or intangible capital. Results are reported in Appendix 1.B1.

We also investigate whether the parameter estimates are similar if we split the sample by firm characteristics. In particular, we allow for differences in the α parameters, fixed cost, default probability coefficient as well as a different constant term for the following groups of firms: large firms (firms with more than 250 employees); high intangible intensity firms (intangible intensity above the 90th percentile) and young firms (less than 10-years-old). We find no significant differences in the parameter estimates for these groups of firms compared to the rest of the sample. The only exception is the PD coefficient for large firms; we find that this is significantly more positive for large firms when compared to SMEs. Results are available upon request.

We include the lag of the ratio of intangible investment to total investment as an additional instrument in our regressions. Results are provided in Appendix 1.B2. With the additional instrument, we can also conduct the Hansen test of overidentifying restrictions (a test gauging instrument validity).[14] We do not reject the null that the instruments are valid.

We check for convergence of the GMM estimator to using different starting values. The estimation routine results in the same estimates for all coefficients of interest regardless of the starting values. The starting values for the main model parameters are 0 (baseline), 0.1, 0.25, 0.5, 0.75, 0.9 and 1.

In addition, we use the structural equation to simulate data on the firm interest rate spread by using actual data on the right-hand side variables in equation (1.6) and picking values of the α parameters between 0 and 1. The error terms for

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

this exercise are drawn from the standard normal distribution. We then estimate the parameters on the simulated data - where we know what the true values are - to check that the GMM estimates are close to the true values.

We find that the GMM estimator provides good estimates of the true parameters when both of the α parameters are at 0.6 or lower; if both α parameters are over 0.6, the estimator does not converge. We also find that if the true α^I is zero, the estimator recovers the true α^T parameter for all values tested between 0 and 1. On the other hand, if the true α^T is set to 0, the estimator is reliable until α^I is above 0.8; for higher values convergence is again not achieved. The likely reason for why the estimation routine does not converge for high values of the αs is that the proportion of firms who have enough recoverable capital to cover debt becomes very large, and there are not many observations left to estimate the parameters with. Regardless, we note that the GMM estimator finds estimates that are very close to the true values for values of the α parameters that cover the range of estimates obtained in previous studies.

Our data on intangibles is not granular enough to estimate separate α parameters for different types of intangible assets. Nevertheless, we can split the intangibles measure into internally generated intangibles and intangible assets reported on the balance sheet, which mainly consist of goodwill. Table 1.4 compares the baseline results, in Column 1, with those obtained by allowing for a different collateral value on intangibles reported on the balance sheet (α^I_{bs}) and internally generated intangibles (α^I_{in}), in Column 2. We find that the collateral value of intangibles reported on the balance sheet, for our sample of firms, is small and not significantly different from zero. One reason for this could be that reported intangibles consist largely of goodwill, which is likely to not be pledgeable as collateral. The collateral value of internally generated intangibles is estimated to be a little bit higher, 15.8%, in comparison to the baseline estimate of 13.4% for the intangible capital stock as a whole.

Our estimated collateral value of intangible capital is lower than the average liquidation recovery rate in Kermani and Ma (2023). However, our estimates are still well within the wide range of industry-level estimates in Kermani and Ma (2023). One reason for the differences between our estimates and those of Kermani and Ma (2023) could therefore reflect a different industry composition of UK firms compared to the US. Other reasons include further differences in the data used, the definition of intangible capital and different methodologies. For example, our measure of intangibles includes internally generated intangible capital (and goodwill in the baseline specification), which are likely to be

Table 1.5: Collateral value of balance sheet intangibles versus internally generated intangibles

	(1)	(2)
α^T	0.381***	0.378***
	(0.0543)	(0.0587)
α^I	0.134***	
	(0.0399)	
α^I_{in}		0.158**
		(0.0571)
α^I_{bs}		0.00831
		(0.0549)
C	7.314***	7.671***
	(1.832)	(2.017)
PD	0.187**	0.207**
	(0.0698)	(0.0678)
Observations	9896	9896
Industry & Year FE	Yes	Yes
Controls	Yes	Yes

Notes: This table shows the estimated proportions of tangible (α^T) and intangible capital (α^I) that can be used as loan collateral, differentiating between internally generated intangibles and those reported on the firm balance sheet in Column 2. The dependent variable in all regressions is the firm interest rate spread. Both regressions include industry and year fixed effects, as well as the following controls: two large firm dummies, one taking a value of 1 if a firm has more than 250 employees, the other if a firm has a turnover of over £50 million; dummies for firms that are older than 10 years and in the 90th percentile in age; public firm dummy; dummy for firms using mainly (over 99%) short term debt; ROA (operating profit over total assets) and cash ratio (bank deposits over total assets). All controls are lagged by one period. Standard errors are given in parentheses and are clustered at the firm level. Stars indicate significance at standard levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

much less pledgeable than the specific intangible assets valued in bankruptcy proceedings included in the analysis of Kermani and Ma.

We also note that our estimation strategy is aimed at identifying the pledgeability of the intangible capital stock as collateral, not the pure liquidation rate estimated in Kermani and Ma (2023). There could be reasons why the collateral value and liquidation rate differ; for example, legal frameworks preventing lenders from lending against intangibles, or difficulty in valuing intangibles, would lower the collateral value of intangibles relative to their liquidation recovery rate.

Our key result that the collateral value of intangibles is significantly lower than that of tangible capital is consistent with Holttinen et al. (2025), who estimate a similar structural equation without the distinction between uncollateralised and collateralised loans. However, they find that whilst tangible capital loosens the borrowing constraint, intangible capital tightens it. They conclude that the negative and significant coefficient on intangibles is likely to capture additional unmodelled effects that result in worse financing frictions for intangible intensive firms. This is because the theoretical limit on the parameter governing the collateral value is zero. The tangible capital recovery rate is also estimated to be an order of magnitude lower than estimates in the literature, which could arise from the large fraction of smaller, potentially uncollateralised loans in the data. Indeed, accounting for uncollateralised loans in the model results in estimated collateral values with expected signs and magnitudes: the estimated recovery rate on tangible capital is within the range of estimates in previous literature, and the estimated recovery rate on intangibles is positive. Hence, the negative coefficient estimate obtained in Holttinen et al. (2025) is likely to reflect the fact that intangible intensive firms are using more uncollateralised lending, which often has worse loan terms than collateralised loans.

1.6 Concluding remarks

We investigate if it is harder for firms to borrow against intangible capital, and 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 interest rate 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 the collateral value of intangibles is lower than for tangible assets. 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 collateral values of the firm intangible and tangible capital stocks, using a large panel of UK firms. We find that there is indeed a large difference in the collateral values of intangible and tangible assets. The estimated proportion of tangible capital that can be pledged as collateral is 38.1%, which is within the range of previous estimates in the literature. On the other hand, the proportion of intangibles that can be pledged is significantly lower, only 13.4%. This result is robust to using alternative intangible capital measures and controlling for other firm characteristics commonly associated with financing frictions (such as firm age, size, profitability and cash holdings). Our results imply that intangible intensive firms have significantly less loan collateral. Hence, an intangible intensive firm faces a tighter borrowing constraint than a tangible intensive firm, conditional on having the same default probability and total capital-to-debt ratio.

The difference in the collateral values of intangible and tangible capital stocks is both statistically and economically significant: the collateral value of intangibles is around 25 percentage points lower than that of tangibles. In addition, our structural results indicate that 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 2.97 percentage points for collateralised loans. This is a large impact compared to the mean firm interest rate for our sample, approximately 4.8%, with a standard deviation of 4.3 percentage points.

The differences in borrowing constraints faced by intangible and tangible intensive firms can lead to potentially large-scale effects on the macroeconomy. Due to the partial equilibrium framework used in this paper, it is beyond the scope of our analysis to estimate broader macro effects arising from the estimated financing frictions. Building on these results, Chapter II of this thesis investigates the impact of financing friction related to intangibles on the broader economy.

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Appendix

1.A Appendix: Data

1.A.1 Sample of firms

The full dataset covers all UK limited companies annually, from 2000 to 2020, provided by Bureau van Dijk (BvD). Default probability data is only available for the 2016 to 2020 period, and hence the estimation is performed on the shorter time series. Table 1.A1 demonstrates the coverage of the full 20-year sample, and how it is affected by missing data on key variables (intangible intensity, debt and interest expenses). Even though the number of firms is reduced, and the resulting sample covers slightly larger and older firms, we are still left with a dataset where around 90% of companies are private SMEs.[15]

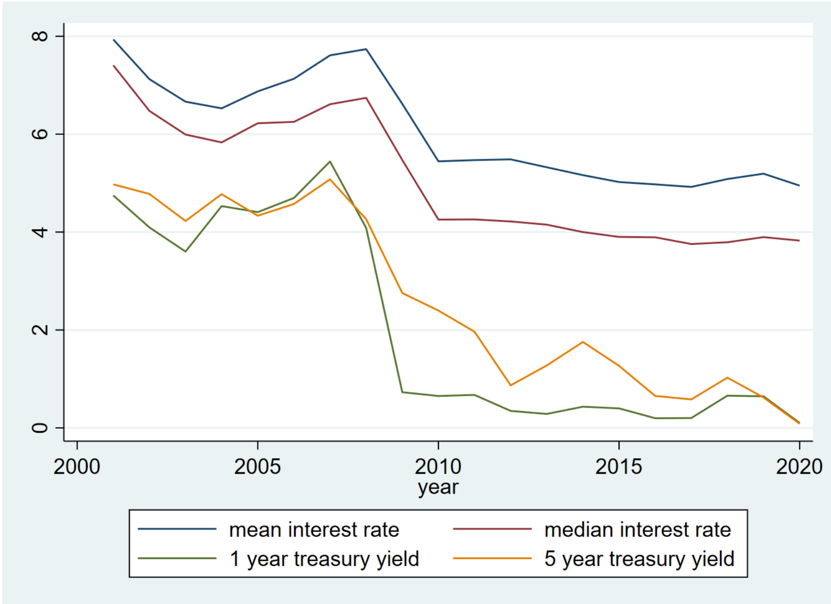
Table 1.A1: Sample of firms

	Full Sample	Intangible intensity not missing	Intangible intensity, debt & interest expenses	Sample for estimation (2016-2020)
Nr of obs	30,278,295	9,681,298	915,814	9,712
Nr of firms	5,158,167	1,043,847	257,267	5,733
Median total assets (000s)	42	82	504	2,662
Median turnover (000s)	91	103	476	8,277
Median employees	2	4	62	118
Median age	5	8	9	20
Prop SMEs (%)	99.6	98.8	92.7	89.0
Private firms (%)	99.8	99.3	97.6	91.6

Source: BvD data

[15]Using the UK SME definition: firms with less than 250 employees are considered to be SMEs

Figure 1.4: Interest rate trends

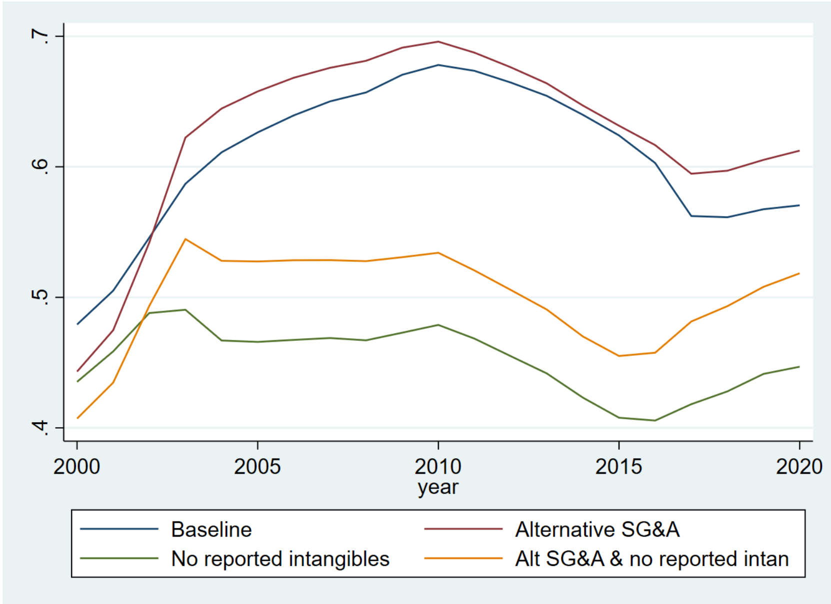


1.A.2 Variables needed

The following variables are required for the analysis (at the firm level): interest rate spread, intangible capital stock, tangible capital stock, total debt and default probability. Tangible capital and debt are relatively straightforward to measure from firm balance sheet data, whilst the former three present more challenges. Firstly, we do not have loan level data, and therefore use a proxy for the firm interest rate in order to construct the firm interest rate spread. The proxy is obtained by using interest expenses over 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. The interest rate proxy is quite noisy; we proceed by winsorizing the variable at a 5% level in order to exclude large outliers. The resulting variable, however, looks sensible: Figure 1.4 plots the average interest rate (mean and median) against the one year and five year government bond yields.

It is not straightforward to measure 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 R&D and SG&A (selling, general and administrative) expenses, as in Peters & Taylor (2017) and Falato et al. (2020). The motivation behind this approach is that R&D expenditures reflect investment in “knowledge capital", whereas a proportion SG&A expenditures capture investment into “organisational capital". We consider four alternative measures of the intangibles stock. The dataset does not report SG&A

Figure 1.5: Intangible intensity trends



expenses directly, and hence we use two measures. In the baseline measure, we use the following formula: SG&A = gross profit – operating profit – depreciation. For robustness, we also use reported administrative expenses as a proxy for SG&A. We also use both measures of the intangibles stock including and excluding reported intangibles, which consists mainly of goodwill.[16] The baseline intangibles stock includes externally purchased intangibles. Robustness checks are performed using the other three intangibles proxies.

Figure 1.5 plots the mean intangible intensity over the sample period, defined as the intangble capital stock over total capital (intangible plus tangible), for the four different definitions of 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, on the other hand, has a bigger impact. Most of the hump in intangible intensity prior to 2010, and the following decline, were largely driven by externally purchased intangibles.

We also need to control for (firm specific) default probability (PD) in the estimation. We use PDs based on credit scores by CRIF Decision Solution Limited and Jordans, included in the BvD data used to construct the other variables. However, the time series dimension of the PD variable is limited. It has good coverage only from 2016 to 2020. For these years, 85% of firm-year observations having non-missing values. The mean default probability for all firms is 6.86%; 6.9% for SMEs and 2% for large corporations. Due to the availability of the PD

[16]The dataset does not include goodwill separately, and hence we cannot simply exlcude goodwill alone.

measure, the empirical results are based on data from 2016 to 2020.

The sample is restricted to the pre-Covid 19 period. During and after Covid restrictions there was significant government support to businesses, including government backed loans. Firm debt during this period is therefore likely to be less related to firm fundamentals than before Covid.

1.A.3 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 1.A2 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 1.A2: 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

1.A.4 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 1.A3 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 sold shares publicly at least once in their lifetime.

Table 1.A3: Finance by intangible intensity

Quartile	Leverage	Leverage Inc Intan	Interest rate (%)	ST Debt ratio	Cash ratio	Privately owned (%)	Sold shares, % 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

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 find no raw trends in the share of public companies or the proportion of firms who have (publicly) issued shares. If anything, the most tangible quartile has the largest proportion of firms that have issued shares, however, the proportion of public companies is slightly higher in the most intangible intensive quartile. It should be noted that this is only a superficial glance; for instance, the figures do not capture any financing through mergers and acquisitions, private equity sales or forms of venture capital that do not include equity sales.

1.A.5 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 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.

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).

Figure 1.6: BvD - Worldscope data comparison: interest rate trends

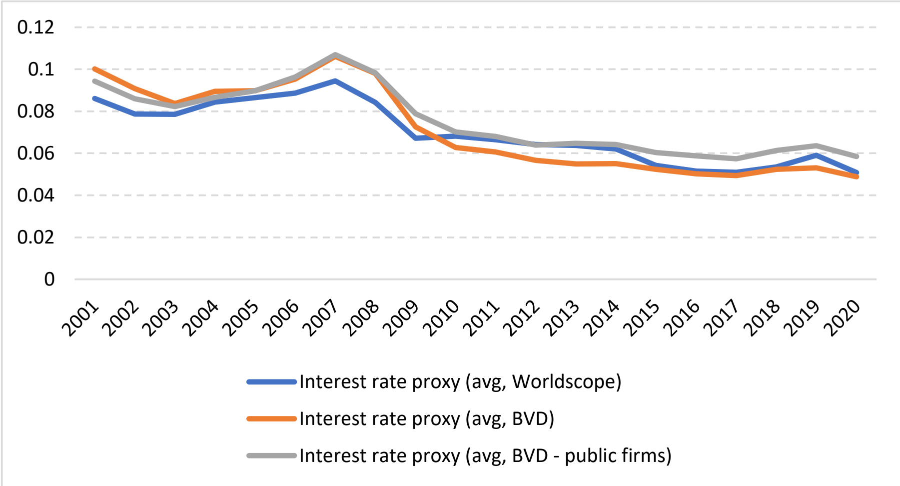
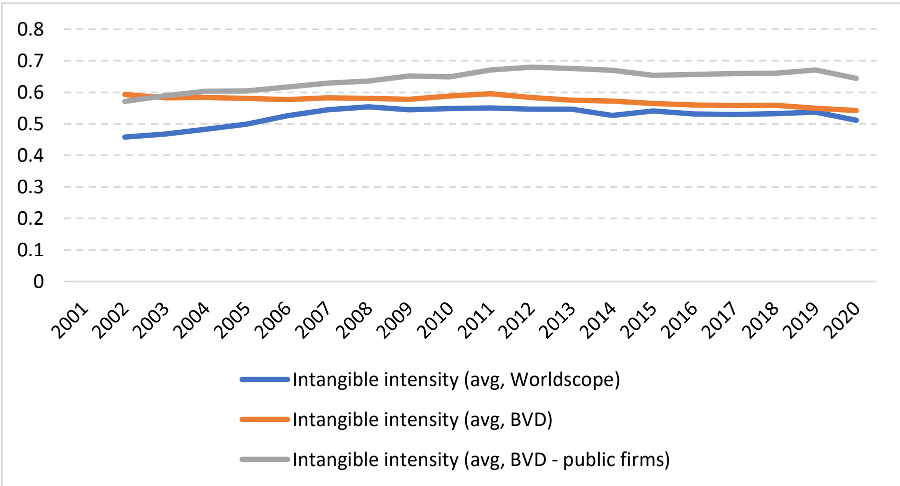


Figure 1.7: BvD - Worldscope data comparison: intangible intensity trends



1.A.6 Characteristics of firm-level debt: motivating the model

Table 1.A4 depicts the percentiles of debt, as well as the percentiles of the proportion of short term debt, for firms with strictly positive debt. We find that many firms have small amounts of debt: for firms with strictly positive debt, the bottom decile have total outstanding debt amounting to 2000 pounds or less, and the median is 36000. In addition, we many firms have a large proportion of short-term debt. In fact, more than half of the firms with non-missing debt only have short-term borrowing, with a share of short-term debt in total debt of 100%.

Percentile	Total debt (000s)	Proportion short term debt
1%	1	0.008
5%	1	0.066
10%	2	0.15
25%	9	0.48
50%	36	1
75%	193	1
90%	838	1
95%	2118	1
99%	17,386	1

Table 1.A4: Characteristics of firm debt

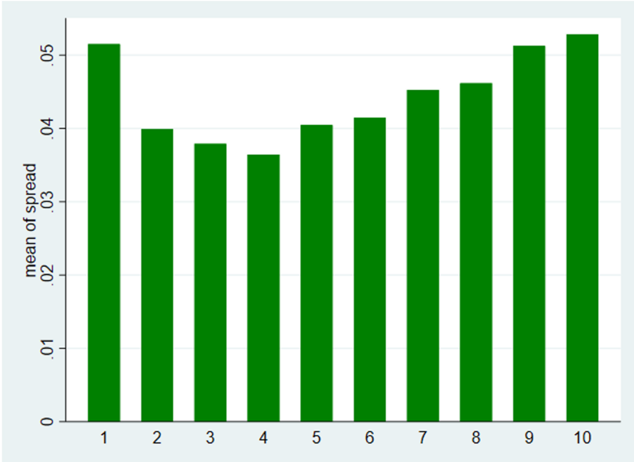
Source: BvD data

Given the prevalence of small debt amounts as well as the large number of firms with mainly short-term debt in our dataset, we expect there to be a large share of uncollateralised debt in our sample of firms. This motivates our approach to include a distinction between uncollateralised and collateralised loans into the model.

Without the distinction between uncollateralised and collateralised borrowing, the model predicts that the firm interest rate spread should be decreasing in the firm capital-to-debt ratio, up until the firm has enough capital to cover all its debt in the event of default. Therefore, the firm interest rate spread should be flat, and then increasing, in firm leverage. However, plotting the firm interest rate spread against leverage (total debt to tangible capital) in figure 1.6 shows that firms in the lowest decile of leverage - with the largest capital-to-debt ratio - have a high spread. This is at odds with the model predictions, whilst rest of the deciles follow a pattern that is consistent with the model.

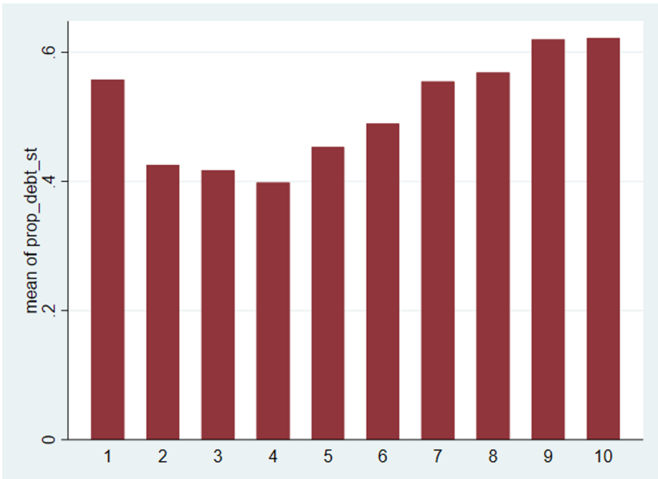
We next plot the mean proportion of short-term debt for each decile by leverage, depicted in Figure 1.7, and note that it follows a very similar pattern. The lowest decile in leverage also have a very high proportion of short term - potentially uncolleteralised - debt, which could contribute to the high firm-level interest rate spread for these firms. Allowing for uncollateralised loans in the model means that the high spread for firms in the bottom decile of leverage should not confound the estimated parameters governing the pledgeability of assets.

Figure 1.8: Firm interest rate spread by firm leverage



This graph plots the average firm interest rate spread for each decile by firm leverage, computed as debt to tangible capital, for the year 2018.
Source: BvD data, author calculations.

Figure 1.9: Proportion of short-term debt by firm leverage



This graph plots the average proportion of short term debt for each decile by firm leverage, computed as debt to tangible capital, for the year 2018.
Source: BvD data, author calculations.

1.B Appendix: Robustness checks

1.B.1 Robustness to alternative intangible capital measures

This section presents the results of parameter estimates obtained using alternative measures of intangible capital. These are depicted in Table 1.B1.1. Column 1 reports the estimates obtained using the baseline measure. The specification in column 2 excludes externally purchased intangibles, which largely consist of goodwill. The results in column 3 are obtained using an intangibles measure that is constructed by using reported administrative expenses as a proxy for SG&A,

and including externally purchased intangibles. Column 4 reports the results obtained by using the same SG&A proxy, but excluding externally purchased intangibles. We find that the estimates are similar regardless of the intangible measure used: the estimated α^T ranges from 35.8% to 38.2%, and the α^I estimates are between 11.3% and 17.0%, with slightly higher estimates for the intangibles measure that excludes goodwill, and uses inferred SG&A instead of administration expenses as to compute the SG&A variable.

Table 1.B1.1: Robustness to alternative intan measures

ln(spread)	(1)	(2)	(3)	(4)
α^T	0.381***	0.382***	0.358***	0.366***
	(0.0543)	(0.0696)	(0.0483)	(0.0535)
α^I	0.134***	0.170**	0.113***	0.132**
	(0.0399)	(0.0655)	(0.0329)	(0.0445)
C	7.314***	7.778***	6.865***	7.206***
	(1.832)	(2.118)	(1.726)	(1.886)
PD	0.187**	0.214**	0.137*	0.157*
	(0.0698)	(0.0679)	(0.0667)	(0.0658)
N	9895	9895	9895	9895

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
All regressions include industry and time fixed effects and the following controls: size, age, proportion of short term debt, return on assets, cash ratio, and a public firm dummy

We also test to what extent our results are driven by firms with only intangible capital (intangible intensity of 1) or tangible capital only (intangible intensity of 0). Table 1.B1.2 shows the baseline estimates in Column 1, and the estimation results when firms with intangible intensity of 0 or 1 are excluded in Column 2. The differences in the estimated parameters are negligible, and we conclude that our results are not driven by firms with zero or only intangible capital.

Table 1.B1.2: Collateral value estimates, excluding firms with zero or only intangible capital

	(1)	(2)
α^T	0.381***	0.385***
	(0.0543)	(0.0569)
α^I	0.134***	0.131**
	(0.0399)	(0.0433)
C	7.314***	7.428***
	(1.832)	(1.901)
PD	0.187**	0.189**
	(0.0698)	(0.0683)
Observations	9896	9882
Industry & Year FE	Yes	Yes
Controls	Yes	Yes

Notes: This table shows the estimated proportions of tangible (α^T) and intangible capital (α^I) that can be used as loan collateral, excluding firms with no intangible capital or only intangible capital in Column 2. The dependent variable in both regressions is the firm interest rate spread. Both regressions include industry and year fixed effects, as well as the following controls: two large firm dummies, one taking a value of 1 if a firm has more than 250 employees, the other if a firm has a turnover of over £50 million; dummies for firms that are older than 10 years and in the 90th percentile in age; public firm dummy; dummy for firms using mainly (over 99%) short term debt; ROA (operating profit over total assets) and cash ratio (bank deposits over total assets). All controls are lagged by one period. Standard errors are given in parentheses and are clustered at the firm level. Stars indicate significance at standard levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

1.B.2 Additional instrument and test for overidentifying restrictions

In the baseline specification, the number of instruments equals the number of parameters and hence we cannot perform a test of overidentifying restrictions to gauge instrument validity. We add the share of intangible investment to total investment as an additional instrument. The results are shown in Table 1.B2, Column 2, next to the baseline results in Column 1 for comparison. The results are very similar, though the estimated collateral value of tangible capital is lower (32.9% compared to 38.1% in the baseline) and the collateral value of intangibles is higher (17.1% compared to 13.4% in the baseline). With the additional instrument, we can also conduct the Hansen test of overidentifying restrictions. The p-value on the J-statistic is 0.185, hence we do not reject the null that the instruments are valid.

Table 1.B2: Share of intangible investment as an extra instrument

	(1)	(2)
α^T	0.381***	0.329***
	(0.0543)	(0.0317)
α^I	0.134***	0.171***
	(0.0399)	(0.0383)
C	7.314***	7.157***
	(1.832)	(1.798)
PD	0.187**	0.209**
	(0.0698)	(0.0734)
Hansen's J-test	-	1.755
J-test p-value	-	0.185
Observations	9896	9717
Industry & Year FE	Yes	Yes
Controls	Yes	Yes

Notes: This table shows the estimated proportions of tangible (α^T) and intangible capital (α^I) that can be used as loan collateral. Column 1 reports the baseline estimates, in Column 2 the lagged share of intangible investment to total investment is added as an instrument. The dependent variable in both regressions is the firm interest rate spread. Both regressions include industry and year fixed effects, as well as the following controls: two large firm dummies, one taking a value of 1 if a firm has more than 250 employees, the other if a firm has a turnover of over £50 million; dummies for firms that are older than 10 years and in the 90th percentile in age; public firm dummy; dummy for firms using mainly (over 99%) short term debt; ROA (operating profit over total assets) and cash ratio (bank deposits over total assets). All controls are lagged by one period. Standard errors are given in parentheses and are clustered at the firm level. Stars indicate significance at standard levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

CHAPTER 2

Financial Constraints and Misallocation in the Intangible Economy

Abstract*

Investment in intangible assets has increased steadily over the last few decades. What impact does the low collateral value of intangibles have on aggregate productivity and resource allocation? I construct a model with heterogeneous firms facing financial constraints and using tangible and intangible capital in production. In addition to reducing investment and employment, the low collateral value of intangibles amplifies opposing mechanisms that have previously been overlooked. On the one hand, the financing friction reduces productivity by limiting default and exit of less productive firms. On the other hand, the presence of intangibles leads to a tighter connection between firm financing costs and productivity. Whilst unproductive firms can mitigate the impact of higher default risk by borrowing against tangible capital, intangibles do not offer the same protection. This leads to a novel mechanism whereby financing frictions can increase productivity by directing resources towards more productive firms. Quantitatively, the former effect dominates and financial constraints have a negative impact on the economy – much larger than when intangibles are ignored.

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2.1 Introduction

The rising importance of intangible assets has been well documented in the literature (see for instance Corrado and Hulten (2010), Corrado et al. (2012), Corrado et al. (2013), Corrado et al. (2016), Andrews and Serres (2012), Demmou et al. (2020)). In some countries, including the UK and the US, intangible investment has recently overtaken investment in tangible assets. This has raised concerns that firms may lack collateral for their loans, as intangible assets may be more firm specific or have a more uncertain liquidation value (e.g. Williamson (1988); Shleifer and Vishny (1992); Hart and Moore (1994); Giglio and Severo (2012); Haskel and Westlake (2018); Falato et al. (2022); Caggese and Perez-Orive (2022); Holttinen et al. (2025)). Given the difficulties in using intangible assets as collateral, what is the impact of financial frictions on output, investment and productivity in the intangible economy? Is it quantitatively important, and what are the main mechanisms at play? Understanding the role of financing frictions in shaping aggregate outcomes is of particular importance in modern economies, which have witnessed a slowdown in productivity growth, coupled with a "productivity divergence", or a widening gap between the most and least productive firms (Andrews et al. (2016); Berlingieri et al. (2017); McGowan et al. (2018)).

In this paper, I study financing constraints in the intangible economy. I construct a model of heterogeneous firms facing financial constraints and using tangible and intangible capital in production. The low collateral value of intangibles results in significant steady state output losses of 7.7%, and welfare losses of 2.11%, partly due to reduced investment and employment of credit constrained intangible intensive firms. The financing friction also impacts aggregate TFP. Whilst the impact of conventional misallocation (due to inefficiently small size of productive intangible intensive firms) is quantitatively negligible, the presence of intangibles leads to a tighter connection between firm financing costs and default risk, highlighting two opposing mechanisms that have been overlooked by previous literature. On the one hand, the intangibles financing friction *increases* aggregate TFP by improving the efficiency of resource allocation. Whilst unproductive tangible intensive firms can mitigate the impact of higher default risk by borrowing against their assets, intangible intensive firms cannot. This directs resources towards productive firms, who can borrow more due to lower default risk. On the other hand, the tight connection between financing costs and default risk reduces the default rate of intangible intensive firms. This limits the positive selection effect of firm default, as fewer unproductive firms exit production. Hence, aggregate TFP is reduced due to a lower average productivity of firms in production. Quantitatively, the latter effect dominates, and the low collateral value of intangibles results in TFP losses of 1.15%.[1]

In Chapter I of this thesis, the collateral value of tangible capital is estimated to be 38.1%, whereas the collateral value of the firm intangible capital stock is 13.4%. Building on these findings, I assess what the estimated difference in borrowing constraints between intangible and tangible intensive firms implies for the intangible economy. I construct a model featuring intangible and tangible intensive firms and endogenous default. In the model, firms also differ in TFP, debt and total capital. The borrowing constraint in the model is of the same form as estimated in Chapter I. Firms that cannot pay back their existing debt and a fixed operating cost default and permanently exit.

I calibrate the model to the UK economy as the empirical results in Chapter I are obtained using UK data. In addition, financing frictions related to intangibles are likely to be particularly relevant in the UK, due to the high levels of intangible investment combined with the prevalence of asset-based lending.[2] Intangible and tangible intensive firms have different recovery rates on their assets, calibrated directly from the estimated borrowing constraint in Chapter I. Hence, firms can borrow against 38% of their tangible capital stock, and 13% against their intangible capital.

I also allow for a difference in the average productivity between intangible and tangible intensive firms. This helps the model match the higher share of employment by intangible intensive firms in the data. In the calibrated model, intangible intensive firms have a higher mean of TFP shocks of approximately 1.9%. The firm level data used is consistent with higher productivity of intangible intensive firms: they have a higher average labour productivity, despite having a lower ratio of total capital-to-debt. Previous literature has also found a positive association between firm intangible intensity and firm-level TFP (Crass and Peters (2014); Lee and Paluszynski (2022); Karmakar et al. (2022); Roth et al. (2023)). The model is consistent with the data regarding the relationship between

[1]These effects are relatively large compared to estimates in the literature for advanced economies. For instance, Midrigan and Xu (2014) find consumption losses of 2% and TFP losses of 0.3% from all financing frictions in their advanced economy benchmark.

[2]The US has a similar share of intangible investment to the UK, however, cash-flow based lending is more common, partly due to the lower chance of asset liquidation in the event of bankruptcy (between 2019 and 2023, 49.5% of bankruptcies in the US resulted in liquidations, compared to 90% in the UK). On the other hand, many European countries also exhibit a higher share of asset-based lending than the US, however, the share of intangibles is also lower. *Data sources:* S&P Global Market Intelligence 2024; UK government statistics on company insolvencies; international comparison of intangible investment shares based on author calculations using EUKLEMS & INTANProd data.

firm age and the relative size of intangible and tangible intensive firms, despite this not being targeted in model calibration.

Accounting for intangibles affects the importance of financing frictions. Without intangibles, the model underestimates both the tightness of financing constraints, as well as the optimal (unconstrained) amount of capital at the firm level. This results in firms that are less financially constrained, and can outgrow the financing constraint quicker. Indeed, I find that the same model without intangibles predicts total output losses from financing frictions that are an order of magnitude lower (0.4%) than in the model with intangibles (8.6%). Accounting for intangibles is, therefore, crucial when assessing the impacts of financing frictions in modern economies.

I assess how the different financing constraints affect lifecycle dynamics of intangible and tangible intensive firms. In the calibrated model, intangible intensive firms have a higher mean of productivity shocks, which helps the model match their higher share of total employment. The higher productivity relaxes the borrowing constraint of intangible intensive firms, as it lowers the firm default probability. On the other hand, the low collateral value of intangibles results in a tighter constraint. For start-ups, the first effect dominates, as both intangible and tangible intensive firms initially rely on uncollateralised lending. Hence, very young intangible intensive firms are *less* constrained than their tangible intensive peers.[3] Once tangible intensive firms grow, they can access collateralised loans, leaving them less constrained than intangible intensive firms. This effect persists for the rest of the firm lifecycle, as tangible intensive firms outgrow the financing friction at a faster rate than intangible intensive firms. Hence, intangible intensive firms are more financially constrained for most of their lifecycle.

I proceed by investigating the macroeconomic impact arising from the low collateral value of intangible assets. I conduct a counterfactual exercise, comparing the baseline stationary distribution (where intangibles cannot be used as collateral) to a counterfactual where intangible and tangible assets can both be used as collateral. The costs of intangibles financing frictions are significant, resulting in steady state output losses of 7.7%, and a 2.11% decline in consumption equivalent welfare. This is partly due to inefficiently low investment and employment by intangible intensive firms, reducing the aggregate capital stock by 7.8% and aggregate employment by 7.7%.

The impact of the financing friction on aggregate TFP is not trivial, due to

[3]This is in contrast with previous literature, where intangible intensive start-ups and very young firms are often considered to be most affected by financing frictions (Caggese and Perez-Orive (2022); Chen (2014); Bøler et al. (2023)).

multiple opposing effects at play. The financing friction disproportionately reduces investment and employment of intangible intensive firms, resulting in TFP losses through resource misallocation between the two firm types. In addition, the presence of intangibles results in a tighter link between firm financing costs and default risk. As lenders can recover a smaller fraction of intangible assets, the firm interest rate increases sharply with default risk, reflecting the larger expected losses in the event of default. This highlights two opposing mechanisms through which financing frictions impact aggregate TFP. On the intensive margin, the tight link between financing costs and default risk is beneficial, as default risk is decreasing in productivity. This is because, ceteris paribus, higher productivity firms are less likely to receive a low enough productivity realisation that would result in default. Hence, the financing constraint is tightly connected to firm productivity, directing resources towards more productive firms. This increases aggregate TFP through improved allocative efficiency. On the extensive margin, however, the tight connection between financing costs and default risk limits firm default and exit. Default has a cleansing effect, as firms receiving low productivity realisations default and exit. A lower default rate reduces positive firm selection, reducing the average productivity of firms in production, thereby lowering aggregate TFP.

Quantitatively, the first conventional misallocation effect plays a minor role, reducing aggregate TFP by 0.02%. The latter two opposing effects are quantitatively much more important. They arise from the interplay between intangibles and default risk, and have previously been overlooked by the literature. On the one hand, the improvement in the efficiency of resource allocation due to the low collateral value of intangibles results in an *increase* in TFP by 1.2%. On the other hand, the low default rate of intangible intensive firms causes TFP *losses* of 2.33%. Overall, the negative impacts dominate, and the financing friction related to intangibles results in overall TFP losses of 1.15%. These are an order of magnitude larger than the TFP losses (approximately 0.1%) from intangibles financing frictions computed in Bøler et al. (2023), whose framework accounts for the conventional misallocation effect only.

What can policymakers do to reduce the sizeable costs of financing frictions in the intangible economy? Given the inherent differences of intangible and tangible assets, it may not be possible to significantly increase the collateralisability of intangibles.[4] This may also not be the optimal way to target intangibles fi-

[4]However, depending on the country specific lending regulations, policymakers may be able to increase the suitability of intangible assets as collateral, for instance by allowing financial institutions to accept intangible capital as collateral, if this is currently prohibited.

nancing frictions: my model illustrates how borrowing against firm assets can reduce allocative efficiency, as it disproportionately benefits larger firms. On the other hand, investment subsidies or other industrial policies increasing the size of intangible intensive firms are unlikely to deliver the full TFP improvements illustrated in the counterfactual analysis, as these are mainly driven by increased exit of unproductive firms. Instead, policies that also increase default and exit of less productive intangible intensive firms, including government backed loans or easier access to cash flow based lending, may be more effective. On a related note, targeting other costs associated with firm default and exit, such as bankruptcy costs and frictions preventing capital and labour reallocation, could amplify the positive selection effects related to default. Finally, developing financial instruments that better discriminate based on firm productivity (instead of collateral) could improve the efficiency of resource allocation in modern economies.

2.1.1 Related literature

This paper contributes to two strands of literature. First, I contribute to the large literature on the links between finance, misallocation and aggregate productivity. Seminal work includes Buera et al. (2011), Gilchrist et al. (2013), Midrigan and Xu (2014), Moll (2014), Gamberoni et al. (2016), and Larrain and Stumpner (2016). For more recent studies, see for instance Ottonello and Winberry (2024), Su (2024), Chen et al. (2023). Most previous studies have not explicitly considered the impact of equilibrium default on misallocation. Some exceptions include Khan et al. (2016) and Schivardi et al. (2022), who find that firm defaults result in lower utilisation of capital and other resources.

In addition, the literature on "zombie" lending (see for instance Caballero et al. (2008), Acharya et al. (2024), Blattner et al. (2019) and Hu and Varas (2021)) shows that extension of credit to firms with weak performance results in misallocation by preventing default and exit of unproductive firms. In contrast, I show that the interplay between intangible capital and equilibrium default highlights previously overlooked mechanisms through which financing frictions affect aggregate productivity. These mechanisms operate in the *opposite* direction compared to those studied in previous literature, and are quantitatively important. I also show that accounting for intangibles significantly increases the macroeconomic impacts of financing frictions.

I also contribute to the literature exploring the economic impacts of intangible capital. De Ridder (2024) investigates how intangibles affect productivity and business dynamism by altering the structure of firm production costs. Altomonte et al. (2021) explore a similar channel, focusing on the impact of firm mark-ups. Chiavari and Goraya (2024) examine how higher adjustment costs related to intangibles affect the economy.[5] Previous literature has also looked at the economic impact of intangibles through financing constraints: Falato et al. (2022) examine the impact of intangibles on corporate cash holdings; Lee and Paluszynski (2022) on shadow financing & credit shocks; Lopez and Olivella (2018) on the transmission of financial shocks. I contribute to this literature by exploring how credit constraints related to intangibles affect output, productivity and misallocation in the economy, as well as firm lifecycle dynamics.

To the best of my knowledge, the only previous studies that explore the output and productivity losses arising from intangibles financing frictions are Caggese and Perez-Orive (2022) and Bøler et al. (2023). Caggese and Perez-Orive (2022) focus on the interplay between tightening credit constraints and low interest rates. In contrast, I consider the impact of intangibles alone, without the impact of exogenous changes in the risk free interest rate. Bøler et al. (2023) identify credit constraints related to intangibles from a natural experiment framework, and calibrate a quantitative model to study the impact of collateral constraints on productivity. Although the framework in Bøler et al. (2023) allows for a very clean identification of the impact of a particular policy on firm financial behaviour as well as aggregate productivity, the benefit of my approach is the ability to shed light on the key mechanisms at play, as well as the possibility to conduct counterfactual analysis. Previous work has also abstracted from the interaction between intangibles and equilibrium default. In contrast, most of the TFP losses in my model arise from the low default rate of intangibles firms. I also show that the presence of intangibles *improves* efficiency of resource allocation, as it tightens the link between firm financing costs and productivity.

The rest of the paper is organised as follows. Section 2.2 outlines the model, and section 2.3 outlines the calibration and model fit. Section 2.4 discusses model results. Section 2.5 discusses avenues for future work. Section 2.6 concludes and discusses policy implications.

[5] Other papers that find different adjustment costs for intangible capital include Belo et al. (2022) and Cloyne et al. (2022).

2.2 Model of heterogeneous firms, intangible capital & endogenous borrowing constraints

Based on the empirical analysis in Chapter I, I conclude that the firm intangible capital stock provides significantly less loan collateral than the tangible capital stock. Hence, an intangible intensive firm faces a tighter borrowing constraint than a tangible intensive firm, conditional on having the same default probability and total capital-to-debt ratio. Does this mean that intangible intensive firms are more financially constrained? If yes, how does the low collateral value of intangibles impact aggregate output, productivity and resource allocation, as well as welfare? Are the effects quantitatively important, and what are the relevant mechanisms?

To answer these questions, I proceed by constructing a model of heterogeneous firms, featuring intangible and tangible intensive firm types, and the same borrowing constraint as estimated in Chapter I. The model builds on Khan et al. (2016) and Ottonello and Winberry (2020). The main difference is the addition of intangible capital: I split firms in the economy into two types, differing in their intangible intensity. This allows me to understand the impact of intangibles financing frictions without the need to introduce additional state variables. Accounting for intangibles reduces the fraction of *total* capital that can be recovered by the lender in the event of default, particularly for intangible intensive firms. It also increases the amount of *total* capital that firms optimally use in production. The financing constraint in the model is also different than in previous work, as it includes the fixed cost of valuing firm assets the lender faces in order to collateralise a loan (following the framework in Chapter I).

I allow for differences in average TFP between intangible and tangible intensive firms in order to match the employment shares of both firm types in the data. The TFP difference is also motivated by the possibility that intangible investments, for instance through R&D, might lead to improvements in firm productivity. In addition, there could be inherent differences in the production processes of intangible and tangible intensive firms. Allowing for a difference in average productivity can be interpreted as a reduced form way of capturing additional unmodelled dynamics between intangible investment and productivity. The productivity difference is also consistent with previous empirical evidence (Crass and Peters (2014); Lee and Paluszynski (2022); Karmakar et al. (2022); Roth et al. (2023)). I also show in Appendix 2.A1 that firm-level data for the

UK highlights a persistent difference in average labour productivity for intangible and tangible intensive firms which cannot be explained by differences in the capital-to-labour ratio.

Both types of firms (intangible and tangible intensive) differ in TFP, capital and debt. The relative shares of intangible and tangible capital used in production vary between the two firm types. Heterogeneity is crucial in this setting, as I want to explore the impact of intangibles financing friction on the lifecycle dynamics of intangible and tangible intensive firms, as well as on the allocation of resources between productive and less productive firms within and between firm types. Investment is funded by retained earnings or non-contingent debt, which firms can default on.[6] The debt-financing friction is of the same form as the financing constraint estimated in Chapter I: the risk of losses to the lender in the event of default leads to endogenous borrowing costs above the risk free rate that increase with debt and default risk, and decrease with collateral. I use the collateral value parameters (αs) estimated in Chapter I to calibrate the financing constraint.

Figure 2.1: Model Flow chart

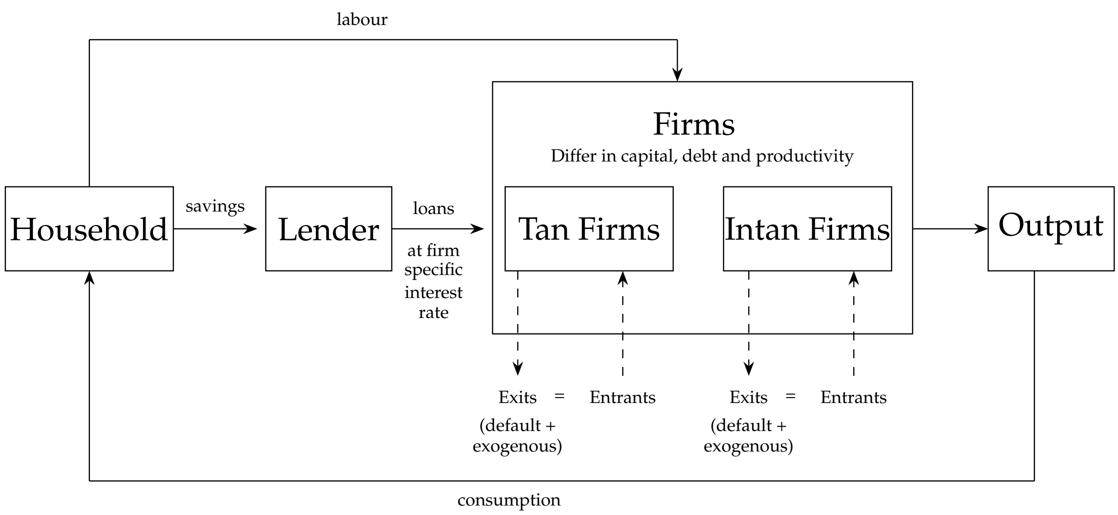


Figure 2.1 provides an overview of the model. Tangible and intangible firms produce a homogeneous output that is consumed by households. Households provide labour for both types for firms at an equal wage, and savings that are priced by the lender at a firm specific interest rate schedule. Firms exit if they receive an exogenous exit shock, or if they default on their debt. Entry is exogenous: the number of entrants equals the number of exits (of each type of firm),

[6]The model does not include equity finance. Even though equity financing is an important source of external funds for some companies, equity financing is also costly (Altinkilic and Hansen (2000); Gomes (2001); Belo et al. (2019)).

keeping the total number of firms of each type as well as the total number of firms in production constant.

2.2.1 Firms

There is a fixed mass 1 of firms; half (mass of 0.5) are intangible intensive and half are tangible intensive. Each firm j produces a homogeneous good y_{jt} using (total) capital k_{jt} and labour l_{jt}. The production function is a decreasing returns to scale Cobb-Douglas production function

$$y_{jt} = z_{jt}(\omega_{jt}k_{jt})^{\theta}l_{jt}^{\nu}. \tag{2.1}$$

Idiosyncratic TFP follows a log-AR(1) process, such that $log(z_{jt+1}) = \rho log(z_{tj}) + \epsilon_{jt+1}$, where ϵ_{jt+1} follows a normal distribution with means μ_T and μ_I for tangible and intangible intensive firms, respectively, and a common variance σ^2. The capital quality shocks related to total capital, ω, are i.i.d. across firms and time. They ensure that the model generates a non-zero default risk for a large cross-section of firms; without any risk to the capital stock, only firms with very low net worth would have a positive default probability.

The timing of the model is as follows. First, entrant firms of each firm type are born, such that the mass of entrants equals the mass of exiting firms, keeping the total mass of firms (and the total mass of each firm type) fixed. Entrants draw an idiosyncratic productivity z_{jt} from the time invariant distribution, such that the log of entrant productivity follows $N\left(\mu_S \frac{\sigma}{\sqrt{(1-\rho^2)}}, \frac{\sigma}{\sqrt{(1-\rho^2)}}\right)$ where $S = \{I, T\}$ for the intangible and tangible intensive types. Entrant firms are endowed with k_0 units of (total) capital from households, and hold no debt. They then proceed as incumbent firms. Next, the TFP, capital quality and exit shocks are drawn. With probability π_d, the firm gets an i.i.d. exit shock, and exits after producing. After shocks are realised, firms default on their debt if they cannot satisfy the non-negativity condition on dividends. In the event of default, the firm immediately and permanently exits. In order to continue, firms must pay last period's debt b_{jt} at the (firm specific) gross interest rate R_{jt}, and a fixed operating cost ξ.

The firms' problem is most straightforward to express in terms of the net worth of the firm. Net worth is given by

$$n = \max_{l} z(\omega k)^{\theta}l^{\nu} - w_t l + (1-\delta)\omega k - R_{jt}b - \xi. \tag{2.2}$$

The Bellman equation for continuing firms is then given by

$$\begin{aligned} v_t(z,n) = &\max_{k',b'} n - k' + b' \\ &+ E_t[\Lambda_{t+1}(\pi_d \chi^1(\hat{n}_{t+1})\hat{n}_{t+1} \times (1-\pi_d)\chi^2(z',\hat{n}_{t+1})v_{t+1}(z',\hat{n}_{t+1}))] \end{aligned} \tag{2.3}$$

subject to $d \equiv n - k' + b' \geq 0$

where Λ_{t+1} is the stochastic discount factor; $\hat{n}_{t+1} \equiv \max_{l'} z'(\omega' k')^{\theta} l'^{\nu} - w_{t+1} l' + (1-\delta)\omega' k' - R_{jt+1}(z,k',b')b' - \xi$ is net worth at time $t+1$ and $\chi^1(n)$ and $\chi^2(z,n)$ are indicator variables taking a value of zero if the firm defaults, conditional on exogenously exiting or not, respectively.

As shown by Khan et al. (2016), the optimal decision is characterised by three cases:

1. Default: firm defaults if $n < \underline{n}_t(z)$
2. Unconstrained: if $n > \bar{n}_t(z)$, the firm is financially unconstrained and follows a "frictionless" capital accumulation policy
3. Constrained: firms with $n \in [\underline{n}_t(z), \bar{n}_t(z)]$ are financially constrained; optimal investment and borrowing decisions solve the Bellman equation.

Total capital consists of intangible and tangible capital: $k_{jt} = k^T_{jt} + k^I_{jt}$. I assume that intangible and tangible capital are used in fixed shares, determined by type specific technology. This is equivalent to assuming a Leontief (fixed proportions) production function. This assumption implies that firms in the model do not face an endogenous choice between intangible and tangible capital, and only choose total capital. This simplifies the model as it reduces the number of state variables, whilst allowing for heterogeneity in intangible intensity. The share of intangible and tangible capital for each firm type $s = \{I, T\}$ is given by the exogenous technological parameter γ_s:

$$\begin{aligned} k^T_{jt} &= \gamma_s k_{jt} \\ k^I_{jt} &= (1-\gamma_s) k_{jt}. \end{aligned}$$

Hence, intangible and tangible intensities for the two firm types are:

$$\begin{aligned} \frac{k^T_{jt}}{k_{jt}} &= \gamma_s \\ \frac{k^I_{jt}}{k_{jt}} &= 1-\gamma_s \end{aligned}$$

for $s = \{I, T\}$; where I is for intangible intensive and T for tangible intensive firms. The firm types differ in intangible intensity ($\gamma_T > \gamma_I$) and average productivity (μ_I & μ_T). Firms of each type also face a different financing constraint due to different recovery rates ($\alpha^T > \alpha^I$) and different productivities which in turn affect the probability of default.

2.2.2 Lenders

The borrowing constraint follows the form used in Chapter I. There is a representative financial intermediary that lends resources from households to firms. 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 and Winberry (2020), firms can borrow more than the amount of collateral they have, exposing the lender to a loss in the event of default. The risk of losses to the lender is priced competitively: the expected return on firm debt equals the risk free rate.

Similar to Chapter I, there is a distinction between collateralised and uncollateralised lending. For collateralised loans, in the event of default the lender recovers a fraction α^T of the firm's tangible capital stock, and α^I of the firm's intangible capital stock. For uncollateralised loans, the lender recovers nothing. There is a fixed collateralisation cost, C, that the lender must pay to value firm assets. Loans are priced competitively such that the expected return on a loan equals the risk-free rate (R^f). The firm specific interest rate, $R_{jt}(z, k', b')$, therefore satisfies the following equation:

$$\begin{aligned} R^f_t =& E_t \left[(1 - \chi_{it+1}) \, R_{jt}(z, k', b') \right] + \\ & max \left\{ E_t \left[\chi_{it+1} min \left\{ \frac{\left[\alpha^T \gamma k' + \alpha^I (1-\gamma) k' \right] (1-\delta) \omega'}{b'}, R_{jt}(z, k', b') \right\} \right] - C, 0 \right\}. \end{aligned}$$

2.2.3 Representative Household

The household has preferences over consumption and labour, represented by the expected utility function

$$E_0 \sum_{t}^{\infty} \beta^t (log C_t - \Psi L_t). \tag{2.4}$$

The household owns all firms in the economy. There is no aggregate uncertainty, and hence the risk-free rate and the stochastic discount factor are linked through the Euler equation:

$$\Lambda_{t+1} = \frac{1}{R_t^f}. \tag{2.5}$$

2.3 Calibration and Model Fit

I calibrate the model to match UK data. This is for two reasons. Firstly, the empirical estimates in Chapter I that are used to calibrate the financing constraint are estimated using UK data. Hence, for consistency, the rest of the calibration also follows UK data. Secondly, the UK offers an interesting landscape to study financing frictions related to intangibles. This is because intangible investment in the UK is similar to the high levels of the US, whereas most other European economies have a lower intangibles share. On the other hand, collateral constraints are likely to be more relevant in the UK compared to the US. This is because the likelihood of asset liquidation in case of bankruptcy, as well as the economic importance of SMEs, are higher in the UK (and other European countries). For example, between 2019 and 2023, 49.5% of bankruptcies in the US were liquidations, compared to 90% in the UK.[7] In addition, the employment share of SMEs is larger (61%) in the UK than in the US (46%).[8] Asset-based lending, for which the liquidation value of firm assets is most relevant, is prevalent among smaller firms as well as in countries where liquidations are more likely (Lian & Ma (2021)). For these reasons, financing frictions related to intangible assets are likely to be particularly relevant in the UK.

Calibration of fixed parameters is given by Table 2.1. I use UK firm-level balance sheet data from Bureau van Dijk to compute intangible and tangible intensities. Firm-level intangible capital stock is computed by capitalising expenditures into R&D and SG&A, following Peters and Taylor (2017). More detail is provided in Appendix 2.A1. I classify firms that are above the median intangible intensity as intangible intensive firms, whereas firms below the median are classified as tangible intensive. The intangible intensity for each type in the model reflects the median intangible intensity in the data for the firms classified as intangible and tangible intensive. The recovery rates on different types of capital, α^T and α^I, are the structural parameter estimates obtained in Chapter I: 38.1% for tangible capital, and 13.4% for the intangible capital stock.

The labour and capital coefficients in the production function are adjusted to

[7]These figures are based on data from S&P Global Market Intelligence 2024 for the US, and UK government statistics on company insolvencies.

[8]Sources: US small business administration, office of advocacy; Business population estimates for the UK and regions 2023 by the UK government.

reflect the inclusion of intangible capital. Compared to Ottonello and Winberry (2020), this results in a lower labour coefficient and higher capital coefficient. The returns to scale in the production function follow Ottonello and Winberry (2020), and the relative values of the labour and capital coefficients are set in line with production function estimates which include intangible capital (Chiavari and Goraya (2024)). The calibration of the remaining fixed parameters follows Ottonello and Winberry (2020).

Table 2.1: Calibration, fixed parameters

Parameter	Description	Value
Household		
β	Discount factor	0.99
Firms		
ν	Labour coefficient	0.55
θ	Capital coefficient	0.33
δ	Depreciation	0.025
γ_T	Tangible intensity, Tan firms	0.89
γ_I	Tangible intensity, Intan firms	0.1
ρ	Persistence, TFP	0.9
Lender		
α^T	Recovery rate, k^T	0.38
α^I	Recovery rate, k^I	0.13

The rest of the model parameters are calibrated to match the calibration targets outlined in Table 2.2. The model is calibrated to match moments for the aggregate economy, instead of moments for intangible and tangible intensive firms separately. The exception is the share of total employment by the two firm types. This helps to discipline the relative mean of idiosyncratic productivity shocks affecting intangible and tangible intensive firms. I set the mean to zero for tangible intensive firms, and calibrate the mean of productivity shocks of intangible intensive firms, μ^I, along with other fitted parameters.

The calibration targets are computed from UK firm level balance sheet data from Bureau van Dijk (BvD). The exception is the mean default rate, as defaults are not well reported in the firm-level data used. The target for the default rate is from S&P data.[9] The average UK default rate for speculative grade rated corporate debt was 3.66% between 1995 and 2023. I chose the speculative grade to

[9]Source: "Default, Transition, and Recovery: 2023 United Kingdom Corporate Default And Rating Transition Study" by Kraemer, Gurwitz and Richhariya, S&P Global, Research article, 2024.

reflect the fact that most of the firm population are SMEs, who are likely to have a higher default probability than large companies.[10] The default rate target is close to the 3% target commonly used in models with a similar financing constraint (Ottonello and Winberry (2020); Bernanke et al. (1999)).

Table 2.2: Calibration targets for fitted parameters

Moment	Data	Model
SD investment rate	0.33	0.37
Mean default rate	3.66%	3.31%
Mean leverage ratio	0.51	0.71
Fraction with positive debt	0.91	0.85
Employment share, age ≤ 1	0.03	0.03
Employment share, age $\in$ (1-10)	0.26	0.36
Employment share, age ≥ 10	0.71	0.61
Annual exit rate	7.5%	7.1%
Share of firms age 1	0.07	0.07
Share of firms age 2	0.06	0.06
II employment share	0.52	0.51

Table 2.3: Fitted parameter values

Parameter	Description	Value
Idiosyncratic shocks		
σ	SD, TFP shocks	0.03
σ_ω	SD, capital quality shock	0.04
Financial frictions		
ξ	Operating cost	0.04
Firm lifecycle		
k_0	Initial capital	0.29
π_d	Exog exit rate	0.01
Productivity difference		
μ_I	Mean of intangible productivity shocks	0.019

The model matches the targeted moments reasonably well despite being overidentified. Similar to Ottonello and Winberry (2020), the model overpredicts the

[10]This is supported by the firm level default probability data used in Chapter I, where the average default probability for SMEs is over 6%, compared to approximately 2% for large corporations.

dispersion of investment rates and the gross leverage ratio, and underpredicts the fraction of firms with positive debt. The model matches the share of employment in recent entrants, but overpredicts the share of employment in firms that are between 1 and 10 years old. The default and exit rates are slightly below target.

In the calibrated model, intangible intensive firms have a higher mean of TFP shocks by approximately 1.9%. The firm level data used is consistent with higher productivity of intangible intensive firms: they have a higher average labour productivity, despite having a lower ratio of total capital-to-debt. See Appendix 2.A2 for more detail. Previous literature has also found a positive association between firm intangible intensity and firm-level TFP (Crass and Peters (2014); Lee and Paluszynski (2022); Karmakar et al. (2022); Roth et al. (2023)).

How well does the model capture untargeted differences between intangible and tangible intensive firms?[11] To assess model fit, I examine differences in production and financial behaviour of intangible and tangible intensive firms. The results are outlined in Table 2.4. The model performs well: the signs of the differences between the two firm types in terms of financial variables, investment rates and production are consistent with the data. The model also captures a substantial share of the magnitude of differences between intangible and tangible intensive firms. The model is quite close to the data regarding the difference in leverage as well as fraction of positive debt between the two types. Despite not featuring capital adjustment costs, which may differ between intangible and tangible capital[12], the model accounts for 40% of the difference between the standard deviations of investment rates of intangible and tangible intensive firms, and 20% of the difference in means. Finally, the model explains 50% of differences in the share of total output, and around a third of the differece in the capital shares, of intangible and tangible intensive firms, and just under a third of the difference in their capital-to-output ratios.

[11] Apart from the relative employment share of intangible and tangible intensive firms, the model is calibrated to match the aggregate economy.

[12] See for instance Chiavari and Goraya (2024), Belo et al. (2022) and Cloyne et al. (2022) for models featuring different adjustment costs for intangibles.

Table 2.4: Intan and tan firm differences (untargeted)

	Tan firms (Model)	Tan firms (Data)	Intan firms (Model)	Intan firms (Data)	**Difference, TI - II (Model)**	**Difference, TI - II (Data)**
Financial						
Leverage	0.73	0.55	0.67	0.47	**+6pp**	**+8pp**
Frac positive debt	0.87	0.96	0.82	0.92	**+5pp**	**+4pp**
Investment						
SD investment rate	0.36	0.30	0.38	0.35	**-2pp**	**-5pp**
Mean investment rate	0.127	0.065	0.128	0.07	**-0.1pp**	**-0.5pp**
Production						
Output share	0.49	0.48	0.51	0.52	**-2pp**	**-4pp**
Capital share	0.49	0.47	0.51	0.53	**-2pp**	**-6pp**
K/Y ratio	5.64	1.89	5.36	0.97	**+28pp**	**+92pp**

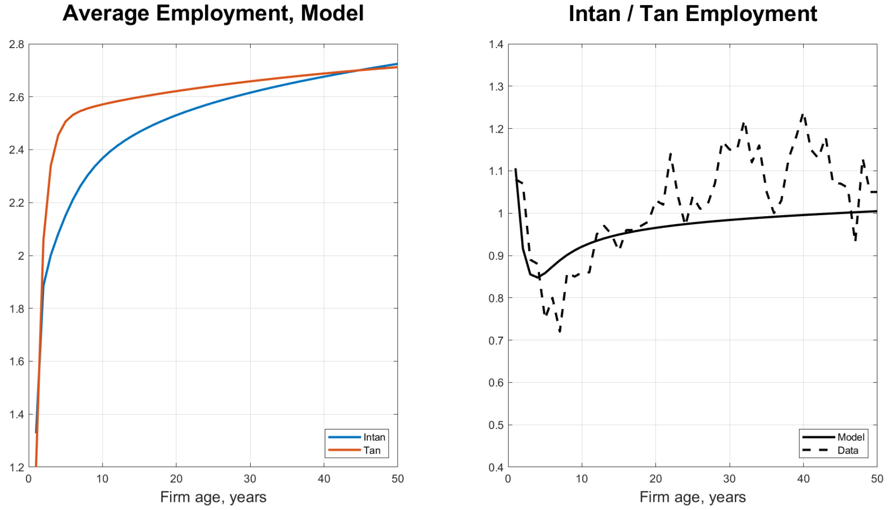
Notes: This table shows untargeted moments in the model and the data, for intangible and tangible intensive firms. The data is balance sheet data for UK companies from BvD.

I also compare the relative lifecycle dynamics of intangible and tangible intensive firms in the model to those in the data. The results are depicted in Figure 2.2. The first panel plots average employment of intangible and tangible intensive firms over firm age. In the model, intangible intensive firms start slightly larger. However, tangible intensive firms initially grow at a faster rate. Hence, average employment of intangibles firms falls relative to their tangible intensive peers. After the first five years, growth in tangible intensive firms slows down, and intangible intensive firms start catching up. However, in the model, the average size of intangible intensive firms only exceeds that of tangible intensive firms when firms are over 40 years old.

The second panel plots the relative size of intangible and tangible intensive firms over age, for the model and the data. Interestingly, the U-shaped pattern of the relative size of intangible and tangible intensive firms can also be seen in the data. The patterns are very similar, both qualitatively and quantitatively. The model captures an interesting difference between the lifecycles of intangible and tangible intensive firms that is also visible in the data, despite the fact that the model is calibrated to match the aggregate employment shares of the two firm types only (and not the relative lifecycle dynamics).

The U-shaped relationship is in contrast with previous work showing that intangible intensive firms start smaller and grow faster than their tangible in-

Figure 2.2: Intan vs tan firms: lifecycle (untargeted)



Notes: This figure illustrates the lifecycle dynamics in firm size for intangible and tangible intensive firms. The left-hand side panel plots the average employment by firm age, for intangible intensive (blue line) and tangible intensive firms (red line). The right-hand panel plots the relative size of intangible and tangible intensive firms, given by the average employment of intangible intensive firms divided by that of tangible intensive firms, over the firm lifecycle. The solid line reflects the lifecycle pattern in the model, the dashed line plots the same ratio in the data. Data is balance sheet data for UK companies from BvD.

tensive peers (Chen (2014)). In contrast to a sample of US public corporations analysed in Chen (2014), the dataset here consists mainly of private SMEs. The better coverage of smaller and younger companies is a potential explanation for the differences in the empirical predictions between this paper and Chen (2014). In fact, including only firms over 5 years of age would result in similar lifecycle dynamics as documented by Chen (2014).

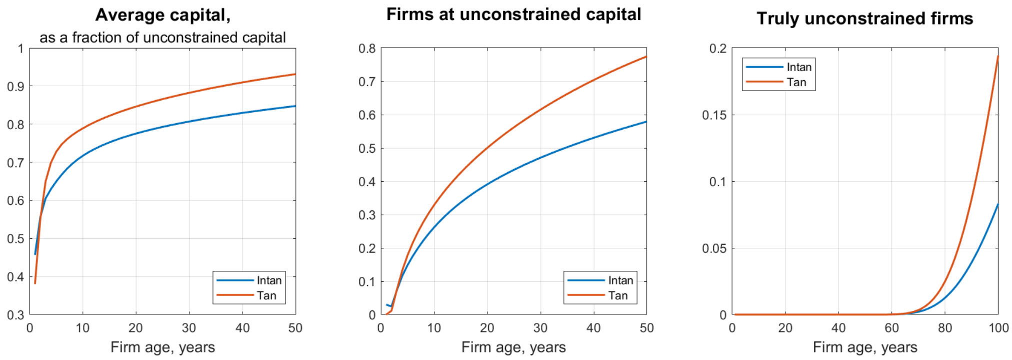
2.4 Model Results

2.4.1 Are intangible intensive firms more constrained?

Figure 2.3 compares financial constraints over the firm lifecycle for intangible and tangible intensive firms. The first panel plots the average capital stock as a fraction of the unconstrained capital stock over the firm lifecycle. The second panel plots the fraction of firms that have reached the unconstrained level of capital at each age. Finally, the third panel plots the fraction of intangible and tangible intensive firms that are truly unconstrained. These firms have fully outgrown the financial constraint: their net worth is large enough that they can achieve the unconstrained level of capital in the current period, and will remain unconstrained in every future state.

Higher productivity of intangible intensive firms relaxes the borrowing con-

Figure 2.3: Financial constraints over the firm lifecycle, intan vs tan firms



Notes: The left-hand side panel plots the average capital stock as a fraction of the average unconstrained capital stock, over firm age. The middle panel plots the fraction of firms that are at the optimal (unconstrained) level of capital, over firm age. The right-hand side panel plots the fraction of firms that are truly unconstrained: these firms have fully outgrown the financing constraint, and can reach their unconstrained capital levels in the current period, as well as in every future state.

straint as it lowers the firm default probability. This is because, ceteris paribus, higher productivity firms are less likely to receive a low enough productivity realisation that would result in default. On the other hand, the low collateral value of intangibles results in a tighter constraint. For start-ups, the first effect dominates, as both intangible and tangible intensive firms initially rely on uncollateralised lending. Hence, very young intangible intensive firms are *less* constrained than their tangible intensive peers. This is in contrast with previous literature, where intangible intensive start-ups and very young firms are often considered to be most affected by financing frictions (Chen (2014); Bøler et al. (2023); Caggese and Perez-Orive (2022)). Once tangible intensive firms grow, they can access collateralised loans, leaving them less constrained than intangible intensive firms. This effect persists for the rest of the firm lifecycle, as tangible intensive firms outgrow the financing friction at a faster rate than intangible intensive firms. Hence, intangible intensive firms are more financially constrained for most of their lifecycle.

In the model, higher productivity does not result in intangible intensive firms outgrowing the financing constraint quicker. This is partly due to the fact that higher productivity also increases the optimal unconstrained level of capital. Hence, with the tighter financing constraint, it takes longer for the average intangible intensive firm to reach their optimal unconstrained amount of capital, and the truly unconstrained state.

2.4.2 Counterfactual: costs of low pledgeability of intangible capital

I proceed by investigating the macroeconomic impact arising from the low collateral value of intangible assets. I conduct a counterfactual exercise, comparing the baseline stationary distribution (where intangibles have a low collateral value, or $\alpha^I = 0.134$) to a counterfactual where intangible and tangible assets can both be used as collateral (their recovery rates are equal: $\alpha^I = \alpha^T = 0.381$). Table 2.5 depicts the results of the counterfactual exercise. Firstly, output increases significantly when the financing friction related to intangible capital is removed: the output losses related to low pledgeability of intangibles are 7.7%. The losses come from inefficiently low investment and employment (capital increases by 7.8% and employment by 7.7% if the friction is removed); as well as aggregate TFP losses (1.15%). Removing the intangibles financing friction also results in an increase in average leverage (by 9 percentage points), and the default rate (3pp).

I compute the consumption equivalent welfare losses arising from the low collateral value of intangibles. Specifically, I ask how much consumption would need to increase in the baseline (where intangibles are harder to pledge as collateral), for the representative household to be indifferent between the baseline and the counterfactual (where the collateral value of intangibles is equal to that of tangibles). The resulting figure is 2.11%, meaning that consumption would have to increase by 2.11% in the baseline for the household to be as well off as in the counterfactual.

Table 2.5: Counterfactual results

	Baseline ($\alpha^I = 0.134$)	No intan friction ($\alpha^I = \alpha^T = 0.381$)	Change
Output	1.42	1.53	+7.7%
Capital	7.96	8.58	+7.8%
Investment	0.323	0.348	+7.7%
Employment	0.604	0.652	+7.9%
TFP	1.007	1.0187	+1.15%
Leverage	0.71	0.80	+9pp
Frac Positive Debt	0.85	0.83	-2pp
Default rate	3.31%	6.30%	+3pp
Frac Unconstrained	0.50%	0.56%	-0.06pp
Welfare (Consumption Equivalent)			+2.11%

Notes: This table shows the results of the counterfactual exercise. The first column shows model aggregates for the baseline scenario, where intangibles have a lower collateral value than tangible assets. The second depicts the same aggregates for the counterfactual, where intangible and tangible capital have identical recovery rates, and hence it is easy for firms to pledge both types of capital as collateral.

Figure 2.4 shows the decomposition of the output gains. It is constructed using the following formula:

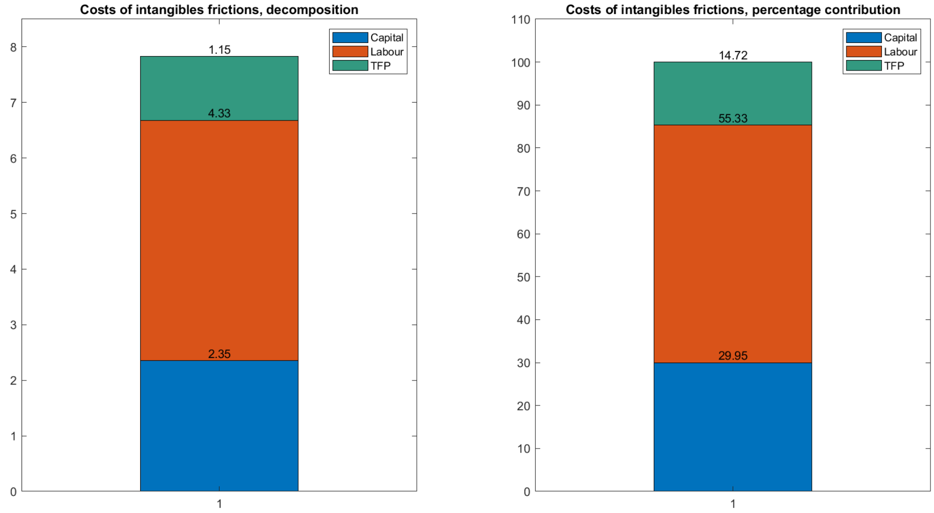
$$\%\Delta Y = \%\Delta TFP + \theta\%\Delta K + \nu\%\Delta L.$$

The figure shows that a large fraction of the costs can be attributed to inefficiently low steady state employment (55%) and capital stock (30%); however, the role of TFP losses is also sizeable (15%).

I next investigate the sources of TFP losses related to the low collateral value of intangibles. I perform the Olley-Pakes decomposition to assess the relative contributions of changes in average productivity and allocative efficiency between firms. I examine this within and between firm types. Table 2.6 shows the results of the decomposition. Figure 2.5 illustrates further.

There are three effects at play. Interestingly, the aggregate TFP improvement mainly comes from increased average productivity of firms in production, driven by intangible intensive firms. On the other hand, allocative efficiency *declines* when the collateral value of intangibles is increased to the level of tangible capital. These effects are also present for tangible intensive firms, however, they are

Figure 2.4: Sources of output losses



Notes: Output cost decomposition. The left panel depicts the percentage points by which changes in factors of production (labour and capital) and TFP increase output when intangible and tangible assets have an equal collateral value. The right panel depicts the proportions of the output increase that can be accounted for by the change in capital, labour and TFP.

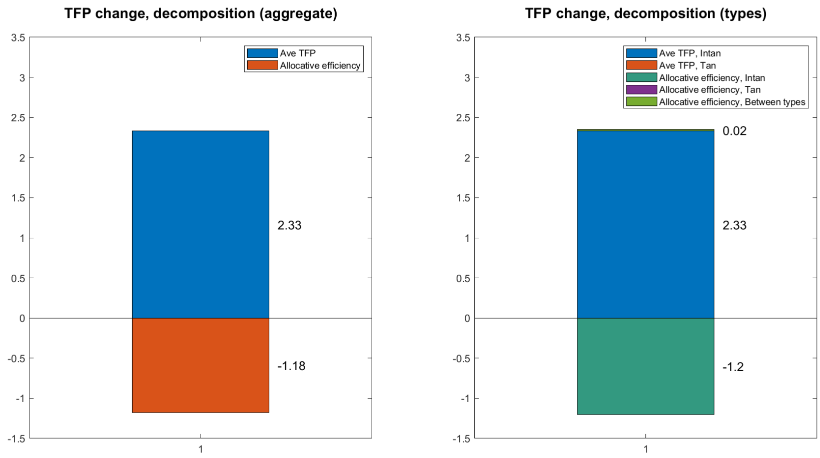
quantitatively negligible and hence barely visible in Figure 2.5. There is also a small improvement in the allocation of resources between firm types, as more productive intangible intensive firms become larger.

Table 2.6: TFP decomposition

	Intan friction ($\alpha^I = 0$)	No intan friction ($\alpha^I = \alpha^T$)
TFP Intan	1.0048	1.0276
Ave TFP Intan	0.9687	1.0258
Cov Intan	0.03604	0.001753
TFP Tan	1.0095	1.0095
Ave TFP Tan	1.0112	1.0112
Cov Tan	-0.001716	-0.001709
TFP (aggregate)	1.0071	1.0187
Ave TFP (aggregate)	0.9900	1.0185
Cov (Aggregate)	0.01710	0.0001823
Cov, Within types	0.01716	0.00002
Cov, Between types	-0.00007	0.000160

Notes: This table shows the decomposition of aggregate TFP for the counterfactual exercise. The first column shows the TFP decomposition for the baseline scenario, where intangibles have a lower collateral value than tangible capital. The second depicts the same decomposition for the counterfactual, where intangible and tangible capital have identical recovery rates, and hence both types of

Figure 2.5: Counterfactual - TFP Decomposition



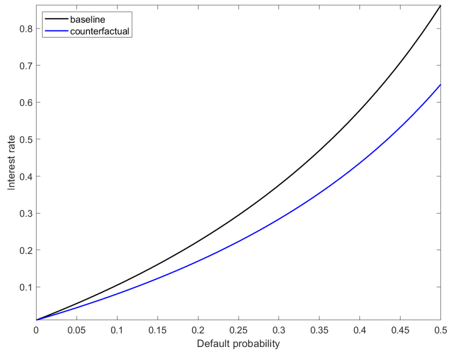
This figure shows the decomposition of the change in TFP between the baseline (where intangibles cannot be pledged as collateral) and the counterfactual (where intangible and tangible capital have the same recovery rate and can both be used as collateral). Using the Olley-Pakes decomposition, the change in aggregate TFP is split into the change in average (unweighted) TFP and the change in allocative efficiency, reflecting the covariance between firm size and TFP. The left-hand panel shows the decomposition for the aggregate economy. The right-hand panel depicts the decomposition for each firm type (intangible and tangible intensive), as well as the allocative efficiency between the two types.

capital can be used as collateral. Using the Olley-Pakes decomposition, aggregate TFP is split into average (unweighted) TFP and a covariance term reflecting the covariance between firm size and TFP. This is done within firm types (first 6 rows), as well as for the aggregate economy (final 5 rows).

Why does average productivity increase and allocative efficiency decline when the pledgeability of intangible assets improves? Both of these effects stem from the impact of intangibles on the link between firm financing costs and default probability. Figure 2.6 illustrates how the relationship between firm financing costs and default probability for intangible intensive firms changes, when intangible assets can be used as collateral in the same way as tangible assets in the counterfactual. In the baseline, intangible intensive firms do not have much collateral. Hence, the lender faces large losses if the firm defaults. This results in a sharp increase in the financing costs of intangible intensive firms when firm default risk increases, as the lender is compensated for the increased risk of significant losses. However, in the counterfactual, intangible intensive firms can pledge a larger proportion of their assets as collateral, significantly lowering the losses faced by the lender in the event of default. Therefore, the firm interest rate increases much more gradually with the firm default probability.

The dampening of the relationship between firm financing costs and default probability in the counterfactual has two opposing effects on productivity. On

Figure 2.6: Relationship between firm interest rate and default probability

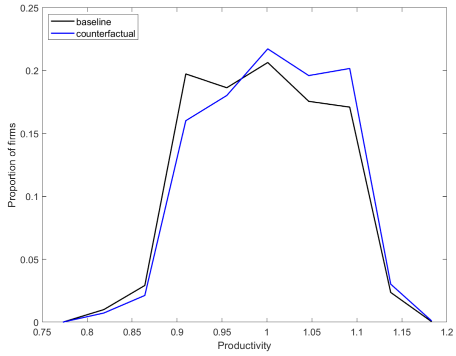


Notes: This figure depicts the relationship between the firm-level interest rate and default probability for intangible intensive firms, in the baseline (intangibles have a low collateral value, black line) and the counterfactual (intangible assets are as collateralisable as tangible assets, blue line). For simplicity, I abstract from capital quality shocks, meaning there is no uncertainty about firm capital. The graph is drawn varying default probability but keeping everything else fixed: firm capital and debt choices (for values $k' = 1$ and $b' = 1$) as well as firm net worth ($n = 0$).

the one hand, it increases the default rate of intangible intensive firms. This is because in the baseline, intangible intensive firms take on very little debt, and have a low equilibrium default rate, as it would be very costly for these firms to incur a significant risk of default. In the counterfactual, intangibles can be pledged as collateral as easily as tangible assets, and intangible intensive firms can incur a higher default risk without the sharp increase in borrowing costs, leading to increased default in equilibrium. In the model, default has a cleansing effect, as firms receiving low productivity realisations default and exit. A higher default rate in the counterfactual therefore increases average productivity of firms in production, by strengthening positive firm selection. Figure 2.7 illustrates the effect of the higher default rate on the distribution of firm productivity: in the counterfactual (green line) the productivity distribution shifts to the right, as a larger mass of low productivity firms default and exit.

On the other hand, the looser connection between default risk and financing costs when intangibles can be pledged as collateral *reduces* allocative efficiency between firms in production. This is because of the positive relationship between default risk and productivity in the model: ceteris paribus, higher productivity firms are less likely to receive a low enough productivity realisation that would result in default. Hence, the tight link between firm financing costs and default risk in the baseline implies a tight link between borrowing costs and productivity. Figure 2.8 shows how the link between borrowing costs and productivity changes when intangibles can be pledged as collateral in the counterfactual. In the counterfactual, the looser connection between default risk and financing

Figure 2.7: Productivity distribution of firms in production

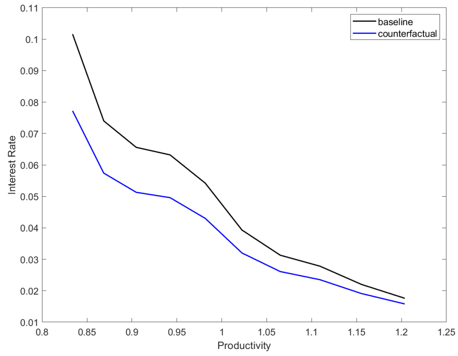


Notes: This figure illustrates the impact of increased ability to pledge intangibles as loan collateral on the productivity distribution of firms in the economy. The back line shows the baseline (intangibles have a low collateral value) productivity distribution. The blue line shows the productivity distribution of firms in the counterfactual, where intangibles can be used as loan collateral in the same way as tangible assets. In the counterfactual, the productivity distribution shifts to the right, as more unproductive firms are defaulting and exiting.

costs results in a dampening of the relationship between borrowing costs and productivity. Interestingly, being able to pledge a larger share of assets as collateral has a minor impact on high productivity firms. This is because these firms have a lower default risk, ceteris paribus, and can therefore borrow with a relatively lower interest rate, even with limited collateral. For low productivity firms, being able to pledge more assets as collateral is particularly beneficial, as these firms have a higher default risk and hence the liquidation value of their assets matters much more for loan pricing. Pledging intangible assets as collateral therefore disproportionately benefits firms with lower productivity. Hence, allocative efficiency between intangible intensive firms in production *declines* when the pledgeability of intangible assets improves.

It is important to note that the graph depicts the *conditional* relationship between firm interest rate and productivity, keeping everything else fixed (capital and debt decisions as well as firm net worth). Importantly, in equilibrium, the raw relationship between productivity and firm interest rate is not as clear. This is because high productivity firms with low net worth may still have higher financing costs than low productivity firms with high net worth, as the latter type may have a lower default risk. Default risk, and hence financing costs, depend on firm net worth and the amount of debt in addition to the level of productivity. Crucially, however, being able to pledge firm assets as collateral is unlikely to benefit high productivity firms with low net worth, as these firms are likely to be small firms with limited amounts of capital. In fact, being able to use assets as collateral disproportionately benefits larger and older firms with high levels

Figure 2.8: Relationship between firm interest rate and productivity



Notes: This figure illustrates the impact of pledging intangibles as loan collateral on the link between financing costs and productivity. The black line shows the baseline where intangibles have a low collateral value. The blue line shows the same relationship for the counterfactual, where the collateral value of intangibles is equal to tangibles. In both cases, the line shows the conditional relationship between the two variables, keeping everything else fixed (firm net worth, as well as debt and capital choices). In the counterfactual, the relationship between productivity and financing costs is less pronounced, as firms can use assets as collateral, reducing the impact of default risk (which is negatively linked to productivity) on borrowing costs.

of capital, irrespective of productivity. Hence, the counterfactual doesn't exhibit improved efficiency of resource allocation.

The financing friction also reduces investment and employment of productive intangible intensive firms relative to tangible intensive firms, resulting in TFP losses through resource misallocation between intangible and tangible intensive firms. Quantitatively, this conventional misallocation effect plays a minor role, resulting in TFP losses of 0.02%. Instead, the two effects described above, arising from the interplay between intangibles and default, have a much larger impact. On the one hand, the improvement in the efficiency of resource allocation due to the low collateral value of intangibles results in an *increase* in TFP by 1.2%. On the other hand, the low default rate of intangible intensive firms causes TFP *losses* of 2.33%. Overall, the negative impacts dominate, and the financing friction related to intangibles results in overall TFP losses of 1.15%. I note that the losses are an order of magnitude larger than the TFP losses (approximately 0.1%) from intangibles financing frictions computed in Bøler et al. (2023), whose framework accounts for the conventional misallocation effect only.

My results illustrate two mechanisms through which financing frictions can impact aggregate productivity, that (to the best of my knowledge) have previously not been discussed in the literature. Firstly, tight financing frictions can reduce average productivity by limiting default and exit of less productive firms. The outcome is similar to that of the zombie-lending effect (see for instance Caballero et al. (2008); Acharya et al. (2024); Blattner et al. (2019); Hu and Varas

(2021)), however, the mechanism is different. In the zombie-lending framework, lenders extend credit to weak firms, reducing default. In effect, firms have access to *too much debt*, preventing default. In contrast, in my model, the reduction in default is driven by the low recovery rate of intangibles, which reduces equilibrium default. Constrained firms optimally take on *too little debt*, resulting in a low equilibrium default rate.

Secondly, tight financing frictions can increase efficiency of resource allocation; in most of the literature, financing frictions unambiguously reduce the efficiency of resource allocation. This effect is similar to the one highlighted by Gopinath et al. (2017), who find that increasing the availability of credit can reduce allocative efficiency, if credit is allocated based on firm size instead of productivity. In contrast, my mechanism does not operate through increased availability of credit, but rather an increase in the fraction of assets that can be used as collateral. I show that increasing access to collateralised lending can hamper allocative efficiency, as it reduces the impact of default risk (and productivity) on firm borrowing constraints. If all firms are restricted to using uncollateralised loans, unproductive firms cannot mitigate the impact of higher default risk by borrowing against their assets.

In my model, these two effects - arising from the interaction between intangibles and default risk - are quantitatively much more important for aggregate TFP compared to the conventional misallocation effect arising from inefficiently low investment and employment by intangible intensive constrained firms.

2.4.3 Importance of financing constraints in the intangible economy

I finish the analysis by illustrating how accounting for intangible capital affects the relevance of financing frictions. I compare the calibrated model with intangibles to a similar model that includes tangible capital only. In this version of the model, there is only one firm type that uses tangible capital and labour in production. The recovery rate of firm assets is set to 0.381, reflecting the estimated recovery rate on tangible assets. Moreover, the firm production function parameters reflect a higher share of labour and lower share of capital, consistent with estimates obtained when only tangible capital is included in production function estimation. I use the same parameters as Ottonello and Winberry (2020), who set the labour coefficient to 0.64 and capital coefficient to 0.21. The rest of the model parameters are calibrated to match the same targeted moments that were used to calibrate the model with intangible capital (without the target reflecting the relative employment share of intangible and tangible intensive firms).

In the model without intangible capital, almost two thirds (64.8%) of firms can reach the optimal unconstrained level of capital. In addition, 2.72% of firms have reached the truly unconstrained state. These firms can finance the optimal level of capital stock whilst borrowing at the risk free rate, and there is no possible future state in which they would become financially constrained. In contrast, accounting for intangible capital reduces the proportion of firms able to reach the unconstrained level of capital to just over a third (34.25%), and the fraction of truly unconstrained firms to 0.5%. Comparing the firm lifecycle dynamics in the two versions of the model, I find that the average firm reaches the unconstrained level of capital after approximately 7 years of production in the model without intangible capital, whereas it takes more than 3 times longer (26 years) for the average firm to reach the optimal unconstrained amount of capital in the model accounting for intangibles. Accounting for intangibles increases the relevance of financing frictions, as a significantly larger proportion of firms are financially constrained, and firms outgrow the financing constraint at a much slower rate.

Table 2.7: Impact of accounting for intangibles on losses from financing frictions

	Baseline, intan	Unconstrained, intan	Baseline, no intan	Unconstrained, intan	**Change (intan model)**	**Change (no intan)**
Output	1.422	1.544	0.977	0.981	**8.6%**	**0.4%**
Capital	7.961	9.224	3.985	4.110	**15.9%**	**3.1%**
Investment	0.323	0.374	0.162	0.167	**15.8%**	**3.1%**
Employment	0.604	0.634	0.599	0.601	**5.0%**	**0.3%**
TFP	1.0071	1.0188	1.0139	1.0101	**1.16%**	**-0.4%**

Notes: This table illustrates the impact of accounting for intangible capital on the costs of financing frictions in the model. The first column shows aggregates for the model with financial frictions and intangible capital. The second column provides the same aggregates for the model with intangible capital without financial frictions, or the unconstrained version of the intangibles model. The third column reports the aggregates for the model with financing frictions, but only tangible capital (excluding intangibles), calibrated to match the same moments as the model with intangibles and financing frictions. The fourth column shows the unconstrained (no financing frictions) version of the model with tangible capital only. The last two columns provide the percentage change between the unconstrained stationary distribution and the stationary distribution with financing frictions, for the model with intangibles and the model with tangible capital only.

Table 2.7 illustrates the total losses from all financing frictions in the two versions of the model. I compare the unconstrained stationary distribution and the baseline stationary distribution (with financing constraints) in the model with intangibles, and the model with tangible capital only. The aggregate output losses from financing frictions are an order of magnitude larger in the model with intangibles (8.6%) compared to the model without intangibles (0.4%).[13] The impacts of financing constraints on aggregate investment, capital and employment are also much larger in the model that accounts for intangible capital. Finally, aggregate TFP is 1.6% higher in the unconstrained version of the model with intangibles, whereas there is a small *decline* in TFP when financing frictions are removed in the model with tangible capital only.[14] It is clear that not accounting for intangible capital significantly reduces the economic impact of financing frictions.

2.5 Discussions

In this section, I discuss how extensions to the current model might affect the main results. In particular, I consider the impact of allowing for alternative financing options; endogenous firm entry; the potentially higher risk related to intangible investment; additional bankruptcy costs and the difference between partial- and general equilibrium analysis.

2.5.1 Alternative sources of financing

Intangible intensive firms may be particularly likely to use equity financing given the lack of collateral. The model does not feature equity financing, as dividends have a lower bound of zero. Allowing firms to use equity financing may undo some of the effect that financing frictions have on intangible intensive firms, particularly if equity financing is a cheap and easy alternative for younger and smaller firms, which are more constrained by the lack of collateral. However, as firms can also use uncollateralised loans in the model, and larger, older and more productive firms have access to relatively cheap uncollateralised loans due low default risk, allowing for equity financing may not have a large impact, particularly on the outcomes for large firms.

[13]The losses from financing frictions are quantitatively small compared to previous literature on the costs of financing frictions in advanced economies. For instance, Midrigan and Xu (2014) find losses to consumption of around 2%. One of the reasons for the small losses in the model without intangibles is the fact that there is no hard borrowing limit, meaning firms are more likely to be able to reach the optimal unconstrained level of capital. It should be noted that this impact is also present in the model with intangibles, dampening the costs of financing frictions in the model.

[14]the TFP decline is driven by the cleansing effect of firm defaults in the model. In the unconstrained stationary distribution, there is no default and hence lower productivity firms do not exit. This reduces the average productivity of firms in production, lowering aggregate TFP.

The seminal work of Lian and Ma (2021) and Drechsel (2023) highlights the importance of "cash-flow based lending". They demonstrate that loans with favourable terms, depending explicitly on the level of cash flow (rather than firm assets) are prevalent especially amongst large firms in the US. These loans provide an important source of financing also in many other advanced economies, particularly amongst larger firms. Intangible intensive firms may be particularly likely to use cash-flow based loans, as they circumvent the need for collateral. Even though my framework does not allow for explicit lending against firm cash-flows, my model includes uncollateralised lending, where loan terms are fully determined by firm default risk. As firms with high net worth (which is linked to cash-flow) are unlikely to default, these firms can use cheap uncollateralised loans. I therefore expect that allowing larger firms access to cash-flow based lending may not have a major impact in the model, though it may result in older and larger intangible intensive firms outgrowing financing constraints at a somewhat faster rate.

I note that some of the literature defines "cash flow loans" as any loans that are not collateralised. My model already accounts for loans that are implicitly linked to cash-flow through firm default risk, and firms have access to these loans in the model through uncollateralised lending. Overall, the fact that the current model does not feature a strict borrowing limit determined by collateral, but instead allows for lending beyond the amount of collateralisable assets, is likely to dampen the impact of introducing alternative financing options. Nevertheless, future research could assess the extent to which intangible intensive firms can circumvent tighter (asset-based) financing constraints by using cash-flow based loans, or equity finance.

2.5.2 Endogenous entry

In the current version of the model, entry is exogenous: the mass of entrants is simply determined by the mass of exiting firms of each firm type, such that the mass of firms in production (and the mass of intangible and tangible intensive firms) is fixed over time. However, financing frictions are also likely to have an impact on the number of firms entering the market, and on the number of firms selecting to become either intangible or tangible intensive types. The result that higher default rate is beneficial for the economy, as it increases the average productivity of firms in production, relies partly on the assumption that defaulting and exiting firms are replaced by new entrants. If a higher default rate results in less firms in production, aggregate output may decline despite the increase in productivity. However, in the counterfactual analysis, removing the financing friction related to intangibles would likely lead to increased entry, particularly by intangible intensive firms. Therefore, having endogenous entry may also amplify the benefits of removing intangibles financing frictions in equilibrium.

2.5.3 Higher risk associated with intangible investment

Intangible investment may feature higher rates of uncertainty than tangible investment (Barth et al. (2001), Himmelberg and Petersen (1994)). This may be another reason why it is harder to finance intangible investment. In the model, I currently only allow for a difference in the mean of productivity shocks for intangible and tangible intensive firms. Future research could investigate whether allowing for a higher variance of productivity shocks (or alternative ways to capture potentially higher risks) for intangible intensive firms would impact the results of the analysis in this paper. In particular, given that the TFP effects of intangibles financing frictions mainly stem from the interaction between intangibles and default risk in the model, having links between intangibles and risk may amplify or dampen some of the current mechanisms.

2.5.4 Additional bankruptcy costs

In the model, firm bankruptcy is costly: part of firm capital stock ($(1-\alpha^T)$ of tangible capital and $(1-\alpha^I)$ of intangible capital) is lost when a firm defaults. As there is no aggregate uncertainty, and given that the expected losses given default are fully priced into firm loans, there are no losses to the lender arising from equilibrium default. However, these costs related to bankruptcy manifest in higher financing costs for firms, reducing investment, employment and and hence aggregate production and consumption.

Adding further costs related to default, such as fixed bankruptcy costs faced by the lender if the firm defaults, or frictions preventing labour moving from defaulting and exiting firms into firms in production, would increase the negative impact of default on the economy. These would likely reduce the benefits of positive firm selection arising from firm default. Hence, accounting for these features could lower the aggregate benefits in the counterfactual, as pledging intangibles as loan collateral increases firm default in the model.

2.5.5 Partial versus General Equilibrium

Finally, the risk free interest rate in the steady state of the model is fully determined by the household discount factor, and is not affected by investment demand. Intangibles financing frictions may also affect the equilibrium interest rate, as they reduce aggregate investment. If the model featured a fixed supply of savings, and the equilibrium interest rate would adjust to clear the market, there could be further channels through which intangibles financing frictions affect the economy. In fact, Buera et al. (2021) find that the TFP benefits arising from looser financing constraints are much larger when the equilibrium interest rate adjusts in the general equilibrium framework, compared to their partial equilibrium framework where the interest rate is fixed.

2.6 Concluding remarks

I study the impact of the low collateral value of intangible assets on firm financing constraints, as well as on aggregate output, investment, productivity and resource allocation. I construct a model of heterogeneous firms, featuring intangible and tangible intensive firms and an endogenous borrowing constraint. The model illustrates that accounting for intangibles is crucial when assessing the importance of financing frictions in modern economies, where total capital is increasingly intangible. Excluding intangibles results in an underestimation of the impact of financing frictions: in a model with tangible capital only, 65% of firms reach their optimal unconstrained level of capital, compared to only 34% in the model accounting for intangibles. In addition, it takes over three times longer for the average firm to reach the optimal unconstrained level of capital when intangibles are taken into account. The aggregate output losses from financing frictions are an order of magnitude larger in the model with intangibles (8.6%) compared to the model without intangibles (0.4%).

Empirically, I document that the relative size of intangible and tangible intensive firms follows a u-shape over the firm lifecycle. The model generates the same u-shaped relationship between relative firm size and firm age. In the model, intangible intensive entrants are larger, as they are less financially constrained than their tangible intensive peers, due to both types of firms relying on uncollateralised loans and the higher productivity of intangibles firms. On the other hand, tangible intensive young firms grow faster, as they have better access to collateralised loans. Due to higher productivity, intangible intensive firms eventually overtake tangible intensive firms in firm size. However, they remain financially constrained for longer, as their optimal unconstrained level of total capital is higher than for tangibles firms. Apart from very young firms, the average intangible intensive firm is more financially constrained than the average tangible intensive firm, throughout the firm lifecycle.

The costs of intangibles financing frictions are significant, resulting in steady state output losses of 7.7%, as well as (consumption equivalent) welfare losses of 2.11%. This is partly due to inefficiently low investment and employment by intangible intensive firms, reducing the aggregate capital stock by 7.8% and aggregate employment by 7.7%. Aggregate TFP is also affected through multiple opposing effects. The financing friction disproportionately reduces investment and employment of intangible intensive firms, resulting in TFP losses through resource misallocation between the two firm types. In addition, the presence of intangibles results in a tighter link between firm financing costs and default risk. As lenders cannot recover intangible assets, the firm interest rate increases sharply with default risk, reflecting the large expected losses in the event of default. This highlights two opposing mechanisms through which financing frictions impact aggregate TFP. On the intensive margin, the tight link between financing costs and default risk is beneficial, as default risk is decreasing in productivity. This is because, ceteris paribus, higher productivity firms are less likely to receive a low enough productivity realisation that would result in default. Hence, the financing constraint is tightly connected to firm productivity, directing resources towards more productive firms. This increases aggregate TFP through improved allocative efficiency. On the extensive margin, however, the tight connection between financing costs and default risk limits firm default and exit. Default has a cleansing effect, as firms receiving low productivity realisations default and exit. A lower default rate reduces positive firm selection, reducing the average productivity of firms in production, thereby lowering aggregate TFP.

Quantitatively, the first conventional misallocation effect plays a minor role, reducing aggregate TFP by 0.02%. The latter two opposing effects are quantitatively much more important. They arise from the interplay between intangibles and default risk, and have previously been overlooked by the literature. On the one hand, the improvement in the efficiency of resource allocation due to the low collateral value of intangibles results in an *increase* in TFP by 1.2%. On the other hand, the low default rate of intangible intensive firms causes TFP *losses* of 2.33%. Overall, the negative impacts dominate, and the financing friction related to intangibles results in overall TFP losses of 1.15%. These are an order of magnitude larger than the TFP losses (approximately 0.1%) from intangibles financing frictions computed in Bøler et al. (2023), whose framework accounts for the conventional misallocation effect only.

My results suggest that policies targeting the low pledgeability of intangible assets can have significant benefits by increasing aggregate investment, employment and TFP. Given the inherent differences in characteristics of intangible and tangible assets, it is unlikely that policymakers can alter the recovery rates of intangible assets substantially. This may also not be the optimal way to target intangibles financing frictions: my model illustrates how borrowing against firm assets can reduce allocative efficiency, as it disproportionately benefits larger firms, irrespective of productivity. Future research could investigate the best policies aimed at targeting financing frictions related to intangible assets. Based on the analysis in this paper, investment subsidies or other industrial policies increasing the size of intangible intensive firms are unlikely to deliver the full TFP improvements illustrated in the counterfactual analysis. This is because these policies are unlikely to increase exit of unproductive intangible intensive firms. On the other hand, policies that also increase default and exit of intangible intensive firms with lower productivity, including government backed loans or easier access to cash flow based lending, may be more effective.

The analysis in this paper illustrates that firm defaults can result in positive firm selection. It may therefore be beneficial for policymakers to reduce the costs related to firm default and exit. These costs include the low recovery rates of firm (intangible) assets studied in this paper, as well as other factors outside the current analysis, such as other bankruptcy costs and frictions preventing capital and labour reallocation from defaulting firms into firms in production. Finally, my results illustrate that borrowing against firm assets can dampen allocative efficiency, as this disproportionately benefits firms with more collateralisable assets, irrespective of productivity. Developing financial instruments that better discriminate firms based on productivity could improve the efficiency of resource allocation in modern economies.

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Appendix

2.A Appendix: Calibration

2.A.1 Calibration targets

To compute the intangible intensities in Table 2.1 as well as most of the calibration targets in Table 2.2, I use UK firm-level balance sheet data from Bureau van Dijk (BvD). It is not straightforward to measure 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 R&D and SG&A (selling, general and administrative) expenses, as in Peters and Taylor (2017) and Falato et al. (2022). The motivation behind this approach is that R&D expenditures reflect investment in "knowledge capital", whereas a proportion SG&A expenditures capture investment into "organisational capital". The dataset does not report SG&A expenses directly, and hence I use the following formula: SG&A = gross profit – operating profit – depreciation.

I classify firms that are above the median intangible intensity as intangible intensive firms, whereas firms below the median are classified as tangible intensive. The intangible intensity for each type in the model reflects the median intangible intensity in the data for the firms classified as intangible and tangible intensive. The reason for splitting firms by firm-level intangible intensity rather than by industry is that in the data, there is even more variation in intangible intensity within industries than between industries - though between industry variation is also large.

The rest of the model parameters are calibrated to match the calibration targets outlined in Table 2.2. The model is calibrated to match moments for the aggregate economy, instead of moments for intangible and tangible intensive firms separately. The exception is the share of total employment by the two firm types. This helps to discipline the relative mean of idiosyncratic productivity shocks affecting intangible and tangible intensive firms. I set the mean to zero for tangible intensive firms, and calibrate the mean of productivity shocks of intangible intensive firms, μ^I, along with other fitted parameters.

The calibration targets are computed from the UK firm level balance sheet data from BvD. The investment rate is computed as total investment (intangible + tangible) over total capital (intangible + tangible) at the firm level. The firm-level leverage ratio is computed as total debt (short term + long term) over total capital (intangible + tangible). The fraction with positive debt is the number of firms with debt that is strictly positive, over the total number of firms with non-missing reported debt in the data. The share of employment by intangible intensive firms is given by total number of employees by firms classified as intangible intensive (firm-level intangible intensity above the median intangible intensity) over the total number of employees for firms with non-missing intangible intensity and non-missing number of employees.

The target for the mean default rate is not computed using the BvD data, as defaults are not well reported. Instead, I use S&P data.[15] The average UK default rate for speculative grade rated corporate debt was 3.66% between 1995 and 2023. I chose the speculative grade to reflect the fact that most of the firm population are SMEs, who are likely to have a higher default probability than large companies. This is supported by the firm level default probability data used in Chapter I, where the average default probability for SMEs is over 6%, compared to approximately 2% for large corporations. The default rate target is close to the 3% target commonly used in models with a similar financing constraint (Ottonello and Winberry (2020); Bernanke et al. (1999)).

2.A.2 Productivity difference between intangible and tangible intensive firms

Table 2.A2: Productivity and K/L ratio, intan & tan intensive firms)

	Labour productivity, mean	Labour productivity, median	K/L ratio, mean	K/L ratio, median
Intan firms	4.65	4.70	4.28	3.70
Tan firms	4.50	4.50	4.74	3.87

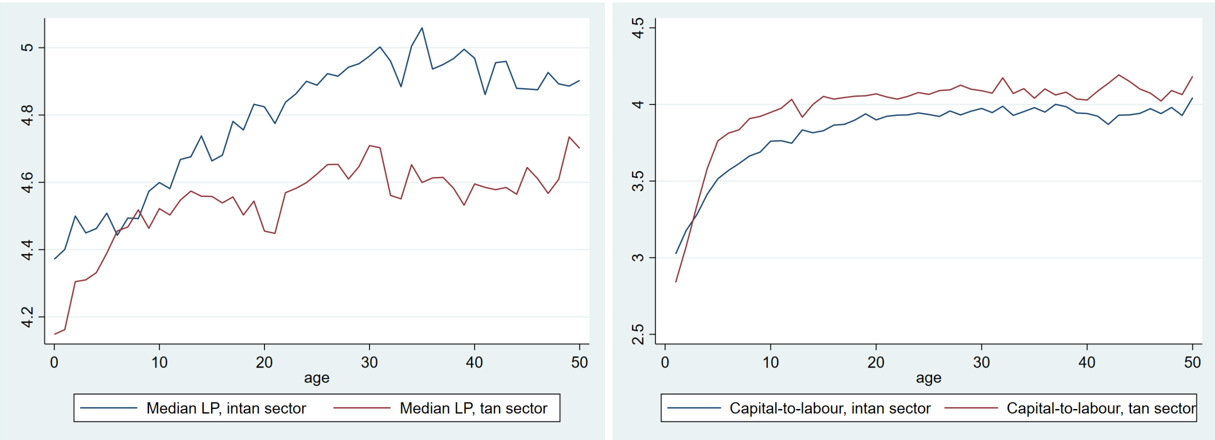
Notes: This table shows the mean and median of the natural logarithm of labour productivity and capital-to-labour ratio, for intangible and tangible intensive firms. Capital includes

[15]Source: "Default, Transition, and Recovery: 2023 United Kingdom Corporate Default And Rating Transition Study" by Kraemer, Gurwitz and Richhariya, S&P Global, Research article, 2024.

intangible and tangible capital. Source: balance sheet data for UK companies from BvD, author calculations.

In this section, I document differences in labour productivity and the capital-to-labour ratio of intangible and tangible intensive firms. Table 2.A2 shows the mean and median of the natural logarithm of labour productivity and capital-to-labour ratio, for intangible and tangible intensive firms. Intangible intensive firms have a higher average labour productivity, despite having less total capital per worker. Figure 2.9 shows the evolution in average labour productivity and capital-to-debt ratio over the course of the firm lifecycle.

Figure 2.9: Productivity difference between intangible and tangible intensive firms



Notes: This figure depicts the evolution in average (log) labour productivity and (log) capital-to-debt ratio over the course of the firm lifecycle, for intangible and tangible intensive firms. Capital consists of intangible and tangible capital. Source: balance sheet data for UK companies from BvD, author calculations

CHAPTER 3

Explaining Patterns in Gross Capital Flows

Abstract[*]

Previous empirical evidence shows that gross capital flows are positively correlated and procyclical. In particular, the "retrenchment" of domestic investment following adverse shocks has attracted considerable interest in the literature. This paper examines the ability of frictionless open economy models to generate empirically consistent patterns in gross capital flows. A simple model with two assets and two countries is used to evaluate patterns in gross capital flows triggered by income shocks. The model highlights a previously overlooked mechanism that can generate positively correlated capital flows: standard shocks change hedging properties of assets, causing optimal adjustments in the portfolios of domestic and foreign investors. When negative domestic shocks improve the hedging properties of home assets, a retrenchment of domestic capital follows.

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3.1 Introduction

Since the Global Financial Crisis, there has been considerable interest in international capital flows. Disruptions to these flows, such as the "taper tantrum" in 2013 and more recently the COVID-19 pandemic highlight the importance of understanding the drivers of capital inflows and outflows.

One of the features of gross capital flows that has received considerable attention in the literature is that capital inflows from foreigners (CIF) and capital outflows by domestic investors (COD) are positively correlated and procyclical.[1] The behaviour of foreign investors is intuitive: capital inflows increase during domestic booms, when returns on domestic assets are likely to be high, and drop during domestic recessions or financial crises. However, the mirror image of capital outflows by domestic investors is more puzzling. Why do domestic agents invest more abroad during domestic booms? What could explain the"retrenchment" of domestic capital during recessions or crises? What generates the asymmetric behaviour of domestic and foreign investors? These questions are of particular significance to policy makers, especially in emerging economies where volatile capital inflows from foreign investors are often a concern. If domestic investment returns when foreign agents pull out of the domestic markets, at least some of the risks posed by volatile capital inflows are mitigated.

This paper highlights a previously overlooked mechanism that can generate positively correlated and procyclical gross capital flows in standard macroeconomic models, without relying on financial frictions or information asymmetries. I use a simple two-asset, two-country endowment economy model with incomplete markets and examine the patterns in gross capital flows generated by income shocks. I find that the simple model can produce responses in gross capital flows that are consistent with empirical evidence, if a) home agents optimally hold more home assets in the steady state and if most of home income fluctuation is driven by shocks to dividend income; or b) home agents optimally hold more foreign assets and home income fluctuations are mainly generated by shocks to non-dividend income. In these cases, the puzzling retrenchment of domestic capital after a negative domestic shock is triggered by an improvement in the hedging properties of home assets, causing home households to adjust their portfolio holdings to include more home and less foreign assets.

In the model, shocks trigger capital flows due to consumption smoothing,

[1] See for instance Broner et al. (2013), Forbes and Warnock (2012).

and changes in hedging properties of assets. Consumption smoothing results in negatively correlated capital flows: after a positive domestic shock, domestic investors smooth consumption by buying both domestic and foreign assets, leading to an increase in capital outflows and a reduction in capital inflows. However, shocks also endogenously alter second moments related to assets: the covariance between dividend income and non-diversifiable income, as well as the variance of returns, are affected by income shocks. This leads to changes in the hedging properties of assets, causing investors to alter the relative portfolio shares of domestic and foreign assets. This effect moves capital flows in the same direction, resulting in positively correlated capital flows. If domestic assets become a better hedge against home labour income fluctuations, for instance, domestic investors increase their holdings of home assets and reduce their holdings of foreign assets, leading to a reduction in capital outflows and capital inflows. If the changes to the hedging properties of assets are strong enough, capital flows are positively correlated; and if the direction of the change in hedging motives is such that negative home shocks improve hedging properties of domestic assets, capital flows are procyclical.

In the model, negative (positive) correlation of domestic dividend and non-diversifiable income results in domestic agents optimally holding more (less) home assets in their steady state portfolio, resulting in different asset demands for home and foreign investors due to investors holding more home (foreign) assets to hedge home non-diversifiable income risk. The key finding of this paper is that these differences in steady state portfolios between home and foreign investors can lead to empirically consistent patterns in capital flows triggered by standard income shocks that endogenously alter the hedging properties of assets. No other frictions or asymmetries, such as financial frictions or asymmetric information, are required. Interestingly, if home dividend and nondiversifiable labour income are negatively correlated, the simple model produces both the well-documented “home bias" in the steady state portfolio as well as the positive correlation and procyclicality of capital flows. This is becuase home assets are a good hedge against home labour income risk, and become an even better (worse) hedge during domestic downturns (booms). Whilst the former result has been well discussed in the literature (see for example Coeurdacier and Rey (2013)), to the best of my knowledge, the latter has previously been overlooked.

In light of these findings, I review why frictionless models in previous literature (Hnatkovska (2010) and Tille and van Wincoop (2010)) can produce some of the empirical patterns in gross capital flows. I conclude that as long as assets provide a strong enough hedge against domestic non-diversifiable income, or against exchange rate fluctuations, foreign and domestic households will have sufficiently different asset demands such that changes to the hedging properties of assets caused by shocks lead to adjustments in portfolio shares, resulting in positively correlated capital flows. The procyclicality of capital flows, on the other hand, is more sensitive to the specific calibration used. Parameters governing the cyclicality of flows include any parameters that affect the sign and magnitude of correlations between asset returns, non-diversifiable income, and relative prices. For example, parameters determining the share of dividend income in total income, the substitutability of different goods in the economy, as well as the relative volatility of different shocks, can all affect the direction of changes in hedging properties of assets after shocks, and hence the cyclicality of capital flows.

3.1.1 Related literature

This paper contributes to the broad literature on international capital flows. This literature is too large to cover extensively, however, see for instance Fernández et al. (2015), Benigno et al. (2016) and Farhi and Werning (2014) on optimal capital controls; Calvo (2012) and Ventura (2012) on capital inflows and bubbles; and Evans and Hnatkovska (2014) on international financial integration and volatility; Chari et al. (2021) on US monetary policy and capital flows to emerging countries, and Gelos et al. (2022) on policies targeting capital flows.

More specifically, I contribute to the literature examining and explaining patterns in gross capital flows. Broner et al. (2013) document stylised facts of gross capital flows, focusing on patterns over the business cycle and during financial crises. They find that gross capital flows are positively correlated and procyclical. During expansions, foreign agents increase their purchases of domestic assets and domestic agents increase their purchases of foreign assets, whilst the opposite occurs during contractions and crises. These findings are not driven by any single flow type, and the patterns are broadly similar for all sample countries. The magnitude and volatility of gross capital flows have increased over the sample period with increased financial globalisation, and the correlation between CIF and COD has become increasingly positive.

Other empirical work supports these findings. Earlier studies examining gross capital flows in the U.S. (Dvorak (2003); Hnatkovska (2010); Tille and van Wincoop (2010)) find a positive correlation between domestic purchases of foreign equity and foreign purchases of domestic equity. Forbes and Warnock (2012) find that the Global Financial Crisis was followed by stops (sharp declines in CIF) and retrenchment (sharp declines in COD) in most countries in their sample. Jeanne and Sandri (2017) document positively correlated capital outflows and inflows. Contessi et al. (2013) find evidence for procyclical gross capital inflows. Adler et al. (2016) find that gross capital inflows decline as a result of adverse global risk aversion or monetary policy shocks, whilst retrenchment of domestic investment only takes place in response to the former.

The empirical literature predicts that standard models without financial frictions or asymmetries should not be able to produce positively correlated gross capital flows. For instance, Broner et al. (2013) state: "Intuitively, in the absence of financial frictions productivity shocks do not lead naturally to a positive correlation between CIF and COD. For example, if a negative productivity shock during a crisis lowers the incentives for foreign agents to invest in the domestic economy, it should also probably increase the incentives for domestic agents to invest abroad." Tille and van Wincoop (2014) state that time variation in expected asset returns moves capital inflows and outflows in the opposite direction.

Most of the literature explaining these empirical patterns has examined frictions that result in gross capital flows that are consistent with the data. Caballero and Simsek (2020) develop a partial equilibrium framework in which foreign investors (banks) are "fickle" by construction, selling their risky assets in any foreign location that experiences a liquidity shock, regardless of asset prices. Local banks are then able to purchase local assets at fire-sale prices. Hence, liquidity shocks generate procyclical CIF (by assumption) and procyclical COD. Tille and van Wincoop (2014) show that the empircial patterns in gross capital flows arise in a DSGE model with private information. Kumhof et al. (2020) develop a model that tracks domestic and international gross positions between banks and households, where all transactions are settled through banks. They show that highly correlated gross capital flows result automatically from bank bookkeeping. In contrast to these papers, I investigate whether frictionless models can generate empirically consistent patterns in gross capital flows, and if so under which conditions. I contribute to this literature by showing that models without frictions can also replicate the empirical patterns in gross capital flows due to changes in hedging properties of assets following standard shocks.

I contribute to the literature exploring gross capital flows in models without asymmetric information or financial frictions. Hnatkovska (2010) develops a standard two country model with tradeable and nontradeable goods and finds that it generates positively correlated and procyclical gross capital flows triggered by shocks to the nontradeable sector. Devereux and Sutherland (2010) present a simple two country model with nominal bonds, in which the "right" pattern in capital flows is triggered by shocks to the endowment. Tille and van Wincoop (2010) examine capital flows in a two country model, and find that gross capital flows triggered by productivity shocks are positively correlated, though countercyclical.

Davis and Van Wincoop (2018) examine how different types of shocks affect capital flows in a standard two country model. They show that an exogenous increase in savings in both countries can result in positively correlated capital flows if this results in increased investment in capital and thus an increase in available assets. In addition, they consider a "retrenchment shock" that leads to positively correlated capital flows. Davis and Van Wincoop (2024) show that a shock to global risk aversion lead to a fall in asset prices, which in turn shifts the wealth distribution towards investors that are less willing to hold foreign assets, resulting in retrenchemnt of domestic investment.

I contribute to these findings by investigating the mechanisms that trigger capital flows in two-country models without financial frictions or asymmetric information, following standard income shocks, and shed light on the conditions required to generate empirically consistent capital flow patterns. Furthermore, I reflect on why some of the models in previous literature generate empirically consistent patterns whilst others do not.

The rest of the paper is organised as follows. Section 3.2 outlines the model, solution method and calibration. Section 3.3 shows the results. Section 3.4 discusses the mechanisms and provides intuition. Section 3.5 relates the findings of this paper to previous work. Section 3.6 concludes and discusses avenues for further research.

3.2 Model

I use a simple model that generates gross capital flows: a two-asset, two-country endowment economy model with incomplete markets. The countries - Home and Foreign - are identical in preferences and size, and both issue one asset. The utility function of the representative household is

$$U_t = E_t \sum_{j=0}^{\infty} \theta_j u(C_{t+j}) \tag{3.1}$$

where C is consumption, θ is the discount factor and the per period utility function is given by standard CRRA preferences $u(C) = C^{1-\rho}/(1-\rho)$.

I close the model by endogenising the discount factor. This is one of the simplest ways to eliminate unit root dynamics, and is standard in open economy models.[2] The approach is based on Uzawa (1968) and Schmitt-Grohe and Uribe (2003). The discount factor follows

$$\theta_{t+1} = \theta_t \beta \tilde{C}_t^{-\eta} \quad , \quad \theta_0 = 1 \tag{3.2}$$

I calibrate η very close to zero, so that it has virtually no impact on the behaviour of the model other than ensuring a gradual return to the symmetric steady state in the absence of further shocks.

The budget constraint for Home is

$$Q_t s_{1t} + Q_t^* s_{2t} = (Q_t + D_t)s_{1,t-1} + (Q_t^* + D_t^*)s_{2,t-1} + (1-\gamma)Y_{Lt} - C_t \tag{3.3}$$

where Q and Q^* denote the prices of home and foreign assets, respectively; s_1 and s_2 are home holdings of home and foreign assets, respectively; D and D^* are home and foreign dividends; and C is consumption. Y_L is home "labour" income - the proportion of home endowment that is not linked to the home asset. Dividends are given by

$$D_t = \gamma Y_{Kt} \quad , \quad D_t^* = \gamma Y_{Kt}^* \tag{3.4}$$

where Y_K is home "capital" income - part of the endowment related to the home asset.

With two assets (Home and Foreign) and two shocks (to Home and Foreign endowment), perfect risk sharing between the countries is achieved. I introduce incomplete markets for two reasons. Firstly, perfect risk sharing has been rejected by many empirical studies (for instance Backus and Smith (1993), Kollman (1995) and Ravn (2001)). Secondly, in a complete markets setting the real allocation is computed independent of asset holdings, and capital flows are "merely and accounting device" (Obstfeld and Rogoff (1996)). Although there are multiple ways to introduce incomplete markets, I follow Devereux and Sutherland (2011) and split the endowment into two components. This approach is computationally simple, and allows me to easily investigate the impact of market

[2]Schmitt-Grohe and Uribe (2003) show that models with different approaches of closing the model deliver virtually identical business cycle dynamics. I chose the endogenous discount factor for its simplicity.

(in)completeness on the results later (see section 3.5 for details). The two components are labeled "capital income" Y_{Kt} - or dividends income - and "labour income" Y_{Lt} such that Home endowment is

$$Y_t = \gamma Y_{Kt} + (1-\gamma) Y_{Lt}, \tag{3.5}$$

which equals Home income in the absence of asset trade. It should be noted that in this model, capital and labour income are simply labels of the two components of the endowment: there is no production, no capital stock and no endogenous labour supply choice.

Both components of the endowment follow an AR(1) stochastic process

$$lnY_{Kt} = \rho_K lnY_{K,t-1} + \varepsilon_{Kt} \tag{3.6}$$

$$lnY_{Lt} = \rho_L lnY_{L,t-1} + \varepsilon_{Lt} \tag{3.7}$$

Hence, there are four shocks (shocks to Home and Foreign capital and labour income) but only two assets, meaning that perfect risk sharing cannot be achieved.

The assets are one-period equity claims on Home "capital" income (asset 1) and Foreign "capital" income (asset 2). Gross returns are given by

$$r_t = \frac{\gamma Y_{Kt} + Q_t}{Q_{t-1}} \quad , \quad r_t^* = \frac{\gamma Y_{Kt}^* + Q_t^*}{Q_{t-1}^*} \tag{3.8}$$

Given the asset returns are determined by the capital component of endowment, the "capital share" γ becomes a measure of market completeness in this simple model: if γ equals 1, markets are complete and perfect risk sharing between the countries is achieved. Similarly, the closer γ is to 0, the less households can hedge consumption risk via purchasing equities and the more incomplete markets are.

The first order conditions to Home household's problem give the Euler equation

$$C_t^{\eta-\rho} = \beta E_t[C_{t+1}^{-\rho} r_{t+1}] \tag{3.9}$$

and the first order condition for the optimal portfolio is

$$E_t[C_{t+1}^{-\rho} r_{t+1}] = E_t[C_{t+1}^{-\rho} r_{t+1}^*]. \tag{3.10}$$

Gross capital flows are defined as

$$cif_t = Q_t(s_{1,t}^* - s_{1,t-1}^*) = -Q_t(s_{1,t} - s_{1,t-1}) \tag{3.11}$$

$$cod_t = Q_t^*(s_{2,t} - s_{2,t-1}) \tag{3.12}$$

where cif is capital inflows from Foreign to Home (CIF), and cod are capital outflows from the home country to Foreign.

3.2.1 Solution method

To investigate whether the model can generate empirically consistent patterns in gross capital flows, first order behaviour of asset holdings needs to be determined. Given that asset holdings are indeterminate in a deterministic steady state and in a first order approximation (because of certainty equivalence), the model needs to be solved to a higher order. More precisely, to second order to determine the steady state portfolio, and to third order to determine the first order dynamics (Samuelson (1970)). I use the method developed in Devereux and Sutherland (2010, 2011) to solve for the steady state portfolio and the first order dynamics of assets.[3]

The steady state asset holdings are recovered by combining the second order approximation of portfolio equations for Home and Foreign:

$$-\rho E_t[(\hat{c}_{t+1} - \hat{c}^*_{t+1})\hat{r}_{x,t+1}] = 0 + O(\epsilon^3) \tag{3.13}$$

and the first order behaviour of asset holdings is obtained from third order approximation of portfolio first order conditions:

$$\begin{aligned} E_t[-\rho(\hat{c}_{t+1} - \hat{c}^*_{t+1})\hat{r}_{x,t+1} + \frac{\rho^2}{2}[\hat{c}^2_{t+1} - (\hat{c}^*_{t+1})^2]\hat{r}_{x,t+1} \\ -\frac{\rho}{2}(\hat{c}_{t+1} - \hat{c}^*_{t+1})(\hat{r}^2_{1,t+1} - \hat{r}^2_{2,t+1})] = 0 + O(\epsilon^4) \end{aligned} \tag{3.14}$$

In theory, the model needs to be solved to second order to determine the steady state asset holdings and to third order to determine the dynamics. However, it is worth noting that the non-portfolio equations of this simple model with two symmetric countries only need to be solved to first order to determine the steady state portfolio, and to second order to determine first order asset dynamics. This can be seen from the equations above: Equation (3.13) only contains products of first order variables, as the higher order terms cancel out when the portfolio equations for Home and Foreign are combined. The second order solution to a product of variables can be obtained from first order solutions to the individual variables. Hence, to solve for the steady state portfolio determined

[3]For a comprehensive explanation of the solution method, see Devereux and Sutherland (2010 and 2011).

by Equation (3.13) it is necessary to solve for the behaviour of other variables in the model only up to first order. Similarly, combining the third order approximations of the Home and Foreign first order conditions for portfolio choice (which pin down the first order dynamics of asset holdings) results in Equation (3.14), an expression consisting only of products of first and second order terms. It is therefore necessary to solve the non-portfolio equations of the model only up to second order in order to determine first order asset dynamics.

3.2.2 Solution

The steady state holding of home equity by the Home household is given by

$$s_1 = 1 - \frac{1}{2}\frac{1-\beta}{\gamma}\Big(\frac{\gamma}{1-\beta\rho_K}\frac{cov(\hat{y}_{Kt+1} - \hat{y}^*_{Kt+1}, \hat{r}_{x,t+1})}{var(\hat{r}_{x,t+1})} + \frac{1-\gamma}{1-\beta\rho_L}\frac{cov(\hat{y}_{Lt+1} - \hat{y}^*_{Lt+1}, \hat{r}_{x,t+1})}{var(\hat{r}_{x,t+1})}\Big). \tag{3.15}$$

Solving for covariances and variances results in

$$s_1 = 1 - \frac{1}{2}\Big(1 + \frac{1-\gamma}{\gamma}\frac{1-\beta\rho_k}{1-\beta\rho_L}\frac{\sigma_{KL}}{\sigma^2_K}\Big) \tag{3.16}$$

assuming shocks are uncorrelated across countries, and the variance of shocks to "capital" income (σ^2_K) as well as the covariance of "labour" and "capital" income shocks (σ_{KL}) are the same in both countries. If labour and capital income are uncorrelated, σ_{KL} is zero and Home households choose a balanced portfolio. However, if σ_{KL} is negative (capital and labour income are negatively correlated) the Home asset is a good hedge against Home labour income fluctuations: states of the world where labour income is low are likely to coincide with states of the world where capital income is high. Hence, the Home investor optimally chooses to hold more of the Home asset than the Foreign asset (s_1 is greater than $\frac{1}{2}$). Conversely, a positive covariance means that the Home asset is a bad hedge against Home labour income fluctuations, and therefore the Home investor opts to hold more Foreign equity (s_1 is less than $\frac{1}{2}$). The parameter γ also matters; if markets are complete, γ equals 1 and a balanced portfolio will ensure full risk sharing. The less complete markets are, the greater the weight on the covariance term, and hence the more Home (Foreign) assets the Home investor holds if σ_{KL} is negative (positive).

The first order dynamics of home equity holdings are given by linear functions of first order components of state variables:

$$\hat{s}_{1t} = \frac{1}{2}(\hat{s}_{1t} + \hat{s}_{2t}) + \delta_1 \hat{y}_{Kt} + \delta_2 \hat{y}^*_{Kt} + \delta_3 \hat{y}_{Lt} + \delta_4 \hat{y}^*_{Lt} + O(\epsilon^2) \tag{3.17}$$

$$\hat{s}_{2t} = \frac{1}{2}(\hat{s}_{1t} + \hat{s}_{2t}) - \delta_1 \hat{y}^*_{Kt} - \delta_2 \hat{y}_{Kt} - \delta_3 \hat{y}^*_{Lt} - \delta_4 \hat{y}_{Lt} + O(\epsilon^2) \tag{3.18}$$

where $\hat{s}_{1t} = s_{1t} - s_1$ and $\hat{s}_{2t} = s_{2t} - s_2$. Model simulations show that the signs and magnitudes of the δ parameters depend on the covariance between labour and capital endowment shocks; the persistence of shocks; and the capital share γ.[4]

Hence, the first order approximation for gross capital inflows is

$$\hat{cif}_t = Q\Delta\hat{s}^*_{1t} = -Q\Delta\hat{s}_{1t} \tag{3.19}$$

$$= -\frac{1}{2}Q(\Delta\hat{s}_{1t} + \Delta\hat{s}_{2t}) - Q\delta_1\Delta\hat{y}_{Kt} - Q\delta_2\Delta\hat{y}^*_{Kt} - Q\delta_3\Delta\hat{y}_{Lt} - Q\delta_4\Delta\hat{y}^*_{Lt} + O(\epsilon^2) \tag{3.20}$$

$$\hat{cif}_t = -\frac{1}{2}\hat{S}_t - \tilde{\delta}_1\Delta\hat{y}_{Kt} - \tilde{\delta}_2\Delta\hat{y}^*_{Kt} - \tilde{\delta}_3\Delta\hat{y}_{Lt} - \tilde{\delta}_4\Delta\hat{y}^*_{Lt} + O(\epsilon^2) \tag{3.21}$$

where $\hat{S}_t$ is the first order component of savings. Similarly, outflows are given by

$$\hat{cod}_t = Q^*\Delta\hat{s}_{2t} \tag{3.22}$$

$$\hat{cod}_t = \frac{1}{2}\hat{S}_t - \tilde{\delta}_1\Delta\hat{y}^*_{Kt} - \tilde{\delta}_2\Delta\hat{y}_{Kt} - \tilde{\delta}_3\Delta\hat{y}^*_{Lt} - \tilde{\delta}_4\Delta\hat{y}_{Lt} + O(\epsilon^2) \tag{3.23}$$

3.2.3 Calibration

Table 3.1 contains the calibration of parameter values used to solve and simulate the baseline model.

[4] It should be noted that these are not analytical solutions and the model is solved numerically.

Table 3.1: Baseline Calibration		
Symbol	Meaning	Value
β	Discount factor	0.98
η	Degree of endogenous discounting	0.00001
ρ	Coefficient of relative risk aversion	1
ρ_K	Persistence of shocks to "capital" income	0.95
ρ_L	Persistence of shocks to "labour" income	0.95
σ_K^2 , σ_L^2	Variance of shocks to "labour" and "capital" income	1
σ_{KL}	Covariance between "labour" and "capital" income	0, -0.5, 0.5
γ	Market completeness	0.1 - 0.9

The discount factor, coefficient of relative risk aversion, shock persistence and variance of shocks are standard in the literature. I choose a small enough η not to make a difference to first order dynamics - as the model can be solved with η equal to zero, it is easy to compare the results. However, in order to compute the correlations between gross capital flows and income fluctuations, the model does need to be closed to eliminate unit root dynamics. If the model is not closed (η equals zero), some variables have unit roots and hence certain moments of interest, including correlations, are not defined. The covariance between "labour" and "capital" income, as well as the parameter that governs market completeness, are less straight forward to calibrate. I therefore investigate the capital flow patterns in three scenarios: for zero covariance (σ_{KL} = 0); and a negative and positive covariance of 0.5. For these three scenarios, I consider a range of values for market completeness, with γ taking values between 0.1 and 0.9.

3.3 Results

Table 3.2 contains the model implied correlations between gross capital flows and income flunctuations, compared to empirical values from the literature.[5]

Table 3.2: Correlation of gross capital flows in baseline model

		Market completeness					
σ_{KL}	Correlation	0.1	0.3	0.5	0.7	0.9	Data
0	capital flows	-1	-1	-1	-1	-1	0.2-0.9
	inflows,ΔY	-0.11	-0.10	-0.08	-0.04	-0.01	+
	outflows,ΔY	0.11	0.10	0.08	0.04	0.01	+
-0.5	capital flows	0.99	0.99	0.99	**0.99**	**0.99**	0.2-0.9
	inflows,ΔY	-0.58	-0.41	-0.01	**0.40**	**0.57**	+
	outflows,ΔY	-0.56	-0.39	0.01	**0.40**	**0.57**	+
0.5	capital flows	**0.96**	**0.96**	0.96	0.96	0.96	0.2-0.9
	inflows,ΔY	**0.28**	**0.15**	-0.01	-0.16	-0.30	+
	outflows,ΔY	**0.31**	**0.17**	0.01	-0.15	-0.29	+

Table 3.2 shows that the simple symmetric model without frictions is indeed able to generate gross capital flows that are both positively correlated and procyclical. However, capital flows are only positively correlated if the covariance between labour and capital income shocks is non-zero; if σ_{KL} is zero, capital flows are perfectly negatively correlated. Nevertheless, for a covariance of -0.5 or 0.5, capital flows are almost perfectly positively correlated; in fact, they are more positively correlated than values found in the empirical studies.

To produce empirically consistent results regarding the cyclicality of capital flows, the parameter governing market completeness is also important. From Table 3.2 it is clear that for both inflows and outflows to be procyclical, markets need to be sufficiently complete (incomplete) if σ_{KL} is negative (positive). Hence, the model produces capital flow patterns that are consistent with empirical evidence if a) "capital" and "labour" income are negatively correlated and markets are complete enough; b) "capital" and "labour" income are positively correlated and markets are not very complete.

Impulse responses - Balanced portfolio When Home and Foreign hold a balanced portfolio - which is the case when capital and labour income shocks are

[5] See Appendix 3.A for a range of estimates from the literature

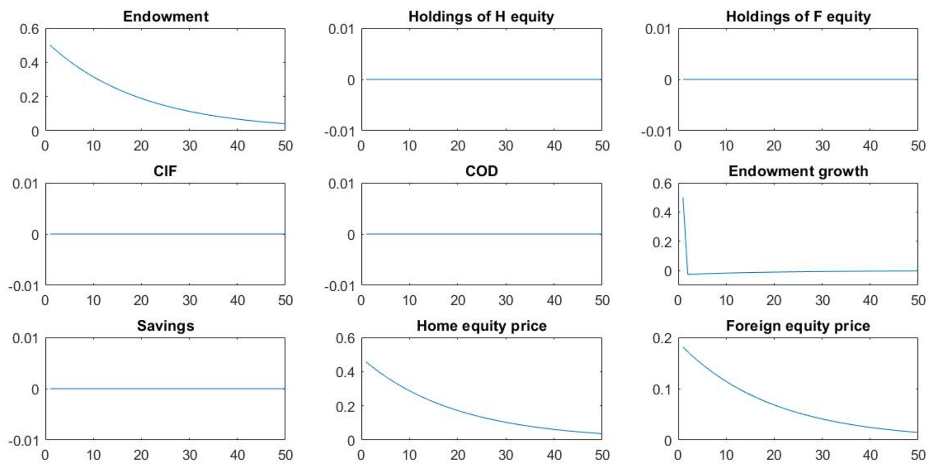

Figure 3.1: Impulse responses to a capital income shock, balanced portfolio

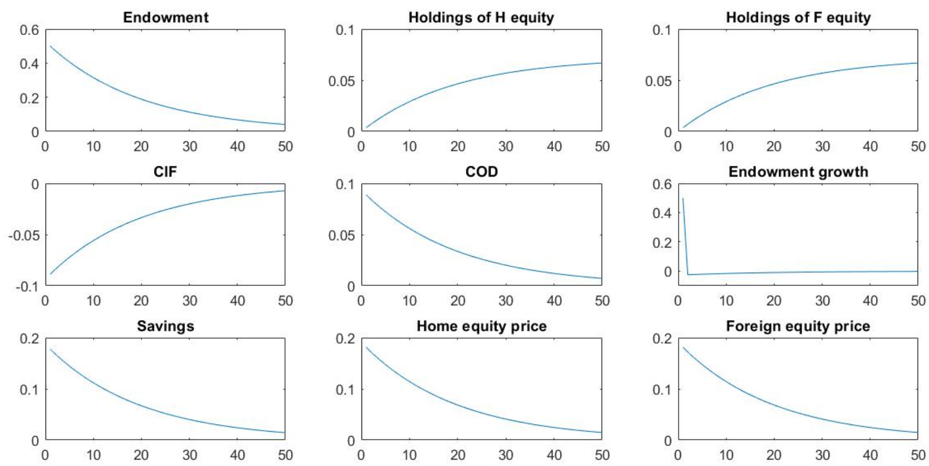

Figure 3.2: Impulse responses to a labour income shock, balanced portfolio

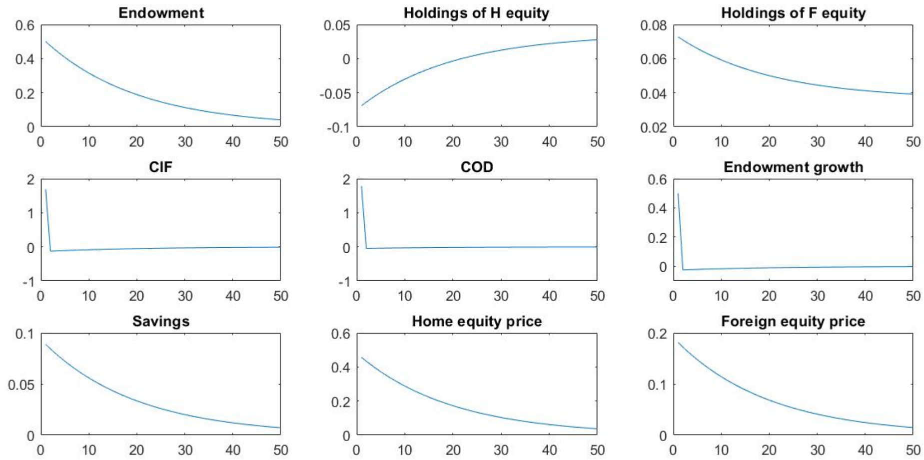

Figure 3.3: Impulse responses to a capital income shock, negatively correlated shocks

uncorrelated - the risk of income fluctuation arising from capital income shocks is perfectly shared. This implies that following a shock to Home capital endowment the increase in income in Home and Foreign is equal. Hence, these shocks affect Home and Foreign investors symmetrically. There are no capital flows; only valuation effects. Investors in both countries would like to increase their asset holdings to smooth consumption, pushing up the price for both assets; Home equity price increases more, because the shock is persistent and hence dividends are expected to stay higher in the near future. However, because investors in both countries would like to buy more assets - and the increase in demand is equal for both countries - equity prices increase but there is no change in asset holdings.

With balanced portfolios, capital flows are only triggered by labour income shocks. Home income increases whilst Foreign income stays unchanged. The Home investor wants to smooth this increase by saving, and hence demands more Home and Foreign assets, pushing up the prices for both assets. Equity prices increase, as well as Home holdings of both assets. This implies that capital outflows from Home country increase, whilst capital inflows from Foreign decline, as Foreign investors sell assets to the Home investor. This is why capital flows are perfectly negatively correlated in the balanced portfolio setting. Moreover, capital inflows are countercyclical whereas capital outflows are procyclical. It is clear that with a balanced portfolio, that is optimal when shocks are uncorrelated, the frictionless model cannot generate empirically consistent patterns in capital flows.

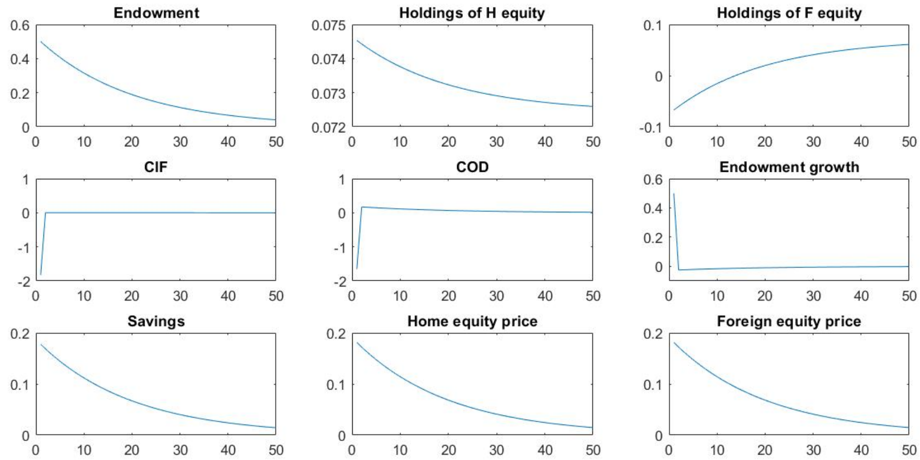

Figure 3.4: Impulse responses to a labour income shock, negatively correlated shocks

Impulse responses - Negatively correlated shocks When shocks to "labour" and "capital" income are negatively correlated, Home investors optimally hold more Home assets in their portfolio. This is because the return on Home assets is likely to be high when Home labour income is low, and vice versa, making Home assets a good hedge against Home labour income fluctuations.

Now, a positive shock to Home capital income leads the Home household to reduce holdings of Home equity (so the Foreign household increases their holdings of Home equity) and increase their holdings of Foreign equity. This implies that capital inflows from Foreign (CIF) increase, as well as capital outflows from Home (COD). They therefore move in the same direction as each other and endowment growth, resulting in positively correlated and procyclical capital flows. Capital income shocks, therefore, trigger capital flows that are consistent with empirical evidence.

A positive shock to Home labour income results in an increase of Home holdings of Home equity (and hence a reduction in Foreign holdings of Home equity), and a reduction in Home holdings of Foreign equity. Hence, both CIF and COD decline, meaning that capital flows triggered by labour income shocks are also positively correlated but countercyclical - whereas flows are procyclical in the data.

Therefore, with negatively correlated shocks within countries, capital flows triggered by endowment shocks follow an empirically consistent pattern (positively correlated and procyclical) if shocks to capital income dominate. This is the case if γ, the share of capital endowment out of total endowment, is high enough. As γ determines market completeness, an alternative interpretation is

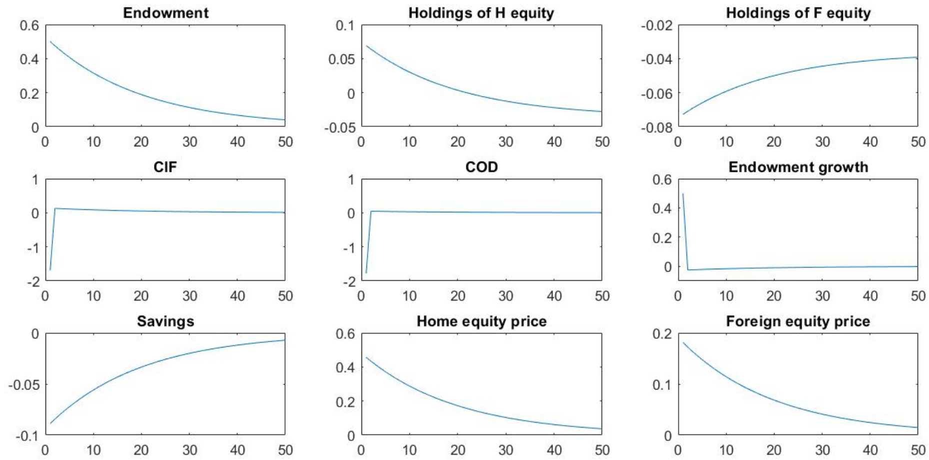

Figure 3.5: Impulse responses to a capital income shock, positively correlated shocks

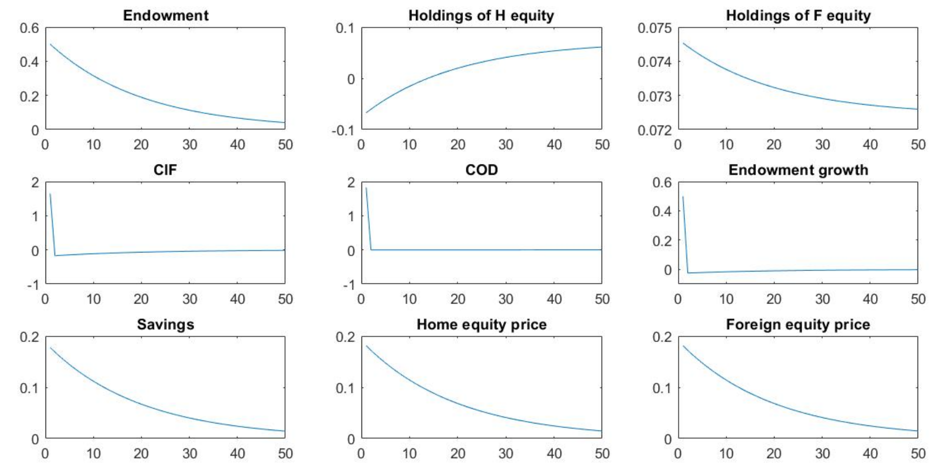

Figure 3.6: Impulse responses to a labour income shock, positively correlated shocks

that the model generates empirically consistent capital flow patterns if markets are complete enough.

Impulse responses - Positively correlated shocks When shocks to labour and capital income are positively correlated, the representative Home household optimally holds more Foreign equity in their portfolio. This is because the return on Home assets is likely to be low when Home labour income is low, and vice versa, making Home assets a particularly bad hedge against Home labour income fluctuations.

A positive shock to Home capital income leads to an increase (reduction) in Home (Foreign) holdings of Home equity, and a reduction in Home holdings of

Foreign equity. This implies that both CIF and COD decline, resulting in positively correlated but countercyclical flows.[6]

A positive shock to Home labour income induces the Home (Foreign) household to sell (buy) Home equity, and increase their holdings of Foreign equity. Both CIF and COD therefore increase, so move in the same direction as each other and endowment growth. Labour income shocks therefore result in empirically consistent movements in gross capital flows.

Hence, with positively correlated shocks within countries, capital flows triggered by endowment shocks are empirically consistent if shocks to labour income dominate. This happens when γ, the share of capital income over total income, is low; or markets are incomplete enough.

3.4 Intuition

The argument in the literature (see for instance Tille and van Wincoop (2014) and Broner et al (2013)) for why frictionless models are unlikely to produce the correct patterns in capital flows is that if all investors face the same expected returns, then CIF and COD should be negatively correlated. This is because home and foreign investment should move in the same direction: if there is an increase in the incentives of foreign agents to invest more in a given country, this should also lead to more home investment in that particular country, as home and foreign agents should act symmetrically. If home and foreign investment move in the same direction, then capital inflows from foreign (CIF) and capital outflows from domestic agents (COD) should move in opposite directions, hence the negative sign of the predicted correlation between them. However, in standard models, anything that affects expected returns alone will increase or reduce the demand by both home and foreign agents. With assets in fixed supply, prices must adjust such that there are no capital flows. Hence, capital flows are not triggered by factors affecting domestic and foreign investors in the same way. This can be seen from the equation that pins down asset dynamics, equation (3.14): the first, second and third order components of excess returns alone cancel out.

On the contrary, the mechanisms that trigger capital flows in the model are those that affect home and foreign investors asymmetrically; it is changes in the

[6]It can also be seen from the IRFs that Home savings decline slightly even though there is a positive shock to Home capital endowment. This is because the Foreign household actually holds more Home assets than Home, meaning that the income of the Foreign household increases more than that of the Home household. The consumption smoothing motive of the Foreign household is therefore stronger than that of Home, leading to an increase in Foreign savings and a decline in Home savings.

relative demand for assets between home and foreign investors that trigger capital flows. These forces arise endogenously even in a simple frictionless model. I next elaborate on what triggers capital flows in the model, and also shed light on why capital flows are negatively correlated when households hold a balanced portfolio, but positively correlated when they hold more home or foreign equity. I also elaborate on why the cyclicality of flows depends on which part of the endowment the shock affects in the case of a non-balanced portfolio.

3.4.1 Drivers of capital flows

Two forces drive capital flows in the model: consumption smoothing and changes in hedging properties of assets.[7]

Consumption smoothing The desire to smooth consumption naturally leads to negatively correlated capital flows. After temporary shocks, households smooth consumption by saving or borrowing. In the model, saving or borrowing is achieved by buying or selling Home or Foreign equity. Consumption smoothing is achieved by increasing (reducing) the size of the portfolio, or buying (selling) equity such that the share of Home and Foreign assets in the portfolio remain constant. Hence the term "portfolio growth". If Home increases its holdings of both assets, capital inflows from Foreign are negative (as Foreign sells Home equity to the Home household), and capital outflows by domestic investors are positive. Capital flows are therefore negatively correlated.

If Households hold a balanced portfolio, the risk of capital income shocks is shared perfectly; after a shock to Home capital endowment, the income of Home and Foreign households increases by exactly the same amount. Both households would like to smooth consumption by saving the exact same amount. This leads to an increase in asset prices, but no capital flows, as the effect of the shock is symmetric. It is not possible for both Home and Foreign to save at the same time and hence asset holdings are unchanged. However, a Home labour endowment shock only affects the income of the Home household. To smooth the temporary shock, Home wants to save more by increasing its holdings of both assets. This pushes up equity prices, and induces the Foreign household to sell both Home and Foreign equity to Home, enabling Home to save some of the increase in income. There is an asymmetric effect that results in capital flows. In the

[7] This is similar to Tille & van Wincoop (2010), who find that "portfolio growth" and "portfolio reallocation" drive capital flows. Here, consumption smoothing results in "portfolio growth", and "portfolio reallocation" is mainly driven by changes to hedging motives.

Balanced Portfolio case, the consumption smoothing effect followed by labour income shocks fully explains capital flows.

If capital and labour endowment shocks are negatively correlated, the share of Home equity in the steady state portfolio is more than a half. Therefore, a positive shock to Home capital endowment increases Home income more than Foreign income, meaning the consumption smoothing motive of the Home household is stronger. Hence the Home household saves by increasing its holdings of both assets. This effect drives CIF down and COD up, leading to negatively correlated capital flows in the absence of other forces. If, on the other hand, capital and labour endowment shocks are positively correlated, Home holds more Foreign equity. In this case, a shock to Home capital endowment increases Foreign income more (as the Foreign household has more Home equity than the Home household). Hence the Foreign household saves by increasing their holdings of both assets, leading to positive CIF and negative COD, again resulting in negatively correlated capital flows in the absence of other forces. As in the Balanced Portfolio case, in both negatively and positively correlated shock scenarios a Home labour endowment shock only affects Home income, resulting in an increase in Home savings, pushing CIF down and COD up.

Hedging An asset is a good hedge against labour income fluctuations if its return is high in states of the world where nondiversifiable labour income is low. On the other hand, the higher the variance of asset returns, the riskier the asset is, and hence the less a risk averse household wants to hold it. The covariance between labour income and asset returns, relative to the variance of asset returns, are therefore crucial for asset demand. If these second moments change over time, asset demand also changes. If these changes affect Home and Foreign demand differently, capital flows are triggered, as relative demands for assets are altered. Hence, time variation in the hedging properties of assets can also drive capital flows.

To demonstrate the consumption smoothing and hedging motives further, I consider a simplifies version of the model introduced in section 3.2. There are 3 time periods: in period 0, the economy is in steady state. Hence, at period 1, the household initially holds the steady state portfolio. However, in period 1, shocks can materialise, which may result to changes in asset holdings at time 1. In the final period, households consume all their income and there are no further savings or portfolio allocation decisions. In addition to limiting the time periods, households in the simplified model maximize "mean-variance" utility. It is straightforward to show that for standard CRRA (constant relative risk aversion) utility functions, a second order approximation yields

$$U(C) = E(C) - \frac{1}{2}\sigma V(C) \tag{3.24}$$

where σ is the coefficient of relative risk aversion.

The household's problem can be split into two decisions: firstly, the household needs to choose how much to consume in period 1 and how much to save for period 2; the consumption smoothing problem. Secondly, for a given level of savings, the household needs to choose how to allocate these savings between asset 1 and asset 2 in order to maximise utility in the final period, period 2. This is the portfolio problem, and I will focus on this part of the problem to illustrate how consumption smoothing and hedging drive capital flows.

For the portfolio allocation problem, the household needs to choose how much of each asset to hold (s_1 and s_2) to maximise utility at period 2, subject to the budget constraint, and for a given level of total savings. Hence, the household chooses s_1 and s_2 to maximise

$$U(C_2) = E(C_2) - \frac{1}{2}\sigma V(C_2) \tag{3.25}$$

subject to

$$C_2 = s_1\gamma Y_{K2} + s_2\gamma Y^*_{K2} + (1-\gamma)Y_L \tag{3.26}$$

$$s_1 + P * s_2 = S \tag{3.27}$$

where S is some fixed level of savings, expressed in terms of asset 1, and P^* is the relative price of the assets, Q^*/Q.

Solving for the optimal s_1 and s_2 results in

$$s_1 = \frac{E(Y_{K2}) - E(Y^*_{K2})P}{\sigma\gamma(V(Y_{K2}) + V(Y^*_{K2})P^2)} + \frac{V(Y^*_{K2})P^2}{V(Y_{K2}) + V(Y^*_{K2})P^2}S - \frac{1-\gamma}{\gamma}\frac{Cov(Y_{K2}, Y_{L2})}{V(Y_{K2}) + V(Y^*_{K2})P^2} \tag{3.28}$$

$$s_2 = \frac{E(Y^*_{K2}) - E(Y_{K2})P^*}{\sigma\gamma(V(Y_{K2})P^{*2} + V(Y^*_{K2}))} + \frac{V(Y_{K2})P^{*2}}{V(Y_{K2})P^{*2} + V(Y^*_{K2})}S + \frac{1-\gamma}{\gamma}\frac{Cov(Y_{K2}, Y_{L2})P^*}{V(Y_{K2})P^{*2} + V(Y^*_{K2})} \tag{3.29}$$

Where P is the relative price expressed as Q/Q^*, and the expectations and variances are conditional on information at time 1. A similar exercise for the Foreign household results in the following asset demand equations:

$$s_1^* = \frac{E(Y_{K2}) - E(Y_{K2}^*)P}{\sigma\gamma(V(Y_{K2}) + V(Y_{K2}^*)P^2)} + \frac{V(Y_{K2}^*)P^2}{V(Y_{K2}) + V(Y_{K2}^*)P^2}S^* + \frac{1-\gamma}{\gamma}\frac{Cov(Y_{K2}^*, Y_{L2}^*)P}{V(Y_{K2}) + V(Y_{K2}^*)P^2} \tag{3.30}$$

$$s_2^* = \frac{E(Y_{K2}^*) - E(Y_{K2})P^*}{\sigma\gamma(V(Y_{K2})P^{*2} + V(Y_{K2}^*))} + \frac{V(Y_{K2})P^{*2}}{V(Y_{K2})P^{*2} + V(Y_{K2}^*)}S^* - \frac{1-\gamma}{\gamma}\frac{Cov(Y_{K2}^*, Y_{L2}^*)}{V(Y_{K2})P^{*2} + V(Y_{K2}^*)} \tag{3.31}$$

As explained earlier, the model has assets in fixed supply and hence anything that affects the Home and Foreign household symmetrically will not lead to capital flows, only an increase in asset prices. It is clear that the first term in all equations, relating to the difference in expected returns, is the same for Home and Foreign households. Hence, any changes to expected returns alone should not result in changes in asset holdings after prices adjust.

Instead, there are two terms that can lead to adjustments in asset holdings following shocks in period 1: the second term, driven by savings S and S^*, and the third term, which embodies the hedging motive. As explained earlier, the consumption smoothing motive drives Home asset demand for both assets in the same direction, hence moving capital flows in opposite directions. However, the final term - or the hedging motive - has opposing effects on the demand for asset 1 and asset 2, and can therefore lead to positively correlated capital flows.

As can be seen, the covariance of labor and capital income, relative to the variance of Home and Foreign capital income is crucial for the hedging motive. Next, I illustrate how shocks to labour and capital endowment affect the covariance between dividend and labour income, as well as the variance of dividend income. The covariance of dividends and labour income tomorrow, conditional on information today, is given by

$$\begin{aligned} Cov(Y_{K,t+1}, Y_{L,t+1}|I_t) &= Cov(Y_{K,t}^{\rho_K} e^{\varepsilon_{K,t+1}}, Y_{L,t}^{\rho_L} e^{\varepsilon_{L,t+1}}|I_t) \\ &= Y_{K,t}^{\rho_K} Y_{L,t}^{\rho_L} Cov(e^{\varepsilon_{K,t+1}}, e^{\varepsilon_{L,t+1}}|I_t) \\ &= Y_{K,t}^{\rho_K} Y_{L,t}^{\rho_L} \tilde{\sigma}_{KL} \\ &= (Y_{K,t-1}^{\rho_K} e^{\varepsilon_{K,t}})^{\rho_K} (Y_{L,t-1}^{\rho_L} e^{\varepsilon_{L,t}})^{\rho_L} \tilde{\sigma}_{KL} \end{aligned} \tag{3.32}$$

where $\tilde{\sigma}_{KL} = Cov(e^{\varepsilon_{K,t+1}}, e^{\varepsilon_{L,t+1}}|I_t)$. If shocks are persistent, a positive shock to capital (labour) endowment today leads to a higher value of $Y_{K,t}$ ($Y_{L,t}$). This makes their covariance more positive if $\tilde{\sigma}_{KL}$ is positive, or more negative if $\tilde{\sigma}_{KL}$ is negative. Therefore, a positive shock to either part of the endowment improves the hedging properties of Home equity if shocks are negatively correlated. On the other hand, Home equity becomes an even worse hedge against Home labour income fluctuations if shocks are positively correlated. If shocks are uncorrelated within countries ($\tilde{\sigma}_{KL} = 0$), shocks have no impact on the covariance as these are multiplicative effects.

Moving on, dividends in levels are given by

$$Y_{K,t+1} = Y_{K,t}^{\rho_K} e^{\varepsilon_{K,t+1}} \tag{3.33}$$

and hence the variance of dividends tomorrow, conditional on information today, is

$$\begin{aligned} Var(Y_{K,t+1}|I_t) &= Var(Y_{K,t}^{\rho_K} e^{\varepsilon_{K,t+1}}|I_t) \\ &= Y_{K,t}^{2\rho_K} Var(e^{\varepsilon_{K,t+1}}|I_t) \\ &= Y_{K,t}^{2\rho_K} \tilde{\sigma}_K^2 \\ &= (Y_{K,t-1}^{\rho_K} e^{\varepsilon_{K,t}})^{2\rho_K} \tilde{\sigma}_K^2 \end{aligned} \tag{3.34}$$

where $\tilde{\sigma}_K^2 = Var(e^{\varepsilon_{K,t+1}}|I_t)$. If shocks are persistent, a positive (negative) shock to capital endowment today increases (reduces) the conditional variance of future dividends.

I next discuss how shocks change the hedging properties of assets in the three cases:

Case 1: Balanced portfolio - covariance between capital and labour endowment shocks is zero. Clearly, neither labour nor capital endowment shocks affect the covariance between dividends and labour income, as the covariance is zero. There is therefore no hedging motive, and no changes to it following shocks. The variance of Home dividends increases following capital income shocks, however, as both Home and Foreign households hold the same amount of Home equity, this affects households in both countries symmetrically, and therefore doesn't affect their relative demand for assets - hence, there are no capital flows following capital income shocks.

Case 2: Negatively correlated shocks; Home holds more Home equity in the steady state. Now, a persistent positive capital income shock increases the variance of dividends, and makes the covariance between labour and capital income more negative. If the increase in the variance is larger (smaller), home assets become a worse (better) hedge against Home labour income fluctuations, causing Home households to reduce (increase) the amount of Home equity and increase (reduce) the amount of Foreign equity in their portfolio. On the other hand, persistent positive labour income shocks make the covariance between labour and capital income more negative (without changing the variance of dividends), improving the hedging property of Home assets. This induces the Home household to increase the share of Home assets in their portfolio following a positive labour income shock.

Case 3: Positively correlated shocks; Home holds more Foreign equity in the steady state. Again, positive capital endowment shocks increase the conditional variance of dividends, but now it also makes the covariance between labour and capital income more positive. If the variance of dividends increases more (less) than the covariance does, the hedging properties of Home assets improve (decline). Home therefore increases (decreases) the share of Home equity in the Home portfolio. Positive labour income shocks, on the other hand, increase the positive covariance between Home labour and capital income further (without affecting the variance of dividends), worsening the hedging properties of Home assets further. Home households therefore reduce the share of Home assets in their portfolio.

3.4.2 Empirically consistent capital flow patterns

Positively correlated capital flows

Under which conditions, then, are capital inflows and outflows positively correlated? The consumption smoothing motive induces capital flows that are negatively correlated; changes in the hedging properties of assets, on the other hand, result in a positive correlation between inflows and outflows. Hence, capital flows are positively correlated if changes in hedging motives are stronger than the consumption smoothing motive. This is consistent with Tille and van Wincoop (2010) who conclude that flows are positively correlated if "there is sufficient time-variation in second moments that affect Home and Foreign portfolios differently". There are two main parameters in the model that affect the strength of changes in the hedging motive - the covariance between shocks within a country, and the persistence of those shocks.

1. Covariance between shocks In the simple model, the covariance between shocks within countries governs the strength of the hedging motive. As mentioned before, the hedging motive is an asymmetric channel; with a non-zero covariance, Home households can use Home assets to hedge non-diverisfiable labour income risk. Similarly, Foreign households can use the Foreign asset for hedging. Changes in the second moments that induce changes in the hedging properties of assets therefore affect Home and Foreign asset demands differently, resulting in capital flows. The stronger the covariance of shocks, the stronger the effects of shocks are, as these are multiplicative effects. Hence, a larger (or more negative) covariance results in larger capital flows. If the covariance is zero, there is no hedging motive and no changes to it following shocks; Home and Foreign asset demand equations are identical, and hence only the consumption smoothing motive drives capital flows. This results in inflows and outflows that are perfectly negatively correlated. However, as long as shocks are positively or negatively correlated, the hedging motive dominates and gross capital flows are positively correlated.

2. Persistence of shocks Tille and van Wincoop (2010) conclude that the *less* persistent shocks are, the more positively correlated capital flows become. This is because persistent shocks result in persistent changes in savings, whereas changes in second moments that induce changes in the hedging motive are only large on impact and small thereafter. However, this conclusion only holds if Home and Foreign household hold different (non-balanced) steady state portfolios.[8] Moreover, even when Home and Foreign households hold non-balanced steady state portfolios, the impact of persistence on capital flow patterns in non-monotone. This is because persistence also affects the strength of changes in second moments. With zero persistence, there is actually no change in second moments, and hence capital flows are perfectly negatively correlated. In fact, the correlation of capital flows initially increases with persistence, until persistence is about 0.6 [9]. For higher levels of shock persistence, increasing persistence further reduces the correlation between capital flows, as predicted by Tille and Van Wincoop (2010).

Procyclical capital flows

When are inflows and outflows procyclical? Gross capital flows are procyclical when they are positively correlated and the hedging motive drives capital flows in the same direction as income growth; after a positive Home shock, Home households buy more Foreign assets and Foreign household buy more Home assets. This happens when shocks are negatively correlated and there are shocks to dividends income; or when shocks are positively correlated and there are shocks to nondiversifiable "labour" income. Hence, gross capital flows are positively correlated and procyclical if

[8]With balanced portfolios, no matter how persistent shocks are, the consumption smoothing motive is the only force driving capital flows. Hence, no matter how low persistence is, capital flows are always negatively correlated.

[9]with rest of calibration unchanged, and covariance of shocks set to -0.5

a) Home holds more Home assets in the steady state (Home shocks are negatively correlated) and shocks to dividends income dominate. This is the case if variation in dividends income contributes most to income variation, which happens if markets are complete enough (or the share of dividends income in total income is high); or the variance of dividends shocks is relatively higher.

b) Home holds more Foreign assets in the steady state (Home shocks are positively correlated) and shocks to nondiversifiable "labour" income dominate. This is the case if overall income variation is mainly driven by labour income variation, which is the case if markets are incomplete enough or the variance of labour income shocks is relatively high.

Under these conditions, the simple frictionless model produces gross capital flows that are consistent with empirical evidence.

3.5 Relation to previous literature

In this section, I briefly discuss the capital flow patterns in models featured in previous literature, in the context of the discussion in Section 3.5. Hnatkovska (2010) uses a symmetric two country model with tradeable and non-tradeable goods to investigate whether portfolio home bias and high turnover of assets will arise simultaneously and endogenously. Households can trade shares in the tradeable sector internationally, however, nontradeable sector shares are all held domestically. In her framework, capital flows are positively correlated and procyclical, consistent with empirical evidence. Capital flows triggered by productivity shocks to the non-tradeable sector are positively correlated and procyclical, whilst productivity shocks to the tradeable goods sector trigger small but countercyclical flows.

The intuition is similar to the case with the simple endowment economy model: productivity shocks change the (value) of dividends, which affects the variance of dividends as well as the covariance between the dividends of different assets. However, in Hnatkovska (2010) shocks also trigger relative price changes of different goods (non-tradeable goods, Home tradeable goods and Foreign tradeable goods), resulting in a richer covariance matrix for (the value of) dividends of assets. The hedging properties of the assets are therefore more complex, as there is also non-zero cross-country correlation in dividend incomes. This means that shocks not only change of the variance and covariance of the asset that is directly affected, but also those of the other assets in the model. With multiple goods, a new hedging motive arises: hedging against relative price changes.

For example, a positive productivity shock to the non-tradeable sector results in an increase of non-tradeable dividends. Hnatkovska (2010) calibrates non-tradeables and tradeables to be complements; therefore, demand for tradeable goods also increases. This results in an increase in the relative price of Home *and* Foreign tradeable goods, causing an increase in the dividend income on Home and Foreign tradeable assets. As shown in Section 3.5, the variance of a larger variable is larger; the variances of all dividends, and also all covariances, therefore increase. It is hence ambiguous whether the hedging properties of Home assets are worsened or improved by positive non-tradeables shocks, and it depends on the calibration used. In Hnatkovska (2010), the calibration is such that a positive non-tradeables shock reduces Home demand for the Home tradeable asset, leading to positive capital outlfows and positive capital inflows.

Tille and Van Wincoop (2010) also use a symmetric two country model. The model features two goods (Home and Foreign), and household preferences display consumption home bias. There are two assets (Home and Foreign equity), and two shocks (Home and Foreign productivity shocks); perfect risk sharing is not achieved, however, as the model features transaction costs when buying non-domestic equity. In the model, productivity shocks result in capital flows that are positively correlated, but countercyclical. There is no labour income hedging in the model[10]. However, because there are two goods, exchange rate fluctuations matter; and given that shocks cause variation in asset dividends and relative prices, assets can be used to hedge against exchange rate fluctuations. As explained in Section 3.5, shocks result in changes in hedging properties of assets, and therefore changes in hedging motives are also relevant in the setting of Tille and Van Wincoop (2010). This explains the positive correlation of capital flows.

Countercyclicality of capital flows implies that Home assets become a better hedge against exchange rate fluctuations after positive Home shocks. The model is calibrated such that there is home bias in the steady state asset holdings, which is achieved through a positive covariance between Home asset returns and Home relative prices. The covariance between relative prices and Home asset returns therefore increases after a positive Home shock, more than the variance of Home asset returns does.

Consistent with the discussion in Section 3.5, Hnatkovska (2010) and Tille and Van Wincoop (2010) models produce positively correlated gross capital flows,

[10] the model features households that only receive labour income when young, and dividends income in subsequent periods

as both models have strong enough hedging motives (that vary endogenously with shocks) that affect Home and Foreign households differently. However, both Hnatkovska (2010) and Tille and Van Wincoop (2010) frameworks result in countercyclical flows when there is a shock to the tradeable sector; in Hnatkovska (2010) only non-tradeable shocks result in procyclical flows. Given that these models feature multiple goods, shocks also generate relative price changes, and assets can be used to hedge against relative price fluctuations. Whether assets are a good hedge - and therefore the direction of the steady state portfolio bias, as well as direction of capital flows following shocks - depends therefore on the parameters that guide whether goods are complements or substitutes, among other model parameters.

To conclude, frictionless models can generate empirically consistent capital flow patterns. As illustrated by the simple model in this paper as well as the models in Hnatkovska (2010) and Tille and Van Wincoop (2010), positively correlated capital flows arise when assets have strong enough hedging properties that induce differences in domestic and foreign asset demands. The hedging motives not only lead to different steady state portfolios for home and foreign investors, but also to adjustments in portfolios following shocks, leading to positively correlated gross capital flows. The cyclicality of capital flows, however, is sensitive to multiple parameters in the model. The crucial parameters are those that guide the correlation patterns between dividends income, non-diversifiable income, and relative prices. Changing the calibration can result in different correlation patterns between dividends of different assets and non-diverisfiable income, as well as relative prices in models with multiple goods. Changing the parameter values that affect hedging properties of assets not only alter the steady state asset positions but also the direction of capital flows following shocks.

3.6 Concluding remarks

I show that a simple model without financial frictions or asymmetries can generate the puzzling pattern in gross capital flows found in the literature: capital inflows from foreign investors and capital outflows by domestic agents are positively correlated and procyclical. In the model, standard shocks to the endowment generate changes in savings, and in second moments that in turn temporarily change the hedging properties of assets. The changes in savings - the consumption smoothing channel - as well as the changes in second moments - the hedging channel - drive capital flows in the model. If the latter channel is strong enough, capital flows are positively correlated. Furthermore, if shocks that generate procyclical rather than countercyclical flows dominate, capital flows are also procyclical. I conclude that according to frictionless models, the empirical finding of puzzling retrenchment of domestic capital after negative shocks could be due to improvement in the hedging properties of domestic assets following negative domestic shocks.

I find that the two key features in the model that determine whether empirically consistent capital flow patterns arise are within-country correlation patterns in shocks, which in turn determine the optimal steady state portfolio; and the degree of market completeness. As long as domestic and foreign households (optimally) hold non-balanced portfolios, the hedging motive affects them differently, resulting in capital flows that are positively correlated. I discuss the conditions under which capital flows are also procyclical. If negative domestic shocks improve the hedging properties of domestic assets, the puzzling retrenchment of domestic capital follows. This is the case if domestic households optimally hold more domestic assets in the steady state and markets are complete enough; or if domestic households optimally hold more foreign assets and markets are not very complete. Under these conditions, the negative shocks that improve hedging properties of domestic assets (and positive shocks that worsen the hedging properties) are responsible for the bulk of endowment fluctuations, resulting in procyclical flows.

In light of these findings, I review why frictionless models in previous literature (Hnatkovska (2010) and Tille and Van Wincoop (2010)) can produce some of the empirically consistent patterns in gross capital flows. I conclude that as long as assets provide a strong enough hedge against domestic non-diversifiable income fluctuations, or against exchange rate fluctuations, foreign and domestic households will have sufficiently different asset demands such that changes to the hedging properties of assets caused by shocks lead to adjustments in portfolio shares, resulting in positively correlated capital flows. The procyclicality of capital flows, on the other hand, is more sensitive to the specific calibration used. Parameters governing the cyclicality of flows include any parameters that affect the sign and magnitude of correlations between asset returns, non-diversifiable income, and relative prices. For example, parameters determining the share of dividend income in total income, the substitutability of different goods in the economy, as well as the relative volatility of different shocks, can all affect the direction of changes in hedging properties of assets after shocks, and hence the cyclicality of capital flows. Finally, the cyclicality of capital flows is also affected by the prevalence of different shocks; if shocks that result in procyclical flows dominate, capital flows become procyclical.

I therefore conclude that frictions are not necessary to generate positively correlated and procyclical gross capital flows, as these can arise endogenously in standard models. However, this result is sensitive to the calibration used; if the model has features that result in balanced steady state portfolios, for instance, gross capital flows will be negatively correlated. Moreover, the sign and magnitude of the correlation between dividends income and nondiversifiable income is crucial, which is treated as exogenous in my simple endowment economy model. With production and endogenous labour supply, the correlation becomes endogenous; and hence parameters that determine the direction and the strength of co-movement of dividends income and labour income will also affect capital flow patterns. Furthermore, in models with multiple goods, assets can also be used to hedge against real exchange rate fluctuations, resulting in an additional hedging channel. This suggests that the empirical patterns in capital flows could serve as additional calibration targets in more complex open economy models with a large number of parameters.

The current analysis focuses on whether models without financial frictions or asymmetries are able to generate empirically consistent patterns in capital flows; further research could build on these results to investigate whether models that are able to match other empirical open economy moments can also generate empirically consistent patterns in gross capital flows. The analysis here is also largely restricted to considering the signs of correlations and impulse responses to shocks. Future research (empirical and theoretical) could further investigate the shapes and magnitudes of the responses.

References, Chapter 3

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Appendix

3.A Appendix: Empirical estimates of the correlation between gross capital flows

Table 3.A1: Empirical estimates of the correlation between gross capital flows

Paper	Estimate	Sample period	Notes
Broner et al (2013)	0.23-0.24	1980s	All sample countries. Correlations are higher
	0.46-0.49	1990s	for high income and lower
	0.69-0.81	2000s	for middle income countries.
Tille and van Wincoop (2014)	0.89	Not reported	
Dvorak (2003)	0.42-0.88	January 1940 - December 1998	Monthly correlations. Range is over different sample countries which include advanced and emerging economies.