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What is productive investment? Insights from firm-level data for the United Kingdom

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Abstract

This paper studies the effects of different types of investment and levels of debt on productivity in the UK, using firm-level data. We set out a stylised model of a dynamic firm profit-maximisation problem, and augment this model with an external financing option in a novel way. We use the model to illustrate why productivity-enhancing investment differs from other uses of company funds in terms of its effects on total factor productivity (TFP), and how these positive effects can be stronger for firms that have higher indebtedness. We then examine the issue empirically with data on listed firms in the UK. Our main finding is that intangibles investment are a good proxy for productivity-enhancing investment, as they have a positive effect on TFP, and in those firms that have high debt and high levels of intangibles, these effects are even more pronounced. On the other hand, we find no consistent evidence of positive TFP effects for other uses of funds, like tangible capital expenditure or dividends and equity buybacks. The effects of debt on TFP are smaller and more tenuous, but we find no evidence of a negative TFP effect of debt in firms that have high levels of intangibles intensity.

Key words: Dynamic programming, firm-level productivity, intangible assets, panel regression.

JEL classification: C61, D22, D24, O30.

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1 Introduction

In this paper, we study the effects of corporate investment and levels of debt on productivity in the UK, using firm-level data. Given the current relatively high level of corporate indebtedness in the UK, the topic is highly policy relevant, both in terms of risks for the financial sector and its macroeconomic consequences. At the aggregate level, UK data suggests a strong positive correlation between corporate debt and investment, whereas the correlation between debt and productivity is more tenuous. However, at the firm level, there is strong evidence in the literature suggesting that high corporate debt leads to lower investment, especially in times of crisis, with negative subsequent effects on productivity. In particular, in the existing literature, high corporate leverage has been identified as one of the leading indicators of firm vulnerability. Typically leverage is assumed to be "good" in the boom phase, as it allows firms to invest in their productive capacity. Debt then becomes "bad" in a downturn owing to debt overhang reasons.

We take a somewhat different approach in our analysis. We hypothesise that one can distinguish between "good" and "bad" leverage more generally, by means of analysing the types of investments and uses of funds that firms undertake. We analyse firms' investment and debt finance decisions to see how well they explain their productivity (measured by total factor productivity (TFP)). In other words, the mechanism through which firm debt should affect firm level TFP is through the investments firms undertake.

Methodologically, we first set up a structural model to illustrate the theoretical channels that we want to focus on, and then use established panel data methods to study the relationships between the key variables on investment, debt and TFP. The stylised structural model we use builds on the traditional neoclassical model of Eberly et al. (2008), Warusawitharana (2015) and Levine and Warusawitharana (2020) (see also Moll (2014) and Midrigan and Xu (2014) for similar approaches). The model is used for illustrative purposes only, and is necessarily a partial equilibrium model, but it is useful in defining the channels through which investment and debt can effect TFP of a profit–maximising firm, with underlying assumptions that are standard in the literature. Importantly and to our knowledge uniquely, we augment the model with an option for external financing, which enters the model both as a control and a state variable and thus allows for a full characterisation of the solution in a more realistic setting than the more basic approaches. We also solve the model numerically to highlight some of the key dependancies in the model.

In terms of the empirical analysis, we use a fairly large (unbalanced) panel of financial accounts data for listed firms in the UK. The granular nature of this dataset means that all the variables needed for the analysis are available for a relatively large sample of firms. We use standard panel regressions with firm and year fixed effects to study the relationship between TFP and a selection of relevant explanatory variables. We also introduce an interaction term between different types of investment and debt to analyse whether debt is always "bad" for TFP. The way we mix interactions between continuous and dummy variables in our models is common in recent micro–level panel data literature (for similar approaches in different setting, see, for example, Buera and Karmakar (2018), Chodorow-Reich (2014), Giroud and Mueller (2017) and Joseph et al. (2020)). However, endogeneity is likely to be an issue in the types of models we use; *ex ante*, it is not obvious whether investment and finance structure causes productivity, or the other way round. We aim to mitigate this problem with, first, using lagged values of the explanatory variables and second, using a system-GMM approach with appropriate instruments (see Roodman (2009)).

Our main contribution to the literature is in showing that high levels of debt are not necessarily bad for TFP, if the debt is accompanied by high levels of productive investment. We show this with a combination of our structural model and empirical analysis of the UK data. Our evidence suggests that a particular type of investment, namely intangible investment, is a good proxy for productive investment. We show its positive effects on TFP. We also show that a combination of high debt and high intangibles investment can be conducive to high TFP. On the other hand, we find no consistent evidence of positive TFP effects for other uses of funds, like tangible capital expenditure, or dividends and equity buybacks.

Related literature

Our paper relates to literature on the effects of debt on investment and productivity, channels between different types of investment and productivity and on the definition of productivity–enhancing investment. In the first strand, typically, the literature on corporate indebtedness has found evidence of a negative effect of excessive indebtedness on corporate investment. This points to frictions deviating from the traditional Modigliani-Miller model of the irrelevance of a firm's capital structure for its value. The links between corporate leverage and investment have been studied in a large, well-established strand of literature, tracing back to the financial accelerator theory introduced by Bernanke and Gertler (1989) and the debt overhang theory of Myers (1977). Since then, this link has been examined both at the aggregate as well as the firm level. Typically, firm-level studies find a negative relationship between high levels of corporate debt and subsequent capital expenditure, accentuated by times of financial crises (see, for example, Fernando et al. (2014), Duchin et al. (2010), Almeida et al. (2009), Jaeger (2003), Goretti and Souto (2013), Kalemli-Ozcan et al. (2018) and Buera and Karmakar (2018)).

With regard to the links between debt, investment and productivity, Duval et al. (2020) study the effects of various financial vulnerabilities on firm-level TFP in advanced economies, finding that firms with weak balance sheets prior to the financial crisis performed worse in terms of TFP since the crisis. In a more structural approach, Gopinath et al. (2017) develop a model that helps to explain how financial frictions can lead to capital misallocation and lower aggregate productivity. Franklin et al. (2015) find that contractions in credit supply after the financial crisis led to lower productivity in a sample of UK firms. Doerr et al. (2018) report negative effects of credit shocks on investment and productivity of Italian firms. Huber (2018) finds evidence for negative aggregate demand effects of lower credit on innovation and productivity for German firms, irrespective of their direct exposure to the credit shocks. Bahaj et al. (2017) show evidence of a U-shaped – and hence non–linear – relationship between UK firms' indebtedness and levels of productivity. The use of external finance for productive/unproductive reasons is also analysed by Anderson et al. (2015) and Bank of England (2016)).

Several papers have also shown evidence for a positive endogenous relationship between different types of productivity–enhancing investment, like intangibles investment, and subsequent productivity growth. For example, Aghion et al. (2010) establish a negative causality between credit frictions and long-term, productivity–enhancing investment.

However, their empirical analysis concentrates on country–level data and a diffrerent definition of the types of investment compared to ours. Anzoategui et al. (2019) apply an endogenous growth model to US data and find that the long-term productivity slowdown is mainly due to lower R&D investment and spillovers. De Ridder (2018) shows that tighter credit conditions during the financial crisis had a negative effect on productivity–enhancing investment and aggregare growth after the crisis. Moran and Queralto (2018) estimate a strong and persistent effect of R&D shocks on TFP with US aggregate data. And OECD (2016) finds a causality from R&D spending to productivity in a large panel of advanced–economy firms. On the other hand, De Ridder (2019) develops a general–equilibrium model, and also finds empirical evidence, for a negative long-term effect of intangible investment on TFP, as large firms carrying out intangible investment gain market power, which deters entry of new firms and creative destruction. These papers are similar in spirit to our analysis in terms of distniguishing between the effects of different types of investment, but our analysis differs from the existing literature in looking at the relationships between debt, different types of investment in and productivity in a unified framework. In particular, our granular firm–level financial account data allows us to define productivity–enhancing investments empirically, with foundations in a structural model.

The rest of the paper is organised as follows. Section 2 sets out the methods used, both for the theoretical and empirical analysis. Section 3 presents the data used in the analysis. In Section 4, we report the results. Section 5 concludes.

2 Methodology

This section describes our methodology, starting with a stylised structural model set-up, and then moving to the various approaches for the empirical estimation.

2.1 Stylised structural model

We use a structural model to set out the mechanisms between debt, investment and productivity that we then study empirically with UK firm–level data. The model builds on a standard firm profit maximisation problem, using dynamic optimisation (see Warusawitharana (2015) and Levine and Warusawitharana (2020) (LW) for the basis of this model). The main feature of this partial equilibrium neoclassical model is a firm that maximises future profits, and these profits can be enhanced by two types of investment; i) "tangible" investment that accumulates the capital stock and ii) "intangible" investment that enhances productivity through a random productivity process[1]. Firms also face convex costs related to both types of investment. [2]

In a novel feature of our model, we augment it with an option for external debt financing, which can only be used for either type of investment, and which carries an interest that needs to be paid on accumulated debt in future periods. The novelty of our approach comes from the way financing stocks and flows are embedded in the model as control and state variables, rather than as residuals of the cash–flows, as in the standard approach (see, for example, Levine and Warusawitharana (2020)). Our approch is arguably more realistic, as it explicitly links investment and financing decisions taken by firms, and it also allows us to study the interactions between finance, different types of investment and TFP directly.

To begin with, we define a standard firm–level Cobb-Douglas production function as follows (assuming labour input=1 for simplicity[3]):

$$Y_t = e_t^Z K_t^\alpha \tag{1}$$

where Y_t is output, Z_t is log-TFP, K_t is capital input at time t and α is the capital share (constrained to be between 0 and 1). This also measures firm cash flows from operations.

The following stylised model then aims to capture the trade-offs firm face in taking

[1]Our approach assumes a random process of productive investment, which does not add to the tangible capital stock of the firm. In this setting, successful productivity–enhancing investments, either flows or stocks of them, have a direct positive effect on how efficiently the firm uses its tangible capital stock. This approach is similar to a large number of notable contributions to this strand of the innovation literature (see, for example Klette and Kortum (2004) and Warusawitharana (2015)), and is consistent with our empirical TFP and investment series. Note that we use "intangible" and "productivity–enhancing" as synonyms for convenience and clarity, but whether intangible investments are in fact productivity–enhancing is an empirical question that we seek to answer with our empirical analysis.

[2]Convex adjustment costs are a standard assumption in these types of models. See Eberly et al. (2008), who provide evidence for this with firm–level data.

[3]This simplification of the model could be relaxed without affecting the main analytical results to derive a profit–maximisation condition with regard to wages and the labour input. Also note that since we are not focusing on labour markets or the household sector in a general equilibrium framework, there is no condition linking labour productivity to the marginal product or wages in the model. However, for our purposes, this partial equilibrium model is sufficient.

on debt and investing in two types of investment flows; output–enhancing ("tangible") capital expenditure (I) and productivity–enhancing ("intangible") investment (R).[4] The firm wants to maximise profits when choosing these investment flows. In financing the investments the firm faces a trade-off in taking on more debt, or using current available dividends to finance the investments. As a result, the firm also has to choose the amount of external financing (F) it takes on in every period. External financing is used both for building tangible and intangible capital at rates ϕ and $1-\phi$, respectively.

$$V(K,S,B,Z) = \max_{I,R,F}\{D(K,S,B,Z) + \beta E[V(K',S',B',Z')]\} \tag{2}$$

$$\begin{aligned} D(K,S,B,Z) = {} & e^Z K^\alpha - I - R - \frac{\lambda_K K}{2}[\frac{I+\phi F}{K} - \delta_K]^2 \\ & - \frac{\lambda_S S}{2}[\frac{R+(1-\phi)F}{S} - \delta_S]^2 - xB - P(K,B,Z) \end{aligned} \tag{3}$$

$$P(K,B,Z) = \psi_3 e^{\psi_2[-\psi_1(e^Z K^\alpha - xB)+I+R]} \tag{4}$$

Equation (2) sets out the value function of the firm (dropping the time subscript for convenience, and denoting the next period with ', and where β is the discount factor) in the four state variables of the model: tangible (K) and intangible (S) capital stock, debt stock (B) and level of productivity (measured as log–TFP, Z) . The profit (or dividend) structure in every period is given by equation (3). Financing intangible or tangible investment from current period production reduces profits. Furthermore, the firm faces quadratic capital adjustment cost scaled by the respective $\frac{\lambda_K K}{2}[\frac{I+\phi F}{K} - \delta_K]^2$ and $\frac{\lambda_S S}{2}[\frac{R+(1-\phi)F}{S} - \delta_S]^2$ states of capital stocks. The functional form of these costs are chosen such that they reflect the typical setup described in Hayashi (1982). The parameters λ_K and λ_S define the size of these costs, and δ_K and δ_S are the depreciation rates of tangible and intangible capital stocks, respectively. The term xB is the share of current debt stock the firm chooses to pay back each period.

Finally, $P(K,B,Z)$ defined in equation 4 is a penalty function on excessive investment

[4]There is nothing that stops tangible investment from also having a productivity–enhancing component, but for simplicity, and to align the terminology with our empirical analysis, we make a distinction between tangible and intangible investments here.

financed from a firm's own output rather than the external financing channel. A penalty function or other kinds of borrowing limit are necessary for this kind of model for the firm to consider a costly external borrowing option rather than choosing to borrow without limit and at no cost from current output. The penalty function makes financing investment – in either type of capital – financed by the firm's current output increasingly costly. Using a certain share of available own resources, which are those parts of firm output that are not yet committed to financing past debt obligations, will incur close to no penalty. Choosing to invest beyond these limits without using the conventional financing channel will become increasingly expensive for the firm. The penalty function thereby supplants a period borrowing limit for the firm, with a continuous function. This concept is similar to putting penalty functions on consumers (see Algan et al. (2014)) instead of hard debt constraints to avoid consumer Ponzi schemes.

Applying this type of a penalty function is less common in a firm profit–maximisation model, such as ours. However, to be able to efficiently numerically solve the model, we need to make the trade–offs between financing the different types of investment from a firm's own output and from external financing explicit and differentiable. Nevertheless, our penalty function also has an economic interpretation. It can be interpreted as non–conventional forms of financing beyond the firm's own resources being available, such as notes payable, bank overdraft, or delayed dividends to owners. These unconventional financing tools will become increasingly more expensive the more the firm uses them. This is captured by the exponential increase of the penalty function as the firm extends its investment beyond the available own resources without using conventional external financing. The parameter ψ_3 allows for controlling the magnitude of the penalty, while the parameter ψ_2 controls the steepness of exponential growth once available own resources for investment have been used. The parameter ψ_1 controls the share of resources from production that may be spent on investment after current debt obligations xB have been taken into account. Given the form of the penalty function, higher values of ψ_2 and lower values of ψ_1 cause an exponentially increasing penalty, while higher values of ψ_3 cause a linearly increasing penalty. In Appendix A, we also illustrate how committing to investment $(I + R)$ beyond available resources from output and conventional external financing quickly becomes punishingly expensive (see Figure A.2).

Next, we turn to the state equations of the model. The state of the firm at the beginning of each period is defined by its tangible capital K, its intangible capital S, its current level of debt B, and its current productivity Z. The state transitions are defined in equations (5(to (8) below.

$$K' = (1 - \delta_K)K + I + \phi F \tag{5}$$

Tangible capital is increased by investment from own resources I or external financing ϕF and depreciates at rate δ_K.

$$S' = (1 - \delta_S)S + (R + (1 - \phi)F) \tag{6}$$

Similarly, intangible capital is increased by investment from own resources R or external financing $(1 - \phi)F$ and depreciates at rate δ_S.

$$B' = (1 + \rho)(1 - x)B + (1 + \rho)F \tag{7}$$

Next period's debt will be defined by the interest rate ρ, and the share of debt paid back in every period. For debt not to be rising without action it is necessary that $(1 + \rho)(1 - x) \leq 1$.[5]

$$Z' = Z(1 - \delta_Z) + S^{\xi}\sqrt{\frac{R + (1 - \phi)F}{S}}\epsilon = Z(1 - \delta_Z) + \pi S^{\xi}\sqrt{\frac{R + (1 - \phi)F}{S}} \tag{8}$$

In line with previous literature, the next period's productivity is a stochastic outcome of investment in intangibles. Productivity may be an auto–regressive process, or may be calibrated to a unit root, depending on the choice of $\delta_Z \geq 0$. ϵ is a random variable with realisation 0 with probability $1 - \pi$ and 1 with probability π. The idea is that only some investments in intangibles work out to improve a firm's productivity. Furthermore, a firm with a large stock of intangible capital will not be able to make the same productivity jumps without increasing investment further than a firm with lower intangible capital.

[5] This is consistent with a traditional no–Ponzi scheme condition, which ensures that external financing cannot be accumulated indefinitely: $\lim_{t\to\infty}(1 + r)^t F_t = 0$.

This is ensured by division through $\sqrt{S^{1-2\xi}}$. The parameter $\xi \in [0, \infty)$ controls the extent to which intangible capital will affect productivity returns on intangible investment. It nests two special cases. When $\xi = 0$ productivity will always return to a steady state, and while increases in intangible capital investment will lead to a temporary increase in productivity, rising intangible capital will lead to these increases being of a temporary nature. One can think of this as a case where in reaction to increases intangible capital investment of a firm, the rest of the industry adjust their intangible capital investment as well, makes similar investments and productivity advantages are competed away in the long-run. The case where $\xi = 0.5$ nests a model similar Algan et al. (2014) where productivity gains are not affected by the current state of intangible capital. When $\xi < 0.5$ the intangible capital stock will reduce productivity gains from further investment, while when $\xi > 0.5$ the effect will be the opposite. Finally, the expected period return in productivity from investing in intangible capital is concave. This is ensured by the choice of the functional form $\sqrt{R + (1-\phi)F}$.

It is also useful to set out the sequencing of events in the model. The firm acquires financing F at the beginning of period t, and this accumulates with interest rate ρ into stock of debt B' at the beginning of period $t+1$. The firm then makes a decision to pay back portion x of the debt, then makes a new financing decision for period $t+1$, and so forth. Consequently, the sequence of events in the model is the following:

1. K, S, B and Z are known from the previous period.
2. The firm makes decisions on I, R and F.
3. The productivity shock ϵ materialises.
4. At the end of the period, K', S', B' (which takes into account accumulated $B(1+\rho)$ and $F(1+\rho)$ and Z' for the next period are known.

Note that F can only be used for R and I, in proportions $(1-\phi)$ and ϕ, respectively, and not to pay off previous debt or to pay out as dividends (D). Hence, total tangible investment is $I + \phi F$ and intangible investment is $R + (1-\phi)F$ in this set-up.

The numerical solution methods of the model are presented in Appendix A. The Appenix also contains graphs further outlining the intution of the model and consequences of investment in either type of capital. Our focus here is on the comparative statics between different investment decisions and productivity, rather than on a precise calibration of the model to a real–world counterpart. To facilitate this, we refer to the following main propositions of the model, for which the proofs are provided in the Appendix:

1. An increase in intangibles (synonymous with productivity–enhancing investment) stock, through intangible investment flow, leads to higher productivity (measured as the level of TFP in the next period).

2. An increase in external debt stock, through external financing flow, leads to higher productivity.

3. An increase in the share of external financing used for intangible investment leads to higher productivity.

4. An increase in tangibles stock, through tangible investment flow, has an ambiguous effect on productivity.

Propositions 1-3 follow directly from the state equation for productivity (8). Proposition 4 is more complicated, as tangible investment does not directly enter into equation (8), but as we show in the Appendix, the existence of the cost constraint P and the external financing option in our model deliver the proof.

These propositions imply that i) different types of investment can have different effects on TFP, ii) debt can have a positive effect on TFP, if it is used for productive (intangible) investment, and iii) if F is restricted to a fixed amount (due to financing frictions, for example), using the debt to become more intangibles intensive has a positive effect on TFP. It is worth noting that propositions 2 and 3 potentially imply two ways in which a combination of higher debt and higher intangibles investment can lead to higher TFP. In the empirical section below, we do not distinguish between the two, as the focus of our study is not on firm–level measures of financial vulnerabilities, frictions or risk premia. For our purposes, it is important that the mechanisms exist in the structural model and we can then study whether they are consistent with what we find in the data.

2.2 Empirical models

Next, we describe how we study the propositions of the stylised model in our empirical framework. Our regression equations will have firm–level productivity (measured as TFP) as the left–hand side variable. As explanatory variables, we use three types of investment/use of funds variables (described in more detail in the Data section below); i) capital expenditure (proxy for tangible investment), ii) intangible investment (proxy for productivity–enhancing investment) and iii) other uses of funds (dividends and equity buybacks). The purpose of using these three variables is to study the implication of the structural model suggesting different types of investment can have different effects on TFP.

Given that a key aim of our exercise is to study the effects of debt on TFP, we also include a measure of debt as an explanatory variable. As also implied by our structural model (propositions 2-3), the interaction of debt with different types of investment can be important on determining how debt affects TFP. To study this effect, we include an an interaction variable between firm leverage and the different measures of investment. This will allow us to distinguish between "good" and "bad" leverage. We hypothesise that leverage per se is not detrimental, if it is used to finance productive investment and therefore, there needs to be a distinction between "good" and "bad" leverage. We also control for various firm characteristics (firm age, size, cash holdings and profits) that can be expected to have an effect on how productive a firm is. All our baseline regressions include firm and time fixed effects.

The different types of regression equations used are detailed below. To set the scene, to motivate the regression analysis that follows and to study general correlations between different parts of the distributions of the main variables of interest, we start with a simple four–way split of the dataset into high (=above median)/low (=below median) buckets of the data. We then proceed to using fixed–effects panel OLS and system GMM methods in our baseline regressions.

1. Category regressions

To illustrate the relationships between different categories of the data, we use a regression of the following form:

$$z_{it} = a + \beta_1 I_{c,t} + controls + e_{it} \tag{9}$$

where z_{it} is firm-level measure of TFP for firm i at time t, $I_{c,t}$ is category variable (for each of the three different investment variables in turn) taking values 1...4, where 1=[low debt, low I], 2=[low debt, high I], 3=[high debt, low I], 4=[high debt, high I], *controls* includes firm characteristics (sector, age, size, profits, cash) as controls and e_{it} is an i.i.d. error term.

2. Panel regressions

We use two types of panel regressions for our baseline analysis. First, the OLS panel regression specification with lagged explanatory variables is the following:

$$z_{it} = \alpha + \beta_1 D_{i,t-1} + \beta_2 R_{i,t-1} + \beta_3 D_{i,t-1} R_{i,t-1} + c_i + f_t + X_{i,t-1} + e_{it} \tag{10}$$

where $R_{i,t-1}$ are the three different investment variables and $D_{i,t-1}$ is the debt ratio. To facilitate the interpreration of the interaction variable, and to focus on the high–investment firms, the investment variables are 0/1 dummies, with value 1 if the firm's investment ratio is in the top quartile of firms for a particular year, and 0 otherwise[6]. We also use industry median corrected values for the debt ratio[7]. c_i and f_t are firm and time fixed effects, respectively.

Second, we also use a system–GMM specification with contemporaneous explanatory variables:

$$z_{it} = \beta_1 D_{it} + \beta_2 R_{it} + \beta_3 D_{it} R_{it} + c_i + f_t + X_{it} + e_{it} \tag{11}$$

The reasons for using two specifications of the regression model for the estimation are twofold. First, the structural model suggests the TFP effects happen with a lag. But

[6]The results we present below are also qualitatively robust to other choices, and we explore some of the non-linearities of the effects with different thresholds for dummies below.

[7]This approach is similar with Levine and Warusawitharana (2020) and provides a way of controlling for time-varying industry-specific effects. The main results below are also largely robust to not using the median corrections.

given that we do not know how long this lag is in practice (in other words, which actual time period one period in the structural model relates to), it appears useful to study empirical models with both lagged and contemporaneous explanatory variables.

Second, and more importantly, in our panel data models, identification of the parameters comes from variation in TFP across firms and time. However, there are obvious endogeneity issues in our framework, in particular related to simultaneity bias. Choices on the uses of funds by a firm are likely to depend on how productive the firm is; for example, decisions on debt dynamics can depend on the level of TFP. In the OLS method, we mitigate these issues by including lagged, rather than contemporaneous values of all RHS variables in equation (10). This removes the simultaneity bias by definition, as the lagged RHS variables cannot depend on current level of TFP. To make a more robust correction for these issues, we also estimate a system-GMM estimator of the model in equation (11) (as introduced by Arellano and Bover (1995) and Blundell and Bond (1998)). This estimator includes the equation in both levels and first differences and uses lagged levels as instruments for the first–differenced equation and lagged first differences as instruments for the equation in levels. This strategy thereby uses instruments (which we will detail below) to address the endogeneity concerns, and makes the validity of the instruments a testable statistical property. The estimator allows for an AR(1) component in the error term, which accounts for possible serial correlation so that the lagged variables in levels will be uncorrelated with the differenced error term.

3 Data

In this section, we describe the data used for the analysis.

The firm–level data used in the analysis comes from Refinitiv Worldscope, which is a proprietary dataset that includes financial account information on large (mainly listed) UK firms since the 1980s. Table 1 introduces the data series we use for our analysis for a sample from 1990 to 2018 (Worldscope identifiers are given in the last column). The key series for our analysis are the dependent variable, productivity (measured by firm–level TFP), and the main explanatory variables, debt, and tangible, intangible and other investment. The exact definitions of the firm–level financial account data series and the aggregate level deflator data are provided in Annex B.1.

There are different options for measuring firm–level productivity empirically, none of which is without its challenges. The simplest measure, revenue productivity, divides a firm's revenue (turnover) by its number of employees. As has been suggested in the literature, this is not a satisfactory measure of technological progress at firm level (see, for example, Comin (2010)). For that, one needs a measure of TFP. However, this is not often easy to calculate from firm–level data, because typically, only proxies for capital, labour and other inputs are available in the data, and there is no firm–level data on prices.[8]

For this study, we are specifically interested in TFP shocks, but we want to remain relatively agnostic about the way to measure them. Consequently, we will use two established methods based on production function approaches, the first introduced by Olley and Pakes (1996) (with a theoretical correction suggested by Ackerberg et al. (2015)), the second introduced by Wooldridge (2012).[9] These are described in more detail in Annex B.3.

To preserve consistency with the set-up in our structural model, where the TFP process depends on (potentially) different types of investment flows, we use both tangible (i_{it}) and intangible (ii_{it}) investments as instruments to yield he following proxy for TFP (ω_{it}) in our empirical TFP calculations:

$$\omega_{it} = h(i_{it}, ii_{it}, \mathbf{x}_{it}) \tag{12}$$

where $\mathbf{x}_{it}$ is the state variable (capital stock) and $h(.)$ is a monotonous, increasing function

[8]Strictly speaking, the measure we are using is revenue TFP (TFPR), and in the absence of firm–level price data, the underlying measure of firm–level technological progress cannot be estimated. This is an important caveat to keep in mind when interpreting our results, and implies i) that the regression coefficients are downward biased, and ii) the TFPR measure may include a demand shock component (see Barterlsman and Wolf (2018)). Nevertheless, using real values (deflated wtih relevant aggregate GDP and investment deflators) for the revenue TFP measure is closer conceptually to the technological progress than pure revenue productivity, and we will call it TFP for simplicity in the analysis that follows.

[9]In what follows we only report results from the first approach, but the results from the second approach are very similar

of unknown form.[10] From the point of view of the production function estimation, TFP is assumed to be an exogenous Markov process, while the TFP process in our empirical specifications can potentially depend on variables other than only the ones included in the production function. The inclusion of both tangible and intangible investment in equation (12) helps to mitigate this unavoidable conceptual discrepancy.

We use the following firm financial account items as measures of types of investment/use of funds:

- intangibles assets (intans for brevity) (as defined below). This is the main candidate as a proxy for productive investment.
- capital expenditure (capex). Thsi is the main proxy for change in tangible assets.
- other uses of funds (oth) (consisting of dividends (74%, on average) and equity buybacks (26%)). This is the main proxy for other uses of funds, which could in principle be both productive and non–productive.

Tables 2–3 show the main features of selected key variables used in the analysis, weighted by firm size. In these tables, we restrict the sample to firm–year observations for which the main explanatory variables of interest are available. TFP is available for 26,869 observations, which will mainly dictate the sample size for the regressions below. Overall, the dataset is large enough for meaningful analysis to be carried out with the panel data methods we use.

Table 2 reveals that there is a lot of variation in some of the variables; standard devations are high and the differences between the largest and smallest values are large. The mean values of the variables look generally sensible. The average TFP growth is around 1.5% per annum, which is relatively high compared to estimates of aggregate TFP growth during the same time. This most probably reflects the nature of the dataset capturing only the largest firms, which tend to be more productive, on average.

Table 3 reports contemporaneous cross-correlations between the main variables of interest. The correlations are generally low, reflecting large cross-sectional heterogeneity. It

[10]The role of $h(.)$ in the solution methods we use is described in more detail in Annex B.3.

is, however, worth noting that the level of TFP has a positive correlation with intans stocks and negative correlation with capex. Clearly, overall, the relationships between the variables go beyond simple correlations, and they can have different lags and distributions for different variables.

In terms of correlations between the sample investment variables with corresponding aggregate macroeconomic variables – to the extent these can be measured – the correlation of R&D spending with the relevant ONS aggregate series is positive at around 0.37, and the level of R&D spending is higher in the sample than in the economy more generally. A similar comparison between the sum of capex spending divided by total sales with the corresponding aggregate ONS series shows a relatively strong positive correlation of around 0.51, emphasising the importance of large firms for driving business investment dynamics in the UK.

Figure 1 shows *medians* of selected key variables over time. While this hides firm–level heterogeneity, it is a useful sense–check on the data. Some intuitively appealing facts emerge. First, the debt ratio has tended to increase since the financial crisis, whereas the capex–ratio has declined somewhat over time. Third, the other_ratio has increased slightly since the crisis, in line with the popular narrative of increased dividends and equity buybacks in an environment of lower returns on investment. Fourth, the share of intangible assets of total assets has increased steadily over time.

Figure 2 examines the links between the key variables of interest in a slightly more technical way. The scatter plots in the Figure show that there is a positive relationship between TFP and the intans stocks and a negative relationship with capex_ratio (in line with Table 3), but the relationship between TFP and debt looks more complicated. There are some signs of the U–shaped relationship also discovered by Bahaj et al. (2017) with a larger set of UK firms, although there is a lot of variation in this relationship.

The characteristics of firms with high level of intans investment is of special interest to our analysis, so it is worth detailing some of these facts more broadly. As seen in Table 3, the correlations in our sample suggest that intangibles stocks (and flows) are higher in firms that are less indebted, younger, smaller, more cash rich[11] and less profitable than those with smaller intans stocks. Figure 3 shows that the TFP distribution of high-intans firms is higher than that of low-intans, so evidence clearly points to a positive contemporaneous and unconditional relationship between the level of TFP and intangibles. In terms of industry decompositions, high intan firms are heavily concentrated in the manufacturing and ICT sectors (Chart 4). [12]

4 Results

4.1 Main Results

We first report the results of the categorical regressions (equation (9)). Without going into the detailed regression results, the main message is summarised in Figure 5, which shows the category dummy coefficients compared to the base case where the dummy takes the value 1 (low debt, low I). Strikingly, the only case where the effect on TFP is higher than in the base case is with a high intans dummy, combined with both low and high debt. For capex, the opposide effect occurs, and high capex leads to lower TFP. This is the first illustrative result suggesting the effects of the different types of investment can be different, and intans tend to have a more positive effect on TFP than the other investment variables.

We then move on to the structured time series approaches on measuring the effects of the different RHS variables (equations (10) and (11)). Table 4 presents the results of the OLS panel regressions. The effects of the (lagged) intan variables on the level of TFP are strongly positive for both intans stocks and flows (columns (1)-(2)).[13] The effect of the

[11] This is a common finding in the literature (see, for example, Dao and Maggi (2018)); typically, firms with high intangibles spending tend to hold more cash, as it is harder to use external financing for intangible investment projects due to their less collaterisable nature.

[12] We have also compared our data with data from the ONS Innovation Survey (latest data from 2017) (https://www.gov.uk/government/statistics/uk-innovation-survey-2017-main-report), which suggests that internal R&D spending covers over half of all innovation–related expenditure in the surveyed UK firms.This underlines the importance of taking into account accumulated R&D spending in our intans measure, as it is a crucial component of innovation and hence TFP growth. Furthermore, consistent with our industry decompositions, according to the survey, innovation activities are especially important in high–tech manufacturing and knowledge–intensive services.

[13] We only report and discuss the results on our preferred intans measure, which excludes goodwill. The

capex ratio is strongly negative, confirming the results of the categorical regressions above. We do not find any statistically significant effects for the coefficient on other flows (oth). In terms of the debt ratio, the lagged direct effect on TFP is positive, but not significant in all but one of the regressions. To study the full debt effect, we report the p–value of the joint effect of the sum of the direct and the interaction components (last row of Table 4). Interestingly, the total effect of the intans variables is significantly positive, which is in line with the implications of our stylised structural model. The joint effect with capex is zero, but perhaps somewhat counter–intuitively, the oth_ratio joint effect is positive[14].

Table 5 reports the results of the system GMM regressions, along with the relevant diagnostics on the validity of the models (AR1/AR2 p–value and Hansen test p–value). As is conventional in the system GMM set-up, we are using the infinite lags of the explanatory variables as instruments (which are collapsed to avoid proliferation of instruments). We also experimented with other potential instruments, and found the iex_ratio to be a valid instrument that improves the performance of the models. Intuitively, interest expenes can affect some of the RHS variables (like debt_ratio), but it is only likely to have an effect on TFP through the RHS variables. Hence, we include it as an additional instrument.

In terms of the results of the GMM estimations, the first thing to note is that the diagnostics are satisfactory in all the regressions, and we can proceed to studying the coefficients. Again, we find evidence of positive effects of intans on TFP, both for stocks and flows. The capex effect is again significantly negative. However, the direct debt effects are strongly negative this time, but the strongly positive interaction of debt with the intans variables renders the joint debt effect to be effectively zero in all the intans regressions. And the joint debt effect of the oth_ratio is not positive, unlike in the OLS regressions.

Table 6 reports the economic size of the main effects we are interested in in the different regressions. There is a significant and large effect of between 8.2–11.1% on TFP for those firms that are in the highest quartile of intans investment.[15] This effect is somewhat lower

significance and quantitative effects of a measure including goodwill are broadly similar.

[14]It is not obvious why this would be the case. It may be that the ability to pay dividends combined with higher debt has some form of signalling value for positive TFP effects that is not captured by the control variables in the regression.

[15]As noted above, due to the nature of our TFP measure, the regression coefficients may underestimate

for intans flows, and significantly negative for capex flows, whereas the result for other uses of funds is ambiguous. Furthermore, as the second panel of the table summarises, there is evidence of positive lagged debt effects on TFP for those firms that are in the top quartile of intans stocks, though these are quantitatively quite small at around 1%. Consistently throughout the different specifications and intans variables, there is no evidence of negative effects of debt on TFP of high–intans firms.

Overall, the regression results support the evidence of the positive effects of intans on TFP, while there is no such consistently positive effect for capex or other uses of funds. The evidence on the effects of debt are more mixed, but the results do suggest that a combination of high debt and high "productive" investment (as proxied by intans investment) can have a positive effect on TFP, even when the direct effects of debt on TFP for the lowest three quartiles of intans firms can be negative.

4.2 Discussion of the baseline results

The differences in the results between the two regression specifications, especially for the debt variable, deserve additional elaboration. It appears possible that the positive interaction effects of debt and high intans take some time to come through, as the investments financed by the debt are implemented, and hence the debt effects are more positive in the lagged regressions. It is also worth noting that the strongest positive TFP effects accrue from the intan stocks rather than flows. This is consistent with the lagged effects of intans investment that typically come through after several years documented in the innovation literature (see, for example, Hall et al. (2010)).

As detailed above, our structural model suggests the TFP effects happen with a lag. In that sense, the model is more consistent with the OLS regressions than the GMM ones, and the significance of the positive debt effects in the OLS regressions are consistent with this. However, given the rather crude and abstract lag structure in the structural model, we would put more emphasis on two general implications of the model and their consistency with the empirical results, namely 1) different types of investment can have different effects on TFP, but with productivity–enhancing intans invesments exhibiting

the true size of the effects, and hence the estimates in the table should be seen as conservative.

strongly positive effects, and 2) the TFP effects of debt, when accompanied with high intans intensity, are non-negative.

4.3 Non–linearities

The stylised facts presented above suggest that the relationship between the explanatory variables and TFP could be non–linear. This is especially true for the effects of debt on TFP (see also the U–shaped correlation in Figure 2). Therefore, to study these effects, we run the regressions with a dummy for the highest decile of the intans variables, together with above median debt ratios, as explanatory variables[16]. The results for the OLS regressions are reported in Table 7. Columns (1)-(2), with the whole sample, suggest that while the intans effects remain significant and positive, the joint debt effect on TFP is not significant. However, repeating the regressions with firms with high debt ratios only (columns (3)-(4)), shows that while the intans effects are still positive, the joint debt effect is now also positive. This is consistent with the non–linearity of the debt effects, suggesting that *given* a firm is in the high debt bucket, being in the top decile in terms of intans stocks/flows has a strong positive debt effect on TFP.

We also study the effects of different deciles of intans on TFP by shifting the intans dummy decile–by–decile from the 50th to the 90th. Figure 6 shows the results in terms of the size of the coefficient for the intans stock variable for both the OLS and GMM regressions. While there is variation in the coefficients across the regression specifications, they all have their highest values at the 90th decile, suggesting that being in the very top deciles of intans stocks has a more positive effect on TFP than being closer to the median.

4.4 Other Robustness Checks

A main issue with our baseline results is the question of potential reverse causality (see also LW for a discussion of this topic). While our baseline regressions attempt to mitigate endogeneity issues in ways described above, it cannot be excluded that a firm invests in its inputs (like intans) in anticipation of an improvement in its TFP, causing a potential

[16] In these regressions, we include sector, rather than firm level fixed effects to combat the lack of power of the regressions with the low number of firm observations per year.

reverse causality issue. To study this effect in more detail, we follow the method used in LW to split the TFP shock into an anticipated and unanticipated component. Table 8, columns (1)-(2), reports the results of using the unanticipated TFP component (log_tfp_η) as the dependent variable.[17] The intans effects in these regressions are significant and positive, implying that this effect runs from the intans to TFP, rather than the other way round. Hence, reverse causality of this type does not appear to be an issue in our dataset.

There is a question on whether our results would look different depending on the type of external financing we include in the models. In other words, we would like to examine whether the effects of equity, rather than debt financing are different. In Table 8, columns (3)-(4), we report results of a model where we have replaced the debt ratios with equity ratios for all firms. While the effects of the intans stocks remain positive as in the baseline, the direct effects of equity financing on TFP are generally more positive than those of debt financing (this is also true for other investment variables, not shown in the Table). Hence,to the extent that higher TFP contributes to higher firm value, the predictions of the traditional Modigliani–Miller model do not hold, as the effects of equity financing are more positive than those of debt financing. This result also justifies our focus on the effects of debt in our baseline models, as the debt effects are potentially more diverse and less obviously positive.

We also ran several other robustness checks. In Table 8, columns (5)-(12), we report OLS results for different underlying assumptions of the intans stocks. The results suggest that the regressions are very robust to different intans assumptions[18]; intans coefficients remain highly significant, and the joint debt effect remains significantly positive in all cases. We also ran regressions where we interacted the intans variables with firm age, to potentially capture the significance of younger firms doing more intans investment, and this interaction having a different effect on TFP. However, we found this interaction not to be significant in our dataset.

[17]In this section, for clarity and brevity, we report results with OLS regressions only.

[18]Following Peters and Taylor (2017), we allow the R&D depreciation rate in the accumulation of the intans stock to vary between 10 and 25%, and the SGA depreciation rate between 10 and 30%. We also vary the share of SGA that is assumed to be intans investment between 10 and 50%.

5 Conclusion

This paper studies the effects of different types of corporate investment and uses of funds, as well as levels of debt, on productivity in the UK. We combine theoretical propositions of a stylised structural model, featuring a dynamic profit–maximisation problem of the firm, with empirical regression results, using firm-level data. First, we set out a standard neoclassical model , and augment this model with an external financing option. We use the model to illustrate, both analytically and by solving the model numerically, why productivity–enhancing investment differs from other uses of company funds in terms of its positive effects on TFP, and how these effects can be stronger for firms that have higher indebtedness.

Our results suggest that there is a positive effect of intangible investment, especially stocks, on TFP, while there is no such consistently positive effect for tangible capital expenditure or other uses of funds. The evidence on the effects of debt are more mixed, but the results do suggest that a combination of high debt and high intangibles investment has a positive effect on TFP, even when the direct effects of debt on TFP for fims with lower intangibles stocks can be negative. Importantly, we do not find any evidence for negative effects of debt on TFP for firms with high levels of intangibles stocks.

Our paper contributes to the long–standing discussions on the effects of innovation, or intangible investment, as well as of debt, on firm performance. The view emerging from our results is a relatively benign one; accumulation of intangible investments has a positive effect on firm TFP, and a combination of high debt and high intangibles intensity also has a positive effect (albeit economically small). However, our study says little about how these effects could vary in different stages of the business cycles, and especially after crisis periods. We have also only scratched the surface of the non–linearity of the effects of debt in some of our robustness analysis. We leave a closer examination of these issues to other methods and papers, but based on our conjecture and evidence for it, emphasise the importance of understanding what debt is used for, when analysing its effects. This also strikes us as an important consideration when setting policies that affect or operate through firms' debt.

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A. Details of the Structural Model

This Appendix sets out the details of the stylised structural model and highlights some of the key features based on the First Order Conditions (FOCs) and a numerical solution of the model. Many of the model features are similar with LW, however, the addition of external financing flows (control variable) and stocks (state variable) as well as the cost constraint are novel features of our model.

FOCs and model solution:

The model is solved in the four state variables with the endogenous grid method proposed in Maliar and Maliar (2016). This means using the first order conditions together with the envelope conditions. The derivatives of the value function V_K, V_S, V_B, and V_Z are approximated with a polynomial and then iterated on. First order conditions and envelope conditions with μ_K, μ_S , μ_B, and μ_Z as Lagrangian multipliers on the constraints can be found in equations (13) to (23). For simpler notation it is helpful to define the percent investment $G_1 = \frac{I+\phi F}{K}$ in tangible and intangible capital $G_2 = \frac{R+(1-\phi)F}{S}$. We refer the reader to the main text for other variable definitions.

I:

$$1 + \lambda_K[G_1 - \delta_K] + \psi_2 P(K, B, Z) = \mu_K \tag{13}$$

K':

$$\mu_K = \frac{d\beta E[V(K', S', B', Z')]}{dK'} \tag{14}$$

Envelope K**:**

$$\begin{aligned} V_K = {} & \alpha e^Z K^{\alpha-1} + \psi_2\psi_1\alpha e^Z K^{\alpha-1} P(K, B, Z) \\ & - \frac{\lambda_K}{2}[G_1 - \delta_K]^2 + \lambda_K G_1[G_1 - \delta_K] + (1 - \delta_K)\mu_K \end{aligned} \tag{15}$$

R:

$$1 + \lambda_S[G_2 - \delta_S] + \psi_2 P(K, B, Z) = \mu_S + \frac{\pi}{2S^2\sqrt{G_2}}\mu_Z \tag{16}$$

S':

$$\mu_S = \frac{d\beta E[V(K',S',B',Z')]}{dS'} \tag{17}$$

Envelope S**:**

$$V_S = \frac{\lambda_S}{2}[G_2^2 - \delta_S^2] - \frac{\pi 3}{2S^2}G_2\mu_Z + (1-\delta_S)\mu_S \tag{18}$$

F:

$$\lambda_K\phi(G_1 - \delta_K) + \lambda_S(1-\phi)(G_2-\delta_S) = \phi\mu_K + (1-\phi)\mu_S + (1+\rho)\mu_B + \frac{(1-\phi)\pi}{2S^2\sqrt{G_2}}\mu_Z \tag{19}$$

B':

$$\mu_B = \frac{d\beta E[V(K',S',B',Z')]}{dB'} \tag{20}$$

Envelope B**:**

$$V_B = -x - \psi_2\psi_1 x P(K,B,Z) + (1+\rho)(1-x)\mu_B \tag{21}$$

Z':

$$\mu_Z = \frac{d\beta E[V(K',S',B',Z')]}{dZ'} \tag{22}$$

Envelope Z**:**

$$V_Z = e^Z K^\alpha + \psi_2\psi_1 e^z K^\alpha P(K,B,Z) + (1-\delta_Z)\mu_Z \tag{23}$$

Combining these first order conditions and envelope conditions taking the derivate values as given allows for solving for optimal policies for G_1 and G_2, and the amount of external financing F. These can then be used to calculate updated approximations of the value function derivatives V_K, V_S, V_B, and V_Z. These algorithm steps are then applied until convergence, resulting in optimal policy functions and a numerical solution to the model.

Comparative Statics:

For the purposes of our analysis, we focus on the following four propositions of the model:

1. An increase in intangibles stock S, through investment flow R, leads to higher productivity Z'.

2. An increase in external financing stock B, through financing flow F, leads to higher productivity Z'.

3. An increase in the share of external financing used for intangible investment, $(1-\phi)$, leads to higher productivity Z'.

4. An increase in tangibles stock K, through investment flow I, has an ambiguous effect on productivity Z'.

Propositions 1-3 are straight–forward to prove based on model assumptions. In particular, expressing the random TFP process in the following general form (and setting $\delta_Z = 0$ for ease of exposition):

$$Z' = Z + g(R/S, F, (1-\phi), \epsilon) \tag{24}$$

which, for studying effects on Z', can be more conveniently written as[19]:

$$Z' - Z = g(R/S, F, (1-\phi), \epsilon) \tag{25}$$

As in LW, given the concavity assumption of $g(.)$, the following effects on TFP hold, proving proposition 1:

$$\frac{\partial g((R/S, F, (1-\phi), \epsilon)}{\partial R} > 0, \frac{\partial^2 g((R/S, F, (1-\phi), \epsilon)}{\partial R^2} < 0 \tag{26}$$

so $g(.)$ is a concave function on R and intangible investment has diminishing returns to scale.

It is trivial to show that propositions 2-3 also hold for $g(.)$:

$$\frac{\partial g((R/S, F, (1-\phi), \epsilon)}{\partial F} > 0, \frac{\partial g((R/S, F, (1-\phi), \epsilon)}{\partial (1-\phi)} > 0 \tag{27}$$

Proposition 4 is more complicated, as I does not directly enter into equation (24). To show the ambiguity of this effect in the presence of external financing flows and the cost

[19] As in the propositions above, we are interested in the effects on the next period Z', although strictly speaking, the effects are on the growth rate $Z' - Z$. However, given that Z is already known from the previous period, when current period investment decisions are made, the effects are on the next period TFP level.

constraint, we start with the FOC for i, as in equation (13):

$$1 + \lambda_k \left[\frac{(I + \phi F)}{K} - \delta_k \right] + \psi_2 P = \frac{\partial \beta E\left[V(K', S', B', Z')\right]}{\partial K'} \tag{28}$$

Next, we draw on LW (2014), Appendix A, differentiating the productivity effect with respect to I, which yields:

$$\frac{\partial E(Z' - Z)}{\partial I} = \frac{\partial E[g(.)]}{\partial I} = E\left[\frac{\partial g(.)}{\partial R}\frac{\partial R}{\partial I}\right] \tag{29}$$

We know from the concavity of $g(.)$ that $\partial g(.)/\partial R > 0$, so the sign of this effect depends on the sign of $\partial R/\partial I$. To determine this, we first differentiate the FOC for tangible investment (equation (28)) with respect to R:

$$\frac{\lambda_k}{K}\frac{\partial I}{\partial R} + \phi\frac{\lambda_k}{K}\frac{\partial F}{\partial R} + \psi_2^2 P + \psi_2^2 P\frac{\partial I}{\partial R} = \frac{\beta(\partial E[V(.')]/\partial K')}{\partial R} \tag{30}$$

It is then useful to note that the standard Tobin's q-theoretical result, linking marginal to average q, holds with the quadratic investment cost function of the model:

$$q(Z) = \beta\frac{\partial E[V(.')]}{\partial K'} = \beta\frac{E[V(.)]}{K} \tag{31}$$

Here, we define q as the direct marginal cost of tangible investment, excluding the cost constraint, and hence, using the FOC in equation (28):

$$\underbrace{1 + \lambda_k \left[\frac{(I + \phi F)}{K} - \delta_k \right]}_{q(Z)} = \frac{\partial \beta E\left[V(K', S', B', z')\right]}{\partial K'} - \psi_2 P \tag{32}$$

Furthermore, since we know that the effect of R on Z' is positive monotonically, and we know that at time t, exploiting equations (31) and (32) :

$$\begin{aligned}\frac{\partial q(z)}{\partial Z} &= e^Z K^{\alpha-1} + \psi_1\psi_2 K^{\alpha-1}P + \beta\frac{\partial E[V(.')]/K'}{\partial Z'}\frac{\partial Z'}{\partial Z} + \psi_1\psi_2^2 K^{\alpha}P \\ &= \sum_{i=0}^{\infty}\beta^i(e^{Z_{t+i}} + \psi_1\psi_2 P_{t+i})K_{t+i}^{\alpha-1} + \psi_1\psi_2^2 K_t^{\alpha}P_t > 0\end{aligned} \tag{33}$$

we then also know that $\partial q/\partial R > 0$, and hence, the right–hand side of equation (30) is positive. If the model did not include external financing and the cost constraint, this would also imply that $\partial I/\partial R > 0 \Rightarrow \partial R/\partial I > 0$, and $(\partial E(Z' - Z)/\partial I) > 0$. However, this is not necessarily the case in a model with external financing and the cost constraint, since:

$$\frac{\partial I}{\partial R} = \frac{K}{\lambda_k + \psi_2^2 PK}\frac{\partial q(Z)}{\partial R} - \left[\frac{\phi}{\lambda_k + \psi_2^2 PK}\right]\frac{\partial F}{\partial R} - \frac{\psi_2^2 PK}{\lambda_k + \psi_2^2 PK} \tag{34}$$

The right–hand side of this equation can be either positive or negative, depending on the parameters and state of the model. This proves Proposition 4.

Numerical solution:

The model cannot be solved analytically, and as shown above, for the propositions we are interested in, solving the model is not necessary. However, to study and simulate the model in more detail, we solve it numerically using perturbation methods based on Maliar and Maliar (2016).[20].

As an example on how to use the model, we study the effects of different types of investment and debt financing on TFP growth, providing evidence on Propositions 1., 2. and 4. above. The initial variable value ranges, grid spaces and calibrated parameter values are reported in Table A.1.

[20]For an earlier version of the model, we also used value function iteration with the VFI Toolkit. The toolkit, providing solution methods in Matlab for value function iteration, is available at www.vfitoolkit.com. We thank the toolkit author, Robert Kirkby, for his help in setting up the code for our model.

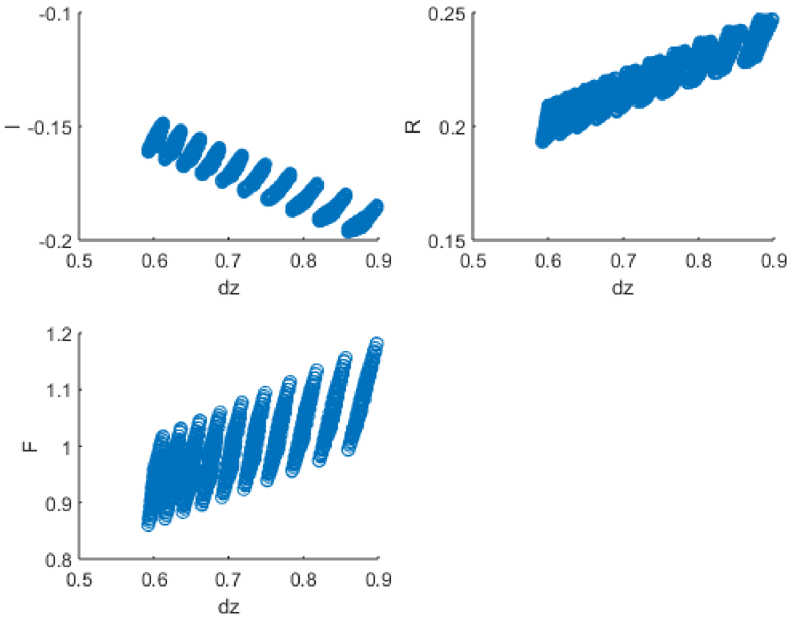
Table A.1: *Variable grids and parameter values*

Parameter	Value
α	0.33
β	0.95
δ_k	0.05
δ_s	0.2
δ_z	0.05
λ_k	10
λ_s	10
ϕ	0.5
ξ	0.05
x	0.15
ρ	0.1
π	0.01
ψ_1	0.1
ψ_2	40
ψ_3	0.01

Variable	Grid Points	Min	Max
K	20	1.55	18.67
S	10	1	12
Z	7	-0.29	0.31
B	10	0.05	25
ϵ	2	0	π

Figure A.1 shows scatter plots between optimal policies for I, R and F versus the optimal $Z' - Z$. The charts include optimal policies for all possible combinations of the nodes in the final state variable grids. The results suggest that, as in the analytical sketch of the solution above, there is a strong positive correlation between Z' with R and F, whereas the correlation between Z' and I is negative. Of course, the exact correlations will depend on the parameterisation of the model, but the signs are robust to sensible ranges in the key parameters.

Figure A.1: *Scatter plots between control variables and TFP (optimal policy)*

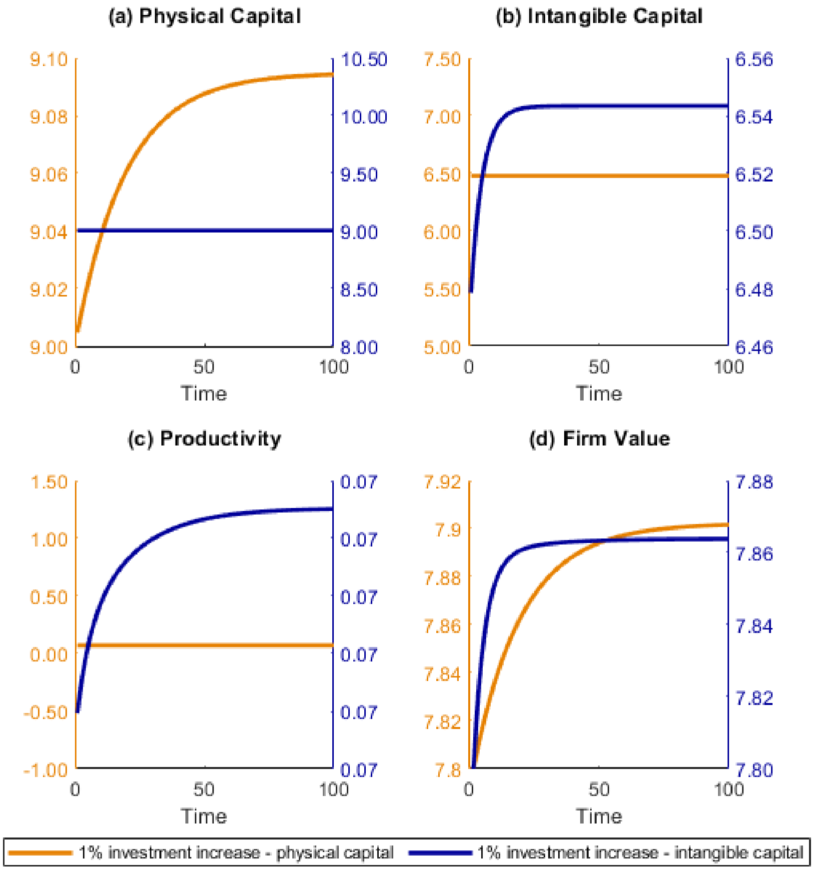


Notes: dprody is TFP growth: $Z' - (1 - \delta_Z Z)$.

The different types of investment flows in the model carry different implications, so it is worth exploring these further in an illustrative example. For intuition, we show in Figure A.2 the impact of a 1% permanent increase in investment of either capital type. Panel a) shows the simulated path for tangible investment and panel b) for intangible investment from steady state investment levels, whilst holding the other investment type path constant at their steady state values.[21] As only intangible investment enters the productivity (TFP) equation directly, only this type of investment has an effect on the level of productivity, causing it to be permanently higher (panel c)). However, the solved value of the firm increases in both cases, given the investment state dynamics (panel d)). In this particular parameterisation, the increase in firm value is somewhat larger for tangible investment than for intangible investment, but as intuition would suggest, both types of investment cause a permanently higher firm value.

[21]Note that for the purposes of this illustrative example, the model is not solved for optimal paths of the other investment type. Also, starting from different levels of the state variables would result in different marginal benefits for the firm from investing in the two different types of capital.

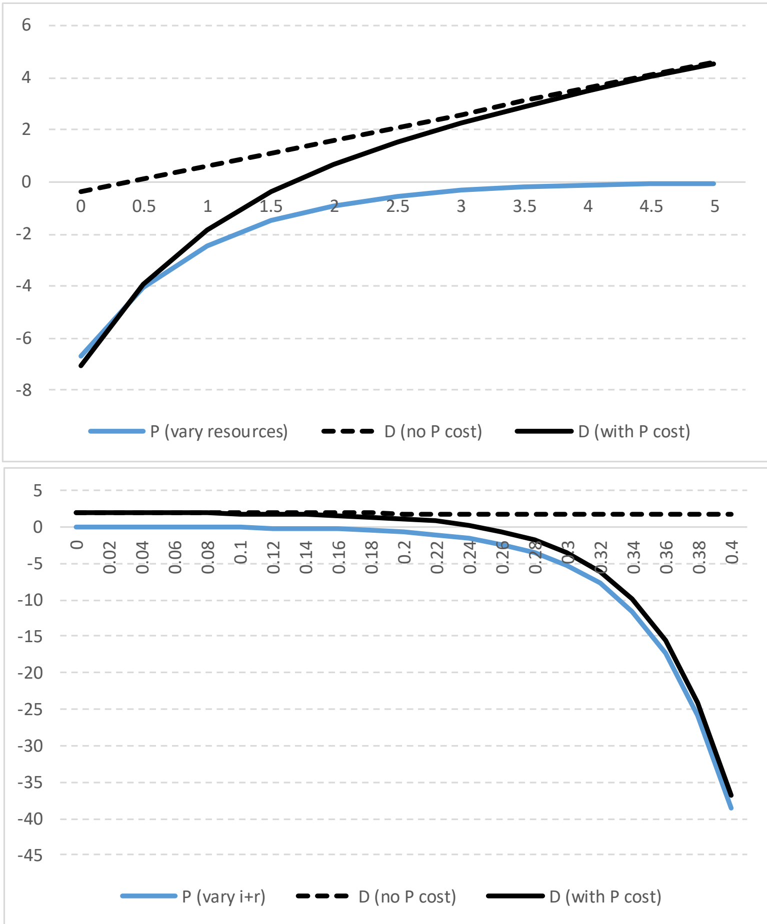
Figure A.2: State paths and firm value paths of a 1% increase in investment in either capital categories. The firm value is computed from the relevant starting state assuming optimal firm policy going forward.



We also illustrate the economic relevance of the cost constraint penalty function (P) (equation (4)) for contemporaneous dividends (D) in a stylised example, where we vary the resources available and the investment in the two types of capital (Figure A.3).[22] In the charts, the solid black line shows the total value of D, taking into account the variation in P (excluding investment adjustment costs for simplicity). The dashed black lines show D excluding P to make the effect of P explicit. The exponential shape of P results in rapidly punishing costs of investment when the resources are low (top panel) and when investments are high (bottom panel).

[22]The other parameters follow Table A.1.

Figure A.3: *Dividends and cost constraint*



Notes: Cost constraint (P) and Dividend (D) values on y–axis, varying resources ($e^Z K^\alpha$) (top panel) and investment $(i + r)$ in P on the x–axis.

B. Data

B.1 Firm–level data

The exact definitions of the variables used in the analysis are as follows:

log_tfp: measure of firm–level real (revenue) TFP, based on the Ackerberg et al. (2015) methodology (see Annex B.3 and the main text for more details).

intan_stock: measure of intangible stocks (defined in Annex B.2) divided by total assets. The suffix d in our regressions indicates a dummy variable, where the highest quartile$\bar{1}$ and 0 otherwise.

intan_stock2: measure of intangible stocks, excluding goodwill (defined in Annex B.2) divided by total assets. The suffix d in our regressions indicates a dummy variable, where the highest quartile$\bar{1}$ and 0 otherwise.

intan_stock_yy: year–on–year change in *intan_stock*. The suffix d in our regressions indicates a dummy variable, where the highest quartile$\bar{1}$ and 0 otherwise.

intan_stock2_yy: year–on–year change in *intan_stock*2. The suffix d in our regressions indicates a dummy variable, where the highest quartile$\bar{1}$ and 0 otherwise.

debt_ratio: total debt divided by total assets (corrected for industry medians).

capex_ratio: capital expenditure divided by total assets. The suffix d in our regressions indicates a dummy variable, where the highest quartile$\bar{1}$ and 0 otherwise.

oth_ratio: other uses of funds ((equity buybacks+dividends) divided by total assets. The suffix d in our regressions indicates a dummy variable, where the highest quartile$\bar{1}$ and 0 otherwise.

age: number of years since firm incorporation

size: real total assets (log level, deflated by GDP deflator)

profit_ratio: profits (EBITDA) divided by total assets

cash_ratio: cash and short-term investment divided by total assets

iex_ratio: interest expense divided by total debt (used as an instrument in system GMM regressions only)

To mitigate the effects of outliers, all variables are winsorised at the 1st and 99th percentiles, as is conventional in the literature.

The following variables are used as inputs into the TFP production function estimations:

output: Log level of revenue (Worldscope:netsales), deflated by GDP deflator
capital input: Log level of net property, plant and equipment (Worldscope:netppe), deflated by GFCF deflator
labour input: Log level of cost of goods sold (Worldscope:cogs), deflated by GDP deflator
tangible investment: Log level of capital expenditure (Worldscope:capex), deflated by GFCF deflator
intangible investment: Log level of year–on–year change in gross intangible assets (as defined in Annex B.2), deflated by GFCF deflator

In addition to the micro data, we use aggregate GDP and GFCF deflators, published by the Office for National Statistics, to transform some of the variables (inputs for the TFP production function estimation and total assets) from nominal into real space. We do not report any stylised facts on these series for brevity, but from 1990 to 2018, the average annual growth rate of the GDP deflator is around 2.4% and the growth rate of the GFCF deflator is around 2%.

B.2 Definition of intangible capital

There is no uniformly agreed measure of intangibles in the literature. For firm-level data, a particular challenge is the fact that intangible investment flows (like R&D spending) are not capitalised into the balance sheet, as they are recorded as expenses in the income account. However, a recent paper by Peters and Taylor (2017) introduces a methodology for measuring intangible stocks and flows, including a method for accumulating expensed intangibles items into stocks. In our definitions, we follow their methodology, which is explained in more detail in this Appendix.

Intangible capital stock (K_{it}^{int}) is defined as:

$$K_{it}^{int} = INT_{it} + A_{it} + B_{it} \tag{35}$$

where INT_{it} is intangible assets in the balance sheet for firm i at time t, A_{it} is accumulated R&D (RD) spending (defined below) and B_{it} is accumulated sales, general and administrative (SGA) spending (defined below).

Accumulated RD spending is defined as follows:

$$A_{it} = (1 - d_{rd})A_{i,t-1} + RD_{it} \tag{36}$$

where d_{rd} is the R&D depreciation rate (assumed to be 15% economy-wide, following previous literature).

Accumulated SGA spending is defined as follows:

$$B_{it} = (1 - d_{sga})B_{i,t-1} + 0.3 * SGA_{it} \tag{37}$$

where d_sga is the SGA depreciation rate (assumed to be 20% economy-wide, following previous literature), and 30% of SGA is assumed to be related to intangible investment.[23]

A choice needs to be made on what to do about starting RD and SGA stocks (A_{i0} and B_{i0}), as the firms are not usually observed from the year they were formed. We assume these to be zero[24]. There is also a small number of cases, where a firm exits the dataset and then re-entres n number of years later. For the accumulation of RD (and analogously for SGA), we use the following proxy formula to calculate the accumulated stocks in the year of re-entry:

$$A_{it} = (1 - d_{rd})^n A_{i,t-n} + (n-1)\left(\frac{(1 - d_{rd})^n RD_{i,t-n} + RD_{it}}{2}\right) \tag{38}$$

As the intangible investment measures used are necessarily only proxies for "true" intangible investment, we want to test the robustness of our result to a number of different intangibles measures. In particular, there is a question on whether goodwill should be included in the intangibles stock. Hence, we also use a measure that excludes goodwill, and given the UK data dynamics, treat this as our preferred measure for the regression analysis. Furthermore, we include flow measures (annual changes in the stocks) in our regressions.

[23] In the Results section, we also examine the robustness of our regressions to different assumptions of the depreciation rates as well as the intangibes share of SGA.

[24] Peters and Taylor (2017) make a similar assumption, but also apply a more complicated method of accumulating stocks from non–zero initial stocks. They find their results look very similar with either method, and given the lack of data on the UK, we do not pursue these comparisons in our intangibles data

B.3 Control Function Approaches For Calculating Firm–level TFP

We need firm–level estimates of total factor productivity (TFP) for our analysis. The main challenge in estimating firm-level production functions is the endogeneity between inputs (capital, labour and internmediate inputs) and output; this positive correlation causes OLS estimates of the production function coefficients to be biased. As is standard in recent literature, we resort to control–function (CF) approaches to calculating TFP. In particular, we use two common measures: 1) Olley–Pakes (OP) with the Ackerberg–Caves–Frazer correction and 2) Wooldridge (W). We discuss each of these briefly below, also drawing on the summary by Mollisi and Rovigatti (2017) but refer the reader to the original sources for more details.

1. Olley–Pakes

In the OP approach (see Olley and Pakes (1996)), the starting point is a general Cobb-Douglas production function of the following form:

$$y_{it} = a + \mathbf{w}_{it}\beta + \mathbf{x}_{it}\gamma + \omega_{it} + \epsilon_{it} \tag{39}$$

where y_{it} is real output for firm i at time t, $\mathbf{w}_{it}$ is a vector of free variables (in most applications, like ours, this is a scalar value of labour costs), $\mathbf{x}_{it}$ is a vector of state variables (typically, capital and intermediate inputs), ω_{it} is unobservable productivity (TFP) process that we are interested in solving for, and ϵ_{it} is an i.i.d. idiosyncratic output shock.

It is assumed that productivity ω_{it} follows a first–order Markov process:

$$\omega_{it} = g(\omega_{i,t-1}) + \xi_{it} \tag{40}$$

where $g(.)$ is based on information available at time $t-1$ and ξ_{it} is the productivity shock.

As is standard, we assume ω_{it} to follow a random walk process.

In the OP method, investment i_{it} can be used as an orthogonal (to $\mathbf{x}_{it}$) instrument to yield the following proxy for TFP:

$$\omega_{it} = f^{-1}(i_{it}, \mathbf{x}_{it}) = h((i_{it}, \mathbf{x}_{it}) \tag{41}$$

which is an unknown function of observables, and plugging this into 39 yields:

$$y_{it} = a + \mathbf{w}_{it}\beta + \mathbf{x}_{it}\gamma + h(i_{it}, \mathbf{x}_{it}) + \epsilon_{it} \tag{42}$$

By approximating $\mathbf{x}_{it}\gamma + h(i_{it}, \mathbf{x}_{it})$ with a higher (2nd) order polynominal function, one can consistently solve for an estimate for $\hat{\beta}$. The model can then be written as (assuming random walk process for ω_{it}):

$$y_{it} - \mathbf{w}_{it}\hat{\beta} = a + +\mathbf{x}_{it}\gamma + \omega_{i,t-1} + e_{it} \tag{43}$$

where $e_{it} = \epsilon_{it} + \xi_{it}$.

Solving equation (43) for e_{it} yields:

$$e_{it} = y_{it} - \mathbf{w}_{it}\hat{\beta} - a - \mathbf{x}_{it}\gamma + \omega_{i,t-1} \tag{44}$$

which allows for solving for an estimate of $\hat{\gamma}$, using a GMM estimator for the moment conditions $E[e_{it}x_{it}] = 0$. In this second stage, $\hat{\gamma}$ is the solution to the following optimisation problem:

$$\hat{\gamma} = argmax \left[\left(\sum_i \sum_t e_{it}x_{it} \right)^2 \right] \tag{45}$$

which then allows for solving the "residual" TFP shock $(a + \omega_{i,t-1})$.

2. Ackerberg–Caves–Frazer (ACF) correction

Ackerberg et al. (2015) point to a potential issue with the OP method by showing how the labour cost coefficient can be consistently estimated in the first stage only if it has variability independent of the orthogonal instrument (in our case, investment i_{it}). Otherwise these two coefficients would be perfectly collinear and hence not identifiable in the first stage. If the labour and investment inputs are chosen at the same time, as is the assumption in the OP method, the collinearity issue arises.

ACF propose assumptions on the sequencing of the choices of the different variables, whereby the state variable (capital) is chosen first, then the labour input (l_{it}), and finally the investment input. This resolves the collinearity problem, and although no coefficients can be solved in the first stage, allows for writing equation (39) in the following form:

$$y_{it} = \mathbf{w}_{it}\beta + \mathbf{x}_{it}\gamma + \mu l_{it} + h((i_{it}, \mathbf{x}_{it}, l_{it}) + \epsilon_{it} \tag{46}$$

where $h(.)$ is the inverrted policy function and the proxy for the TFP process. Denoting equation (46) without the error term:

$$\Phi_{it} = \mathbf{w}_{it}\beta + \mathbf{x}_{it}\gamma + \mu l_{it} + h((i_{it}, \mathbf{x}_{it}, l_{it}) \tag{47}$$

it is possible to construct an algorithm, as shown by ACF, that, once $\hat{\Phi}$ is solved for a candidate vector $(\gamma^*, \beta^*, \mu^*)$, one can obtain the TFP process as residuals:

$$\hat{\omega_{it}} = \hat{\Phi} - \mathbf{x}_{it}\gamma^* - \mu^* l_{it} - \mathbf{w}_{it}\beta^* \tag{48}$$

and consequently the residuals ξ_{it} from the TFP process $\omega_{it} = g(\omega_{i,t-1}) + \xi_{it}$, together with the moment conditions $E[\xi_{it} z_{k,it}]$, for all k, where k is the index of the instrument vector $\mathbf{z} = [\mathbf{x}_{it}, i_{it-1}, l_{it-1}]$ give the following GMM optimisation problem:

$$[\gamma^*, \beta^*, \mu^*] = argmax \left[\sum_k \left(\sum_i \sum_t \xi_{it} z_{k,it} \right)^2 \right] \tag{49}$$

3. Wooldridge

An obvious drawback of the OP method is the lack of firm–level investment data, and also, investment decisions are not necessarily taken every year, as required in the assumptions of the method. Wooldridge (2009) proposes a one–step GMM procedure using different instrument sets in two equations. He shows that by exploiting the Markovian nature of the productivity process, one can derive the following two equations:

$$y_{it} = a_1 + \mathbf{w}_{it}\beta + \mathbf{x}_{it}\gamma + k(\mathbf{x}_{it}, \mathbf{m}_{it})\lambda_1 + v_{it} \tag{50}$$

$$y_{it} = a_2 + \mathbf{w}_{it}\beta + \mathbf{x}_{it}\gamma + k(\mathbf{x}_{it-1}, \mathbf{m}_{it-1})\lambda_1 + n_{it} \tag{51}$$

where m_{it} indicates intermediate inputs and $n_{it} = v_{it} + \xi_{it}$, and $k(.)$ is an unknown function approximated by a 2nd order polynomial (as in the OP case).

One can choose the sets of instruments for each equation based on orthogonality conditions, defined as:

$$\mathbf{z}_{it1} = (1, \mathbf{x}_{it}, \mathbf{w}_{it}, k(\mathbf{x}_{it}, \mathbf{m}_{it})), \tag{52}$$

$$\mathbf{z}_{it2} = (1, \mathbf{x}_{it}, \mathbf{w}_{it-1}, k(\mathbf{x}_{it-1}, \mathbf{m}_{it-1})), \tag{53}$$

$$\mathbf{Z}_{it} = \begin{pmatrix} \mathbf{z}_{it1} \\ \mathbf{z}_{it2} \end{pmatrix} \tag{54}$$

One can then derive the GMM moment conditions from the residual functions:

$$\mathbf{r}_{it}(a_2) = \begin{pmatrix} y_{it} - a_1 - \mathbf{w}_{it}\beta - \mathbf{x}_{it}\gamma - k(\mathbf{x}_{it}\mathbf{m}_{it})\lambda_1 \\ y_{it} - a_2 - \mathbf{w}_{it}\beta - \mathbf{x}_{it}\gamma - k(\mathbf{x}_{it-1}\mathbf{m}_{it-1})\lambda_1 \end{pmatrix} \tag{55}$$

and $E[\mathbf{Z}'_{it}\mathbf{r}_{it}(a_2) = 0$. Solving for these allows for extracting the productivity process $a_2 + k(\mathbf{x}_{it-1}\mathbf{m}_{it-1})$.

B. Tables and Figures

B.1 Tables

Table 1: *Variable definitions*

Variable	Definition	Worldscope code
log_tfp	Ackerberg-Caves-Frazer (2015) measure of TFP (log level)	n/a
intan_stock	intan_stock	n/a
intan_stock2	intan_stock excluding goodwill	n/a
intan_stock_yy	y/y change of intan_stock	n/a
intan_stock2_yy	y/y change of intan_stock2	n/a
debt_ratio	total debt divided by total assets (corrected for industry medians)	totdebt/totass
capex_ratio	capital expenditure divided by total assets	capex/totass
oth_ratio	measure of other uses of funds ((equity buybacks+dividends)/total assets)	(ebuyback+div)/totass
age	years since incorporation	age
size	real total assets (log level, deflated by aggregate GDP deflator)	totass
profit_ratio	profits (EBITDA) divided by total assets	ebitda/totass
cash_ratio	cash and short-term investment divided by total assets	csti/totass
iex_ratio	interest expense divided by total debt	intex/totdebt

Table 2: *Selected key variables - stylised facts*

Variable	Obs	Mean	Std. Dev.	Min	Max
log_tfp	26,869	1.127965	0.589438	-0.60821	4.141734
log_tfp_yy	24,219	0.015334	0.202105	-1.59574	1.35566
intan stock	26,869	0.48576	0.535018	0	4.37014
intan stock 2	26,869	0.378863	0.4979	0	4.37014
intan stock_yy	24,222	0.043263	0.186334	-1.39105	1.948676
intan stock 2_yy	24,222	0.037908	0.188546	-1.67232	1.948676
debt_ratio	26,869	0.201815	0.190997	0	1.336364
capex_ratio	26,869	0.052976	0.055901	0	0.372803
oth_ratio	26,722	0.026392	0.038126	0	0.403295
age	26,869	34.51427	32.79274	0	164
size (assets)	26,869	4.702217	2.08304	-3.41332	12.36988
profit_ratio	26,736	0.065252	0.232903	-2.51777	0.506567
cash_ratio	26,862	0.132	0.159	0.000	0.904

Notes: All variables winsorised at 1st and 99th percentiles.
Data weighted by firm employment.
For definitions of the variables, see main text and Data Annex.

Table 3: *Cross-correlations of selected key variables*

	log_tfp	log_tfp_yy	intan stock	intan stock 2	intan stock_yy	intan stock 2_yy	debt_ratio	capex_ratio	oth_ratio	age	size (assets)	profit_ratio	cash_ratio
log_tfp	1.00												
log_tfp_yy	0.22	1.00											
intan_stock	0.39	0.05	1.00										
intan_stock_2	0.30	0.04	0.95	1.00									
intan_stock_yy	0.05	0.04	0.35	0.36	1.00								
intan_stock 2_yy	0.04	0.04	0.33	0.38	0.93	1.00							
debt_ratio	-0.04	-0.01	-0.08	-0.08	0.02	0.02	1.00						
capex_ratio	-0.14	-0.04	-0.18	-0.11	-0.01	0.00	0.06	1.00					
other_ratio	0.08	-0.02	-0.05	-0.03	0.00	0.00	-0.09	0.06	1.00				
age	-0.18	-0.03	-0.16	-0.12	-0.08	-0.08	0.03	-0.01	0.06	1.00			
size (assets)	0.08	-0.03	-0.32	-0.36	-0.17	-0.17	0.21	0.07	0.17	0.23	1.00		
profit_ratio	0.06	0.01	-0.34	-0.34	-0.36	-0.40	-0.09	0.13	0.31	0.12	0.30	1.00	
cash_ratio	0.17	0.04	0.21	0.26	0.03	0.05	-0.31	-0.11	0.07	-0.17	-0.24	-0.16	1.00

Notes: The table shows contemporaneous correlation coefficients between the variables over the whole sample.
All variables winsorised at 1st and 99th percentiles.
For definitions of the variables, see main text and Data Annex.

Table 4: *OLS panel regression results*

DEPENDENT VARIABLE:

log_tfp RHS VARIABLES:	(1)	(2)	(3)	(4)
debt_ratio (t-1)	0.0249	0.0410	0.0684*	0.0573
	(0.0337)	(0.0337)	(0.0366)	(0.0370)
intan_stock2_d (t-1)	0.0822***			
	(0.0139)			
intan_stock2_yy_d (t-1)		0.0257***		
		(0.00730)		
capex_ratio_d (t-1)			-0.0368***	
			(0.00739)	
oth_ratio_d (t-1)				0.00348
				(0.00653)
debt*RHS variable (t-1)	0.0792	0.0468	-0.0572	0.0148
	(0.0557)	(0.0387)	(0.0385)	(0.0365)
size (t-1)	0.0459***	0.0357***	0.0328***	0.0343***
	(0.00824)	(0.00869)	(0.00794)	(0.00801)
age (t-1)	0.00846***	0.00960***	0.00919***	0.00901***
	(0.000933)	(0.000971)	(0.000940)	(0.000938)
profit (t-1)	0.136***	0.125***	0.127***	0.129***
	(0.0242)	(0.0260)	(0.0242)	(0.0242)
cash (t-1)	-0.0924**	-0.0783*	-0.110***	-0.103**
	(0.0418)	(0.0433)	(0.0424)	(0.0424)
Constant	0.571***	0.584***	0.643***	0.628***
	(0.0416)	(0.0455)	(0.0398)	(0.0401)
Observations	23,639	21,247	23,639	23,521
R-squared	0.832	0.845	0.831	0.830
Joint debt effect	0.050	0.056	0.768	0.034

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
All regressions include time and firm fixed effects.

Table 5: *system GMM regression results*

DEPENDENT VARIABLE:

log_tfp				
RHS VARIABLES:	(1)	(2)	(3)	(4)
debt_ratio	-0.242***	-0.190**	-0.111*	-0.126**
	(0.0770)	(0.0808)	(0.0672)	(0.0627)
intan_stock2_d	0.111***			
	(0.0264)			
intan_stock2_yy_d		0.0405**		
		(0.0205)		
capex_ratio_d			-0.0522**	
			(0.0233)	
oth_ratio_d				-0.0225
				(0.0176)
debt*RHS variable	0.297***	0.251*	-0.0282	0.0386
	(0.113)	(0.136)	(0.134)	(0.0882)
age	-0.00391***	-0.00376***	-0.00413***	-0.00401***
	(0.000358)	(0.000376)	(0.000354)	(0.000369)
size	0.0427***	0.0321**	0.0451***	0.0471***
	(0.0160)	(0.0162)	(0.0152)	(0.0158)
profit	0.337***	0.452***	0.416***	0.381***
	(0.0651)	(0.0726)	(0.0651)	(0.0639)
cash	-0.268***	-0.301***	-0.287***	-0.280***
	(0.0807)	(0.104)	(0.0891)	(0.0941)
Constant	0.833***	1.258***	0.859***	0.842***
	(0.0701)	(0.0870)	(0.0663)	(0.0668)
Observations	26,729	24,102	26,729	26,583
Number of firms	2,610	2,456	2,610	2,607
No of instruments	226	223	226	226
AR1 p-value	0	0	0	0
AR2 p-value	0.290	0.783	0.340	0.459
Hansen p-value	0.109	0.631	0.592	0.699
Joint debt effect	0.524	0.526	0.244	0.267

Notes:Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

All regressions include time and firm fixed effects. iex_ratio used as an additional instrument in the system GMM estimations.

Table 6: *Economic effects*

What is the effect on level of TFP of...

...firm being in the highest quartile of...		
...variable:	*effect :*	
	t-1 (OLS)	t (GMM)
intan_stock2_d	8.2% ***	11.1% ***
intan_stock2_yy_d	2.5% ***	4.0% **
capex_ratio_d	-3.0% ***	-5.0% **
oth_ratio_d	0.3%	-2.0%

...a 10pp increase in debt ratio and firm being in the highest quartile of...		
...variable:	*effect :*	
	t-1 (OLS)	t (GMM)
intan_stock2_d	1.0% **	0.6%
intan_stock2_yy_d	0.9% *	0.6%
capex_ratio_d	0.2%	-1.3%
oth_ratio_d	0.7% **	-0.8%

Table 7: *Non–linearities of debt effects*

DEPENDENT VARIABLE:				
log_tfp				
RHS VARIABLES:	(1)	(2)	(3)	(4)
intan_stock2_d (t-1) (q90)	0.259***		0.191***	
	(0.0287)		(0.0371)	
intan_stock2_yy_d (t-1) (q90)		0.171***		0.144***
		(0.0253)		(0.0286)
debt_ratio (t-1)	-0.0450	-0.0410		
	(0.0379)	(0.0414)		
debt_ratio (t-1) (above median)			0.0404	0.0590
			(0.0528)	(0.0547)
debt*RHS variable (t-1)	0.109	0.184**	0.224*	0.206*
	(0.0955)	(0.0906)	(0.132)	(0.111)
Observations	23,805	21,417	11,783	10,685
R-squared	0.554	0.561	0.616	0.627
Joint debt effect	0.496	0.128	0.036	0.018

Notes:Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

All regressions include the same controls as the baseline regressions, and time and sector (ISIC2 level) fixed effects.

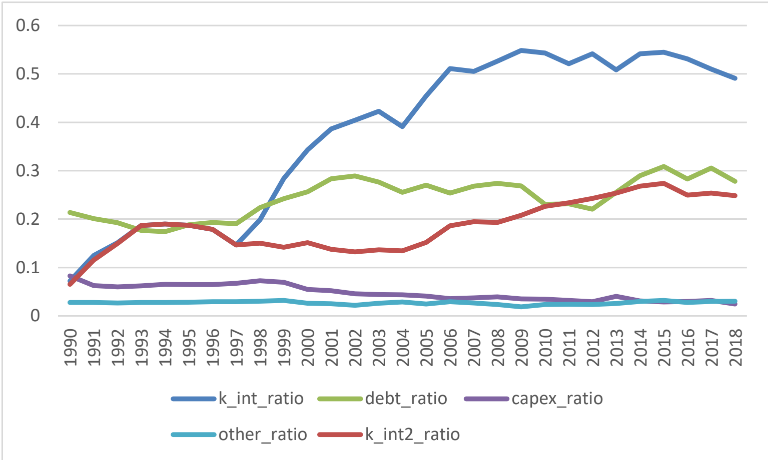
Table 8: *Robustness checks*

DEPENDENT VARIABLE:	log_tfp_eta	log_tfp_eta	log_tfp	log_tfp	log_tfp low d	log_tfp low d	log_tfp high d	log_tfp high d	log_tfp low sga	log_tfp low sga	log_tfp high sga	log_tfp high sga
RHS VARIABLES:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
debt_ratio (t-1)	0.0593**	0.0701**			0.0332	0.0317	0.0183	0.0428	0.0106	0.0342	0.0324	0.0373
	(0.0294)	(0.0320)			(0.0337)	(0.0339)	(0.0337)	(0.0342)	(0.0322)	(0.0335)	(0.0341)	(0.0343)
equity_ratio (t-1)			0.0231	0.0332***								
			(0.0159)	(0.0115)								
intan_stock2_d (t-1)	0.0973***		0.0760***		0.0764***		0.0933***		0.0696***		0.0877***	
	(0.0107)		(0.0133)		(0.0133)		(0.0142)		(0.0132)		(0.0143)	
intan_stock2_yy_d (t-1)		0.0189***		0.0291***		0.0282***		0.0283***		0.0227***		0.0275***
		(0.00594)		(0.00681)		(0.00754)		(0.00710)		(0.00673)		(0.00756)
debt*RHS variable (t-1)	0.0666	0.0404			0.0551	0.0681*	0.0891	0.0431	0.127**	0.0659*	0.0543	0.0557
	(0.0489)	(0.0329)			(0.0556)	(0.0406)	(0.0555)	(0.0374)	(0.0580)	(0.0393)	(0.0553)	(0.0385)
equity*RHS variable (t-1)			0.00955	6.72e-05								
			(0.0161)	(0.00827)								
Observations	23,644	21,252	23,597	21,218	23,639	21,247	23,639	21,247	23,639	21,247	23,639	21,247
R-squared	0.577	0.591	0.841	0.855	0.831	0.845	0.832	0.845	0.831	0.845	0.832	0.845
Joint effect	0.010	0.007	P<0.01	P<0.01	0.099	0.031	0.041	0.055	0.016	0.031	0.098	0.039

Notes:Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Regression specifications for controls (not reported) and fixed effects are similar to baseline OLS models (Table 4).
Columns with "low d" contain results of R%D and SGA depreciation rate of 10%, "high d" rates are 25 and 30%, respectively.
Columns with "low sga" contain results of 10% of SGA spending assumed to be intangibles investment, and for "high sga" the share is 50%.

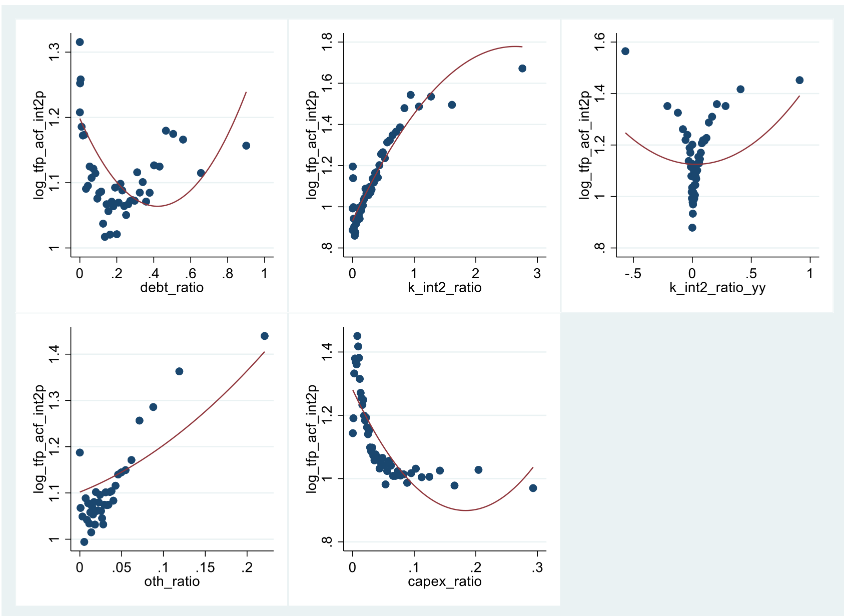
B.2 Figures

Figure 1: *Selected data series - medians over time*



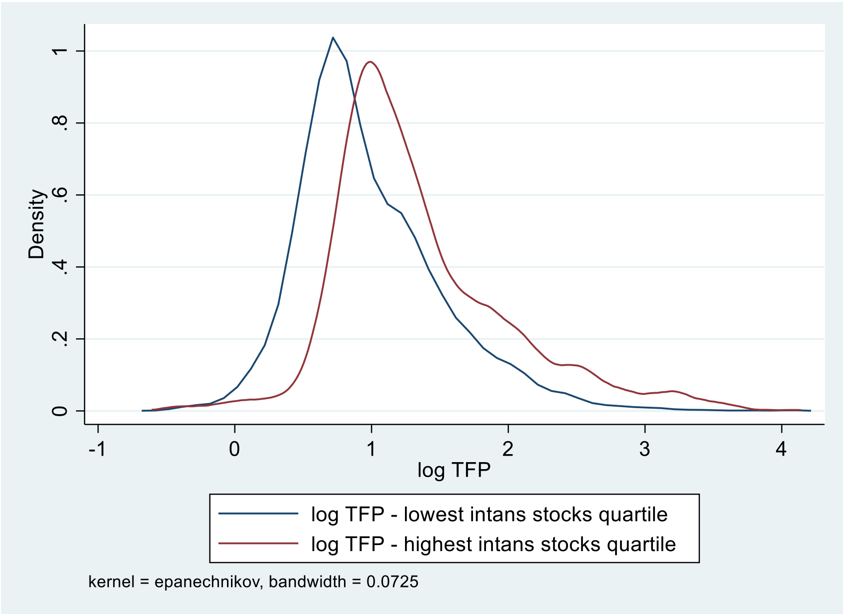
Sources: Worldscope and own calculations.
Notes: Data are employment-weighted medians.

Figure 2: *TFP vs main explanatory variables*



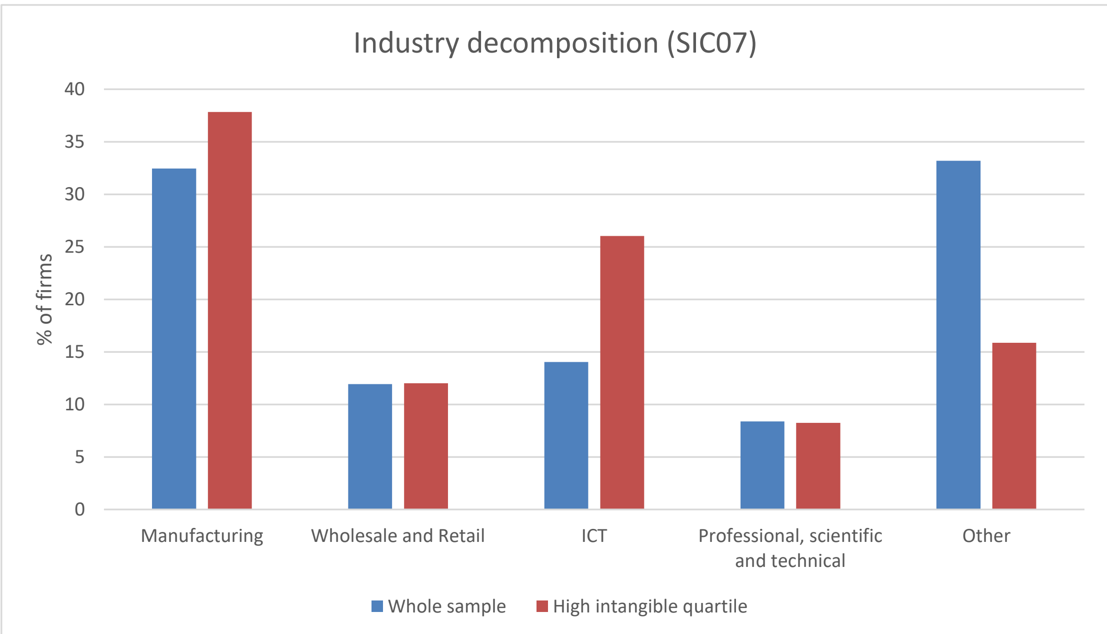
Sources: Worldscope.
Notes: Dots are means 50 equal-sized bins, lines are a quadratic fit through the dots.

Figure 3: *TFP intan densities*



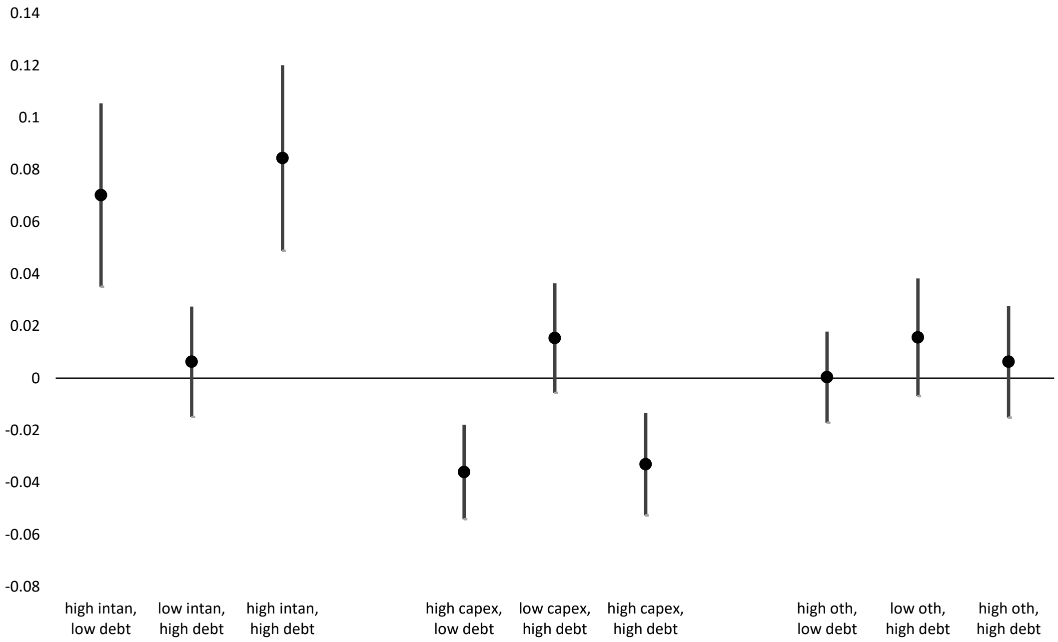
Sources: Worldscope.

Figure 4: *Intangible intensity by industry*



Sources: Worldscope.

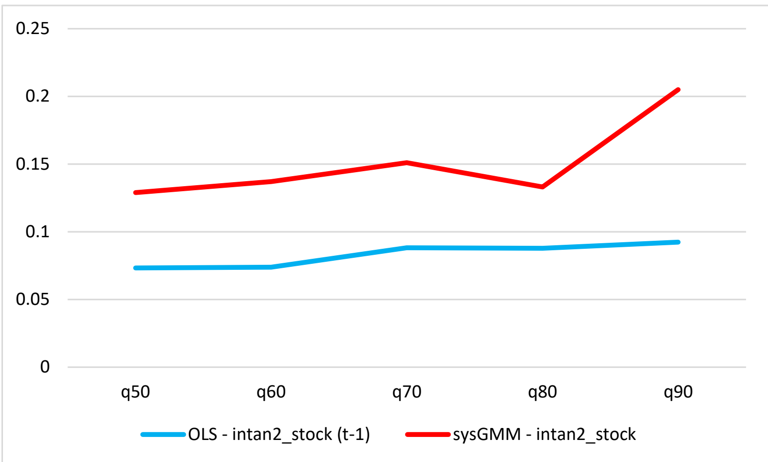
Figure 5: *Debt/intans stock categories*



Sources: Worldscope.

Notes: The chart shows size of coefficients with 95% confidence intervals. The regressions control for industry, year, age, size, profits and cash.

Figure 6: *Intans stock coefficient by quantile*



Notes: The chart shows size of coefficients of intans variable by different quantile regressions. The regressions specifications are similar to baseline regressions.