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Business investment, cost of capital and uncertainty in the United Kingdom — evidence from firm-level analysis

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Abstract

We use new firm-level estimates of the cost of capital and uncertainty to study the drivers of UK business investment in a neoclassical investment model. We construct firm-specific measures of the cost of capital and uncertainty and use new UK survey data to estimate firm-specific investment hurdle rates. There is substantial variation in the cost of capital and uncertainty faced by firms and we find both matter for investment. Firm heterogeneity might help explain the difference in firms' investment paths shortly after the Great Recession. This suggests that, while common shocks, that is, aggregate uncertainty matters, it is also important to capture firm-specific uncertainty to better explain investment dynamics. Overall, between 2000 and 2015 investment responded relatively sluggishly to the cost of capital and more sharply to uncertainty, especially after the financial crisis. There are implications for monetary and macroeconomic policy. The relative importance of measures that alleviate uncertainty compared to changes in monetary policy rates could be larger than generally recognised.

Key words: Investment, micro data, panel regression, hurdle rates, cost of capital, uncertainty.

JEL classification: C23, D22, E22, E44.

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1. Introduction

Investment dynamics are difficult to model, especially in the post-financial crisis world where there have been substantial changes in the environment that firms face. Based on various modelling frameworks used in the literature, investment can expected to be driven by a number of factors including the cost of capital, adjustment costs, value of capital stocks, price of investment goods and uncertainty. However, in practice, identifying the size of the various effects is difficult. Results that are found to be econometrically robust in some settings, do not appear to hold in other cases, especially since the Great Recession (see, for example, Bernanke et al. (1988), Tevlin and Whelan (2003), Gilchrist and Zakrajsek (2007), Gertler and Karadi (2011) and House (2014)).[1] The results differ partly because studies differ in the approach and data used. The difficulty in identifying effects arises because the decision-making process that firms undertake when judging whether to proceed with an investment project is complex and there are elements of the environment the firm is in that are unobserved (outside the firm). The literature provides more robust evidence in relation to the long run drivers of investment, which are likely to be easier to identify relative to short run dynamics.

The contribution of this paper is to use new UK data to construct new firm-level measures of the cost of capital and uncertainty, and then use these measures to estimate drivers of UK business investment. It has been shown that macroeconomic shocks since the Great Recession have increased the dispersion of economic outcomes between firms[2]. There are a number of reasons why changes in the aggregate environment will translate into different effects for different firms. For example, uncertainty related to the exchange rate would be more important for sectors with an export focus, whereas uncertainty about demand may be more pertinent for rapidly growing sectors. We therefore focus on firm-specific conditions in order to better capture effects that would be overlooked in pure macro-level analysis.

We estimate the effects of the cost of capital and uncertainty in a panel regression framework that is theoretically grounded in the neoclassical investment literature that traces back to Hall and Jorgenson (1967). Some of the empirical literature has tended to find

[1] More specifically, Bernanke et al. (1988) find evidence in favour of a financial accelerator type model. Tevlin and Whelan (2003) suggest that traditional investment models, like financial accelerator model, do not work well unless one allows for certain sector-level specifics. Glichrist and Zakrajsek (2007) highlight the importance of accounting for firm-level cost of capital in explaining investment dynamics in traditional models. Gertler and Karadi introduce the effects of financial crisis and unconventional monetary policy measures into a DSGE model and House (2014) shows how to incorporate fixed costs of investment in traditional investment models.

[2] For evidence on increased dispersion of productivity across industries and firms, see Barnett et al. (2014) and Andrews et al. (2016).

evidence in favour of the neoclassical model (see, for example, Oliner et al. (1995), Ellis and Price (2004) and Gilchrist et al. (2014)), although different authors emphasise different factors in explaining investment dynamics in advanced economies. Much of the literature has focused on estimates of the elasticity of investment with respect to the cost of capital. Despite this, there is no consensus on the magnitude of the elasticity, with results tending to vary with methods, data and time periods used. For example, while Chirinko et al. (1999) find relatively low elasticities for US firms while Guiso et al. (2002) estimate large long-term effects for Italian firms.

We also draw on the growing body of work that establishes a link between uncertainty and business investment (see, for example, Bernanke (1983), Bloom et al. (2007), Bloom (2009) and Smietanka (2016)[3]). Following Dixit and Pindyck (1994), we expect higher uncertainty to increase the option value of waiting before committing to an investment project.[4] Specifically, in the presence of partial irreversibility of capital stock choices, uncertainty leads firms to delay investment (in both physical and intangible assets) until the benefit to investment is sufficiently large to outweigh the cost, including the option value of waiting for more information, or until the uncertainty is resolved.

Given the large financial and political shocks that have hit the UK as well as other major economies in recent years, the relationship between uncertainty and macroeconomic outcomes has received a lot of attention. The definition and measurement of uncertainty is not straightforward since it is ultimately an unobservable variable. Typically in recent literature, the definition of uncertainty is related to the second moment (width of the probability distribution) rather than the first moment of the distribution (mean) of future outcomes (see, for example, Jurado et al. (2015)). In reality, the second moment is difficult to measure. A major challenge is to be able to identify movements in uncertainty that are not related to other shocks, i.e. movements that are additional exogenous shocks to the economy. We construct three measures of uncertainty: one firm-level measure based on stock prices, another firm-level measure based on new survey data on firms' reported required rates of return on investment (hurdle rates), and one aggregate measure based on a factor-model composition of different individual uncertainty measures. The hurdle rate reflects the rate of return that is required before a firm is willing to invest including a part capturing the effect of uncertainty.

[3] The latter study is especially closely related to our paper, as it shows that there is a significant relationship between firm specific uncertainty and investment as well as between macroeconomic uncertainty and investment in the UK.
[4] For a formal proof in a 3-period investment model, see Aastveit et al. (2013). The same study also suggests that the responsiveness of investment to changes in interest rates decreases as uncertainty increases.

We find a significant relationship between investment and the firm-level weighted average cost of cost of capital, although the size of the coefficient is relatively low. Our unique survey-based measure of hurdle rates is also an important driver of investment. Although hurdle rates appear to be relatively sticky, when they increase they do tend reduce investment. We find that a stock price based measure of firm-level uncertainty has a robust, significant and negative effect on investment. The impact of a 1 standard deviation change in the uncertainty measure on firm-level investment rates is similar to the impact of a 1 standard deviation change in the hurdle rate although we see the impact of a stock price based measure increase by more following the crisis (such that this measure explains more of the fall in firm investment). We also find that our preferred aggregate level measure of uncertainty has a significant effect on investment. Furthermore, our analysis suggests that the response of investment to our weighted average cost of capital measure is fairly inelastic. But there is evidence that cost of capital had a larger effect on investment before the financial crisis than after it, while the opposite is true for firm-level uncertainty. Overall, the relatively sluggish response of investment to various measures of the cost of capital and the relatively sharp and robust response to firm-level uncertainty could have implications for monetary and macroeconomic policy, especially since the financial crisis; the relative importance of measures that alleviate uncertainty compared to changes in monetary policy rates could be larger than generally recognised.

This paper is structured as follows. We introduce the modelling framework in Section 2. The data, including firm-level uncertainty measures, are discussed in Section 3 and the results are presented in Section 4. Section 5 concludes. Appendices provide further details.

2. Empirical model

Our modelling framework is grounded in a neoclassical user cost of investment equation. Theoretically, this choice can be motivated using a CES production function of the following form[5]:

$$Y_t = \left(aK_t^d + bL_t^d\right)^{1/d} \qquad (1)$$

where $0<a$, $b<1$, $d\leq 1$ and Y_t is GDP, K_t is capital input and L_t labour input at time t. Letting C_t denote the cost of capital at t, the following optimality condition for the firm's desired capital stock (K^*_t) holds:

[5] This section draws heavily on Gilchrist and Zakrajsek (2007) who use a similar framework.

$$a\left(\frac{Y_t}{K_t^*}\right)^{1-d} = C_t \tag{2}$$

It is known that firms do not tend to adjust their capital stocks instantly in the face of a change in conditions because there are adjustment costs. Moreover, there is evidence that those adjustment costs are non-convex (Cooper and Haltiwanger (2006)).[6] However, the actual adjustment process of any firm is likely to be complex (especially as it applies to observed firm level investment, which will represent an aggregate over different capital goods and possibly over multiple plants). This presents a challenge to empirically modelling firm investment. We use an econometric specification that can be seen as a reduced form empirical approximation to some complex underlying process that has generated the observed investment patterns.[7] Specifically, we assume that there is a partial adjustment process between actual and desired capital stocks, which implies the following growth rate of the capital stock (in logs):

$$\Delta \ln K_t = \mu + \theta\left[\ln\left(\frac{Y_t}{K_t}\right) - \left(\frac{1}{1-d}\right)\ln C_t\right] \tag{3}$$

where the parameter $0<\theta<1$ measures the speed of adjustment to the desired capital stock (i.e. some constant fraction, θ, of the gap between the actual and desired levels of the capital stock is assumed to be closed in each period). This adjustment model can be estimated empirically with a regression of the following form:

$$\Delta \ln K_t = \mu + b_y \ln\left(\frac{Y_t}{K_t}\right) + b_c \ln C_t + \epsilon_t \tag{4}$$

where ϵ_t is an i.i.d. error term and $-(b_c/b_y)$ measures the long-run elasticity of capital with respect to the cost of capital.

We estimate both a static and a dynamic version of the model, and we relax the restrictive framework of equation (4) in two ways. In the dynamic version, we allow investment to additionally depend on investment in the previous period and, in both versions, on levels of uncertainty. The former accounts for possible persistence in the investment process. The

[6] Models assuming strictly convex adjustment costs are significantly easier to implement empirically but have been shown to fit the data poorly. In particular, they do not fit with evidence of 'lumpy' adjustment of capital (Doms and Dunne (1998), Nilsen and Schiantarelli (2003)), which can result from non-convex adjustment costs and partial irreversibility. Bond and Van Reenen (2007) provide a discussion.

[7] That is, we do not set up an empirical specification that is explicitly derived as optimal adjustment behaviour for some particular structure of adjustment costs. There are various alternatives to this approach discussed in Bond and Van Reenen (2007).

latter provides an empirically tractable way to investigate the extent to which uncertainty affects investment.

We estimate the following two equations:

$$\ln\left(I_{jt}/K_{jt-1}\right) = \beta_1 \ln S_{jt} + \beta_2 \ln C_{jt} + \beta_3 \ln U_{jt} + \mu_j + \lambda_t + \epsilon_{jt} \tag{5}$$

$$\ln\left(\frac{I_{jt}}{K_{jt-1}}\right) = \alpha \ln\left(\frac{I_{jt-1}}{K_{jt-2}}\right) + \beta_1 \ln S_{jt} + \beta_2 \ln C_{jt} + \beta_3 \ln U_{jt} + \mu_j + \lambda_t + \epsilon_{jt} \tag{6}$$

where I_{jt} is investment (capital expenditure) for firm j at time t, K_{jt} is capital stock at the end of quarter t for firm j, S_{jt} is the firm's sales (at time t) to capital ratio (at t-1) (a measure of economic fundamentals), C_{jt} is the cost of capital and U_{jt} is firm-level uncertainty. λ_t are time fixed effects that will capture common macroeconomic conditions. μ_j are firm fixed effects that will capture differences in average investment rates across firms (for example, those related to firm size or management quality).

Identification of the parameters of the model comes from variation in investment across firms and time. A key difference compared to much of the previous literature is that we observe cross-sectional variation in the cost of investment and uncertainty (measures that vary at the aggregate or industry level are more common). However, firm level measures of the cost of finance and uncertainty are expected to be endogenous to investment rates. For example, they may be correlated with unobserved investment fundamentals (and not captured by firm sales or fixed effects). In the dynamic version of model (equation (6)), lagged investment and firm sales will be also endogenous.[8]

Established fixed-effects OLS panel methods with robust standard errors are used for estimating the static model (equation (5)). We estimate the dynamic version of the model using a system-GMM estimator (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.[9] This strategy thereby uses instruments to address the endogeneity concerns.

[8] Firms choose both output and an optimal set of inputs, such that any shock, for example to firm productivity, translates into changes in both the dependent and 'independent' variables.

[9] 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

We use data from S&P Capital IQ, which is a proprietary database with financial account information for around 300,000 UK firms. In our main results, we work with a smaller sample of just under 200 firms for which we have complete financial account information.[10] Even though the size of the sample is relatively limited, investment (proxied by capital expenditure) by these firms accounts for around 1/3 of aggregate level business investment published in the UK national accounts, on average, between 2000 and 2015.

From this data we measure the investment-to-capital ratio (the dependent variable) as the ratio of capital expenditure to the net book value of plant, machinery and equipment (capital). We define the sales-to-capital ratio as turnover divided by capital. For later robustness checks we calculate a measure of Tobin's Q - defined as the ratio of market to book value of a firm's assets - as the ratio of the stock of debt and market capitalisation to total assets. We add firm-level measures of the cost of capital and uncertainty (described below). The latter two of these measures are – as far as we are aware – unique to this study.

By construction, most of the variables we use are real rather than nominal because we are dividing nominal financial account variables with other financial account variables or because of the way the (mainly interest rate) variables are defined. We highlight below where we additionally use deflators.

3.1. Cost of capital measures

An ideal measure of the cost of capital would provide the cost of each source of funding for an individual firm at a particular point in time. In practice, this is difficult to achieve due to data limitations and it remains rare to have measures that vary at the level of the firm. We use three different firm-level measures of the cost of capital: the firm's average cost of debt, the credit spread and the weighted average cost of capital. In the literature, a measure of marketable debt, i.e. corporate bond yields, is often used because it is easily available. But we do not use this measure because in the UK the number of firms issuing corporate bonds is limited and would dramatically reduce the size of our sample. We prefer instead to focus on the cost of all debt. Additionally, we also calculate the firm-specific cost of equity and construct a weighted average cost of capital (WACC) measure for each firm. *Ex*

[10] The vast majority of the 300,000 firms in the Capital IQ database are missing the financial account data required for the analysis. Data required to calculate firm-specific hurdle rates, hurdle premia and the cost of capital reduces our dataset further.

ante this measure should be better as it captures a wider spectrum of funding sources than just the cost of debt.[11]

The measure of firm-level cost of debt is constructed as the debt interest expense divided by the book value of total debt on the company's balance sheet.[12] This measure is supposed to proxy for funding costs faced by firms. But this measure also includes an economy-wide risk free rate whereas it is possible that more of the variation in funding costs faced by an individual firm might be due to the relative riskiness specific to that firm. We therefore use a measure of the credit spread, the cost of debt less the risk free rate (proxied by 10-year UK gilt yields). Higher risk firms would expect to have access to finance at a greater premium over the risk free rate and this might be another proxy for funding costs.

Our third measure is the WACC, which we define as:

$$WACC_{jt} = \left[\left(r_t^f + ERP_{jt}\right) * w_j^{equity} + \left(r_{jt}^{debt}\right) * w_j^{debt}\right] - \pi_t \qquad (7)$$

where w_j^{equity} and w_j^{debt} represent the share of firm j's combined market value of equity and book value of debt that is attributable to equity and debt at time t, respectively. The nominal cost of debt, r_{jt}^{debt}, is defined as described above. The nominal cost of equity is composed of the risk free rate (r_t^f) plus an equity risk premium (ERP_{jt}) specific to firm j at time t. We calculate the equity risk premium for each publicly listed firm based on a six-stage dividend discount model using firm-level analyst expectations for dividend and earnings growth from the Institutional Brokers' Estimate System (IBES).[13] We then deflate the nominal WACC by ten-year expected inflation derived from ten-year gilt yields and inflation swaps to derive the real WACC for each firm.

3.2. Uncertainty measures

Uncertainty is an elusive concept and various approaches have been adopted in recent literature both to measure it and to capture its effects on macroeconomic variables. Although different authors focus on different aspects of uncertainty, previous literature has

[11] From a theoretical perspective, the user cost of capital measure originally introduced by Hall and Jorgenson (1967) also takes into account taxes and the relative prices of investment goods. However, given our focus on firm-level measures and the lack of observable firm-level variation in these two factors, we abstract from them here. Moreover, while an ideal measure would consider the marginal cost of finance, this is not observed. We therefore use the weighted average cost of capital as an approximation for the cost of capital.

[12] All firms in the sample have debt at some point during the sample period.

[13] For more details of the dividend discount model used in the paper see Inkinen, Stringa and Voutsinou (2010).

emphasised the importance of three key features of a good measure of uncertainty. It should be 1) forward-looking, 2) not include a systematically forecastable component (see e.g. Jurado et al. (2015)) and 3) be a measure of a second-moment (rather than first-moment) shock. The forward-looking nature of the uncertainty measure is related to the forward-looking nature of macroeconomic variables (like investment), and the exclusion of the forecastable component makes a key distinction between measures of volatility (which can be forecastable) and uncertainty (the future movements of which should be unexpected and hence not forecastable).

In our analysis, we use three measures of uncertainty, two of them firm-level and one of them aggregate level. First, we construct a new – to the UK – measure of firm-level hurdle rates and hurdle premia using survey data that asks firms about their required rate of return on investment (hurdle rates).[14] In line with the real options and risk premia type narratives of the effect of uncertainty on investment (Bloom (2014)), we would expect firms facing higher uncertainty to increase their required rate of return, irrespective of changes in their cost of capital. Second, we also construct a more commonly used measure of uncertainty based on firms' stock price volatility. The intuition is that we would expect those firms facing a more uncertain environment to have a more volatile stock price (because investors are also less certain of the net present value of the company). Third, we compare these measures to an aggregate measure based on a simple factor model of the two firm-level measures and a measure of expected aggregate stock market volatility.[15]

The three measures we use are inherently forward-looking and, at least implicitly, they measure second-moment shocks (although in the case of hurdle rates/premia, the second moment shocks can only be proxied by the uncertainty that is embedded in their level). Where feasible we also attempt to purge the measures of the forecastable component so that they should have the desirable features highlighted above. However, no measure can fully satisfy all the various aspects of uncertainty, so our measures should be seen approximations of those aspects that we think are the most relevant for our case.

The following subsections describe each of these three measures in more detail.

[14] See Appendix 1 for more details on the construction of these measures.

[15] Despite being derived exclusively from financial market prices, we expect these measures to capture a range of different types of uncertainty. For example, the volatility of a firm's stock price can be expected to react to both firm-level uncertainty shocks as well as aggregate shocks, like a change in political uncertainty.

3.2.1. Hurdle rates and hurdle premia

A hurdle rate is defined as the firm-level minimum required rate of return used to determine whether to undertake an investment project or not. This rate will reflect the cost of capital of the firm plus any premium that is required to account for uncertainty or any other considerations (for more details on the theory behind hurdle rates, see, for example, Saleheen et al. (2017)). We expect higher uncertainty to increase the option value of delaying investment and hence to lead to a higher hurdle premium and a higher hurdle rate. Therefore, hurdle rates can provide us with information about the uncertainty faced by firms.

Hurdle rates are unobservable in firms' financial accounts and standard firm-level data. We use new data from the Bank of England Agents' Investment Survey and the Finance and Investment Decisions (FID) Survey that explicitly asks firms to reveal their hurdle rates.[16] The FID survey had 1,220 respondents and was broadly representative across industries, firm size and UK regions.[17] We were able to use responses from 459 firms, for which we link hurdles rates to their financial account data. A small number of surveys have linked hurdle rates to firm-specific financial account data in the US (Poterba and Summers (1995), Ben-David et al. (2013) and Jagannathan et al. (2016)). To our knowledge, we are the first to do this for the UK.[18]

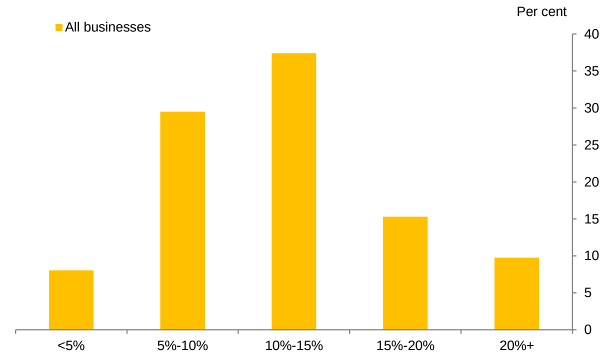
Data from the FID survey suggest that the most common hurdle rate was in the 10%-15% range, with considerable variation across businesses, as shown by Chart 1. Using mid-points for each selected range the average hurdle rate for companies in the survey was 12%, which was in line with the ONS data on the net return to capital and in line with the average actual rate of return across businesses as reported in the survey. Hurdle rates in construction, manufacturing and finance were a little higher than the average across all businesses. The 10-15% hurdle rates are consistent with recent US studies (Jagannathan et al. (2011)).

[16] The Bank conducted a survey on Finance and Investment Decisions in October to November 2016. Details of the survey and the results were published in its Quarterly Bulletin (Saleheen et al. (2017)). In the run-up to that wider survey, the Agents ran a supplementary survey on hurdle rates, specifically for Bank research purposes. We use data from both surveys. For details of the FID Survey, see Appendix 2 and Saleheen et al. (2017).

[17] Unfortunately, it underrepresented younger businesses which were difficult to capture.

[18] There are available estimates of UK hurdle rates from a survey in 1994 (Wardlow (1994)). The 1994 sample was much smaller and focused only on the manufacturing sector. Given changes in the economy since then, including the start of inflation targeting, the estimates (which showed hurdle rates in the 15%–20% range) are not directly comparable with the current survey.

Chart 1: Hurdle rates: Evidence from the Finance and Investment Decisions survey



Source: Bank of England Finance and Investment Decisions Survey.
Question 12: 'If you set an investment hurdle rate, what is it?'

Table 1: Frequency of changes to investment targets

Direction of change at the latest review of investment targets

	Direction of revision [(a)]			
Time last reviewed targets [(b)]	Up/tighter (per cent)	Down/looser (per cent)	Unchanged (per cent)	Total (per cent)
Since the referendum	4.2	8.3	10.9	23.4
In the past year but before the EU referendum	6.3	7.0	14.5	27.8
One to three years ago	5.5	6.2	11.2	22.9
Three to five years ago	1.6	1.4	3.8	6.8
Not within the past five years	1.6	1.6	15.9	19.0
Total	19.1	24.5	56.4	100.0

Source: Bank of England Finance and Investment Decisions Survey.

(a) Question 15: 'When you last reviewed them, in which direction did you revise your set targets?'
(b) Question 14: 'When was the last time you reviewed the targets you set for investment expenditure?'

The survey asked firms for their hurdle rate at a point in time. To construct a time series dimension (which is difficult to elicit directly from a cross sectional survey) we used the approach of Jagannathan et al. (2011).[19] We use a two-stage approach, where we first regress hurdle premia (defined as observed hurdle rates minus the firm-level WACC) on characteristics (C_j) that are thought to be related to the drivers of the hurdle premium (equation (8) below). This hurdle premium can depend on k financial account variables, which we choose to attempt to capture the dispersion of outcomes of future investment opportunities for the firm. For example, we may expect the hurdle premium, including the part reflecting uncertainty, to vary with firms' sales growth, the dispersion of returns and financial position. In the second stage, we then use the estimated coefficients to construct hurdle rates for other years and for firms that were not in the survey sample. Specifically, we select 626 firms from the Capital IQ database, filtering out firms for which relevant financial account variables were not available over a sufficiently long time horizon. We construct measures of the hurdle rate for these 626 firms for the years 1996 to 2015, producing a sample of 2,970 observations. From these firm-level measures we can calculate aggregate-level *imputed* hurdle rate/premia proxies over time as simple averages, weighted by firm-level investment.[20]

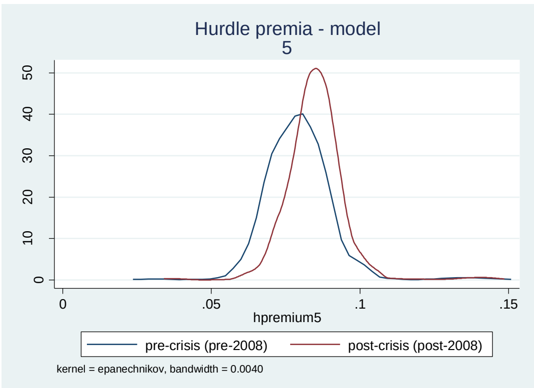
[19] Details of the methodology, variables used and the robustness to alternatives are provided in Appendix 1.

[20] It is worth emphasising the uncertainty around these proxy-type estimates. We are relying on a relatively small sample of firms for the hurdle rate regression before projecting simple averages to economy-wide estimates, as well as assuming that the regression methodology is valid and coefficients are fixed over time. In reality, these assumptions can be challenged, especially in an environment where shocks hit the economy. Given the unobservable nature of hurdle rates, we think this a worthwhile exercise to investigate UK hurdle rates. But it does imply that interpretation should proceed with caution.

$$Hpremium = \sum_{j=1}^{k} b_j C_j + e \tag{8}$$

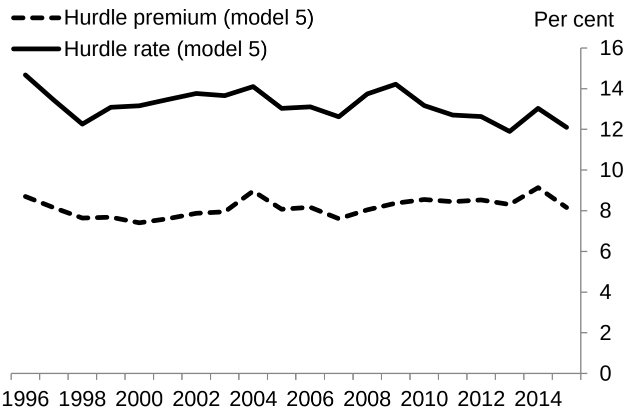
Charts 2 and 3 show the estimated time series and distributions (pre- and post-financial crisis) of the resulting hurdle premia, based on the aggregate-level imputed hurdle rate (and premia). Chart 2 shows that the distribution of hurdle premia moved to the right following the recession (a Kolmogorov-Smirnov distribution equality test confirms this was a statistically significant shift). This is consistent with the idea that uncertainty increased in the recession. However, given that the time series is driven by movements in firm characteristics (which will capture other factors and, to an extent, uncertainty) the estimates and analysis based on hurdle rates should be viewed with caution.

Chart 2: Distributions of firm-level hurdle premia



The chart shows probability density functions from step 1 for model 5 (see Appendix 1 for details), with the percentage of firms for each hurdle premium, before and after 2008.

Chart 3: Imputed hurdle premia and hurdle rates over time



The chart shows time series estimates of imputed aggregate hurdle rate and premia, based on model 5 (see Appendix 1 for details).

Before the financial crisis, the mean hurdle premium in our sample was around 8%. This is substantial. It is also in line with the literature. For example, Jagannathan et al. (2016) find that hurdle rate premia range from 6 to 8% depending on the cost of capital measure used.[21] The authors consider the drivers of hurdle rates. They do not find evidence that high hurdle premia are due to capital rationing. Instead, they conclude that substantial hurdle premia arise because the option of waiting for better investment opportunities is valuable when firms cannot undertake all positive net present value projects. In particular, they point to the availability of physical and human capital and managerial capacity as influences on the level of the hurdle premium. For example, firms with such limited organisational

[21] Jagannathan et al. (2016) highlight that these rates are also supported by evidence in the US, where the Duke/CFO Magazine survey found a hurdle rate premium of around 4-5%.

resources might not take every investment opportunity, but will use higher discount rates to screen projects instead (McDonald (1999) and Jagannathan and Meier (2002)).

Another feature of the data that stands out is that hurdle rates appear to be relatively sticky from year to year. *Ex ante* one would expect more variation in hurdle rates as firms adjust to the changing environment. The estimated aggregated hurdle premium increased briefly around 2004, perhaps reflecting an increase in uncertainty around that time.[22] But following the Great Recession, the aggregate hurdle rate did not respond immediately and only slowly drifted upwards. This is at odds with other measures that show uncertainty increasing more sharply from 2008 (see, for example, Bloom (2014) and Baker et al. (2015)). It is possible that between 2008 and 2015, the cost of capital decreased while uncertainty pushed up on the hurdle premia. Also, our measure might not capture the extent of annual variation in hurdle rates although some of the variables we use, such as the dispersion of industry returns, should be strongly correlated with uncertainty. It is also possible that hurdle rates actually do respond with some inertia to the wider macroeconomic environment. This is supported by results from the FID survey, which also asked firms about when they had reviewed hurdle rates and how much they had revised them by (Table 1). About 20% of businesses had not reviewed their investment targets within the past five years.[23] The infrequency of revisions suggests that hurdle rates are quite sticky. This, in turn, suggests that macroeconomic factors only account for part of the variation in hurdle rate premia.

3.2.2. Stock-price volatility based measure of firm-level uncertainty

We restrict the firms in our sample to be listed firms and exploit measured stock price volatility to provide information on uncertainty, as suggested by Gilchrist et al. (2014). The basic idea of the stock-price volatility based measure of firm-level uncertainty (SVU) is to calculate daily volatility in individual stock prices that cannot be explained by general market variation (within a capital asset pricing model (CAPM) type relationship; see Appendix 1 for details). The remaining volatility should reflect investors' uncertainty about the prospects specific to the firm. The measure has desirable qualities: it's firm-specific, forward-looking (stock prices should include information about future prospects of a firm) and excludes a forecastable component.[24]

[22] Haddow et al. (2013) suggest that uncertainty in the early 2000s might have risen. They note that peaks in their uncertainty indicator coincided with September 11 attacks and the beginning of the Iraq war.

[23] For more details, see Saleheen et al. (2017).

[24] The advantages of this measure in its ability to gauge pure uncertainty as opposed to volatility are also highlighted by Jurado et al. (2015).

We construct the SVU measure for the 626 firms for which we have estimated hurdle rates. The resulting quarterly time series (aggregated over firms) is presented in Chart 4, also separately for large firms (over 250 employees) and SMEs. The aggregate measure is fairly volatile and the SME measure is even more volatile (although these make up a small part of our sample). Furthermore, it is interesting to note that the correlation between hurdle premia and the SVU is positive in every year except one between 2000 and 2015 (Chart 5).

Chart 4: Stock-price volatility based measure of uncertainty (SVU)

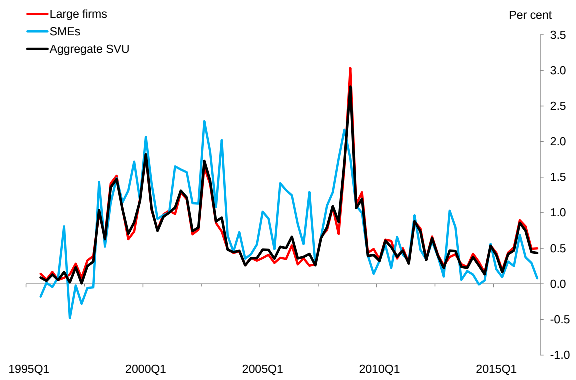
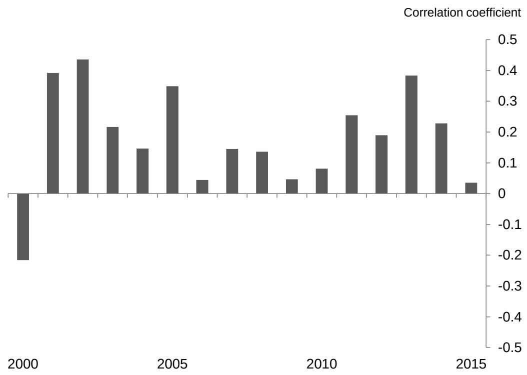


Chart 5: Correlation coefficient between SVU and hurdle premia by year



3.2.3. Aggregate uncertainty measure

We compare firm-level measures of uncertainty to an aggregate measure. For this, we calculate a hybrid factor model (HFM) indicator that combines different measures into one in a state space framework, with the aim of purging idiosyncratic volatility (which can include heterogeneous firm-level uncertainty and noise) and preserving the underlying common component of uncertainty in the different uncertainty measures (see Appendix 1 for technical details). We use three observable variables: the hurdle rate, the SVU and FTSE100 stock index 3-month implied volatility.[25] The state space framework also has the added advantage of accommodating missing values and ragged edges, which allows for hurdle rates to be included in a model that produces quarterly data, even though the hurdle rates time series is annual.[26]

[25] The implied volatility measure captures expected volatility of stock prices. It is included to capture potential "fat-tail" risks, like the financial crisis, which might have disproportionally large negative effects on firms' investment intentions.

[26] Our investment model regressions use annual data, where quarterly data is aggregated with a simple average into annual data.

The variables in the model are shown in Chart 6 and the resulting HFM series (inverted) in Chart 7. The inverse of the HFM indicator has a correlation of 0.37 with annual business investment growth, which suggests that investment and uncertainty share similar dynamics.[27]

Chart 6: Observable variables in the factor model (standardised)

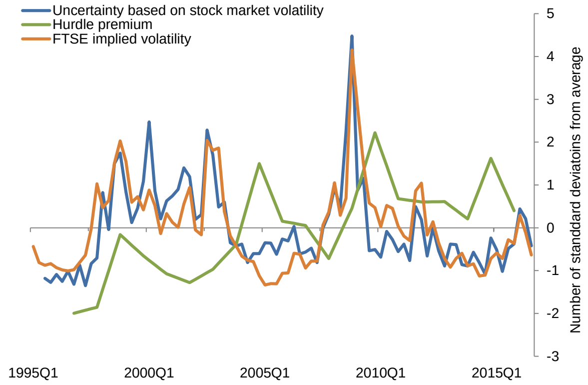
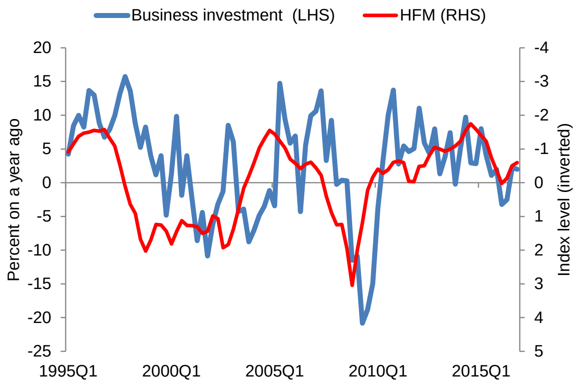


Chart 7: Aggregate uncertainty indicator based on the factor model and UK business investment



3.3. Summary statistics

We estimate equations (5) and (6) using data on 178 firms for which we have complete financial data.[28] The data runs from 2000 to 2015, with 1,447 firm-year observations for the static regressions and 1,213 observations for the dynamic regressions. Table 2 shows summary statistics of the variables used.

The data exhibit large dispersion for the key variables (investment, sales, WACC, firm-level uncertainty). There is heterogeneity across firms and within firms over time. It is also worth noting how much higher the mean hurdle rate (13.1%) is compared to the cost of capital measures (3.9% for WACC and 2% for cost of debt). Meanwhile, the standard deviation of hurdle rates and premia are considerably lower. In other words, hurdle rates are much stickier than our conventional cost of capital measures.

[27] We have also experimented with simple investment vector autoregression (VAR) models with the HFM uncertainty (results not reported here), and discovered that the inclusion of the HFM series improves the investment forecasting capabilities of the VAR model. This again supports our implicit assumption of a link between investment and HFM uncertainty at the aggregate level.

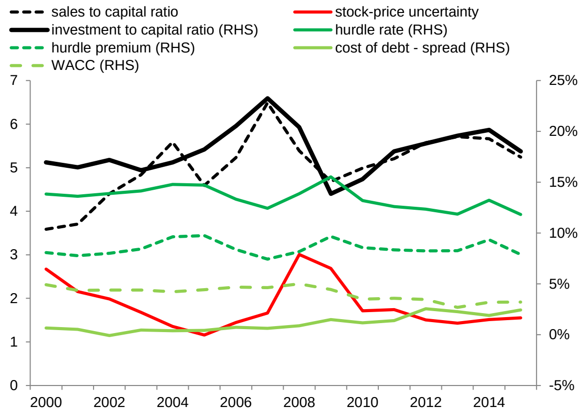
[28] From the 626 firms for which we calculate the firm-level uncertainty measures, the sample is further restricted by empty observations for some of the explanatory variables (notably the WACC, which is only available from 2000) and by the exclusion of outliers (where we broadly follow Gilchrist and Zakrajsek (2007) and exclude observations where the investment rate is 0 or above 0.99, or the sales-to-capital ratio is 0 or greater than 50).

Table 2: Summary statistics for the main variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Investment (£m)	1,447	471.8794	2043.381	0.036	24520
Investment/capital ratio	1,447	0.216977	0.137778	0.003564	0.997288
Sales/capital ratio	1,447	9.02168	9.782503	0.153379	49.40065
WACC (firm-level)	1,447	0.038954	0.019585	0.002293	0.10332
Cost of debt (firm-level)	1,447	0.020229	0.012957	0.000286	0.118401
Hurdle rate	1,447	0.130783	0.011484	0.098161	0.159078
Hurdle premium	1,447	0.083344	0.008785	0.057612	0.105733
Credit spread	1,447	0.01503	0.014459	-0.02216	0.100535
Firm-level uncertainty	1,447	2.004767	1.177195	0.721468	25.08879
Tobin's Q	1,447	1.294989	0.991291	0.082218	10.66878

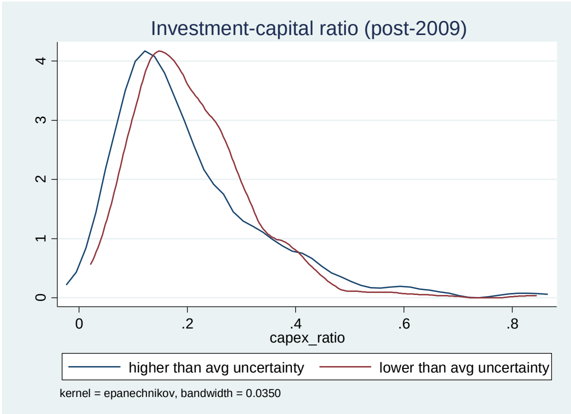
Looking at the dynamics of selected key variables reveals intuitively expected patterns (Chart 8). Investment and sales fell sharply in the wake of the financial crisis while firm-level uncertainty rose. Hurdle rates and premia exhibit similar stickiness as shown above for the larger sample. The WACC declined in the years following the financial crisis while credit spreads increased.

Chart 8: Sample medians for key variables



The chart shows sample medians for the different variables. The left-hand side axis of the chart shows the ratio of sales to capital and level of stock price uncertainty (in %).

Chart 9: Distributions of investment-capital ratio by increases in uncertainty during the crisis



The chart shows sample distributions for investment-capital ratios (since 2009) by size of increases in uncertainty during the financial crisis.

There are tentative signs of weaker investment dynamics for those firms that were more negatively affected by the financial crisis. This can be seen, for example, by comparing firm-level investment since 2009 for those firms whose stock-price uncertainty rose more in 2008 and 2009 than the pre-2008 sample average with those whose uncertainty rose by less. The subsequent distribution of investment-to-capital ratios is higher in the latter group in a statistically significant way (Chart 9). The same is also true for credit spreads; those firms whose credit spreads rose more during the crisis invested less after the crisis. Overall, the raw data appears consistent with the hypothesis that there is dispersion in conditions faced by firms in the wake of the Great Recession and that helps explain why firms differed in their subsequent investment paths.

4. Results

The following tables present the results of estimating equations (5) and (6), which relate firm-level investment (capital expenditure) to economic fundamentals, the cost of capital and investment uncertainty. Table 3 shows the results for the static version of the model (equation (5), i.e. without controls for lagged investment), which is estimated using a within groups estimator.[29] Column (1) is the simplest specification capturing basic relationships between investment, sales (i.e. economic fundamentals) and the cost of capital (measured by firm-level WACC). In columns (2) to (4), we add the three uncertainty variables. In columns (2) and (3) the coefficients on hurdle rates and premia are not statistically significant (and the point estimate does not have the expected sign). However, we expect coefficients in the static regressions to be biased by any unobserved factors that are not captured by the measure of firm fundamentals or fixed effects. In particular, interest rates could be endogenously determined with the level of investment if economic fundamentals change and they are not captured by the sales variable. Alternatively, increased investment could endogenously lead to a higher risk of default and hence higher cost of capital (see Gilchrist and Zakrajsek (2007)). An additional problem with the static specification is that it does not capture the likely persistence in investment dynamics from one year to the next.

Table 4 presents the main results from the dynamic model (equation (6)), which are estimated using a system GMM estimator and are thereby more robust to the endogeneity problems that may be present in the static specification. The model is estimated using orthogonal differences (which are more robust to gaps in the data) and with the first two lags of variables used as instruments.[30] The Arellano-Bond test for second order serial correlation in the first differenced errors fails to reject the null of no autocorrelation, suggesting that the lags of the dependent variables are exogenous. For all the models, the Hansen test fails to reject the null of the instruments being valid (i.e., they are uncorrelated with the error term).[31] And the system GMM estimates of the coefficients for the lagged

[29] Some of the explanatory variables are estimated, such as the WACC and hurdle rates/premia. In the results presented here we do not take into account the additional measurement uncertainty introduced by this. We do not expect this to substantially affect our findings.

[30] Using a single lag or deeper lags creates a weak instrument problem.

[31] The Sargan p-values are zero for all the models, but given the weakness of the test, we have ignored it.

Table 3: Firm-level panel regression results – static model

DEPENDENT VARIABLE investment to capital ratio				
INDEPENDENT VARIABLES	(1)	(2)	(3)	(4)
sales to capital ratio	0.639***	0.649***	0.642***	0.617***
	(0.0910)	(0.0921)	(0.0912)	(0.0910)
WACC (firm-level)	-0.150***		-0.146***	-0.148***
	(0.0487)		(0.0483)	(0.0497)
hurdle rate		0.448		
		(0.590)		
hurdle premium			0.322	
			(0.356)	
stock-price uncertainty				-0.186**
				(0.0725)
Observations	1,447	1,447	1,447	1,447
R-squared	0.264	0.252	0.265	0.271
Number of firms	178	178	178	178

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

Table 4: Firm-level panel regression results – dynamic model

DEPENDENT VARIABLE investment to capital ratio				
INDEPENDENT VARIABLES	(1)	(2)	(3)	(4)
inv to capital ratio (lag 1)	0.473***	0.513***	0.499***	0.485***
	(0.0657)	(0.0650)	(0.0614)	(0.0573)
sales to capital ratio	0.180***	0.141***	0.181***	0.162***
	(0.0462)	(0.0366)	(0.0376)	(0.0406)
WACC (firm-level)	-0.176***		-0.161***	-0.146***
	(0.0510)		(0.0495)	(0.0493)
hurdle rate		-1.873***		
		(0.572)		
hurdle premium			-1.001***	
			(0.324)	
stock-price uncertainty				-0.388***
				(0.0888)
Observations	1,213	1,213	1,213	1,213
Pseudo R-squared	0.521	0.511	0.525	0.517
Number of firms	159	159	159	159
No of instruments	144	144	187	187
AR1 p-value	0	0	0	0
AR2 p-value	0.529	0.382	0.491	0.453
Hansen p-value	0.129	0.178	0.868	0.821

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

All variables are assumed endogenous and are instrumented with the first and second lags of their own levels in the difference equation and the first-difference in the levels equation. The Arellano-Bond tests for first and second order autocorrelation are based on the null hypothesis of no autocorrelation. The models are estimated using forward orthogonal differences and Windmeijer's finite-sample correction for the two-step covariance matrix.

investment variable on the right-hand side of the equation are always between those obtained from a simple OLS estimation and those from a fixed effects (least-squares dummy-variables (LSDV)) estimation, which is a desirable feature of this simple cross-check (see Bond (2002)). It is also worth noting that the pseudo R^2 statistics are considerably higher in the dynamic than in the static models.[32]

The coefficients in Table 4 have the expected signs. There is a statistically significant negative relationship between investment and the WACC, hurdle rate/premia and uncertainty measures by SVU. The size of the coefficients on the WACC in all of the specifications tends to be relatively small at around -0.15 (meaning that a 1% decline in the cost of capital leads to 0.15% increase in investment) compared to estimates in the literature in general (see, for example, Gilchrist and Zakrajsek (2007)) and previous estimates for the UK (see Ellis and Price (2004) and Baumann and Price (2007)). This implies that investment, at least in our sample, reacts relatively sluggishly to changes in the cost of capital. It is possible that investment has become less responsive to interest rates in recent years, as other factors, like uncertainty, have become more important drivers of investment than they used to be (we explore this with a robustness analysis below).[33] This could also be reflected in relatively large coefficients on measures of uncertainty (which are larger than the effect of the WACC). Furthermore, investment also appears to be relatively responsive to changes in hurdle rates. On the other hand, as hurdle rates tend to be sticky (see standard deviations in Table 2), large changes in them are rare.

The coefficients in Table 4 show the impact of a 1% change in the explanatory variables on the investment ratio. But because these variables have different average levels for each firm vary to different degrees, we might not be comparing like for like. To get a better idea of the relative importance and magnitude of the cost of capital, hurdle rates and the SVU, we calculate the effects on investment based on the model coefficients presented in Table 4 and a 1-standard deviation change in the explanatory variables.

To calculate what a 1 standard increase might do, we first calculate firm-level means and standard deviations for the cost of capital, hurdle rates and hurdle premia over time. We then calculate what effect a 1 standard deviation increase in the relevant explanatory variable, multiplied by the relevant coefficient from Table 4, would have on investment for

[32] The R^2 for the dynamic models are calculated as the squared correlation between the actual and fitted left-hand side variables.

[33] It is also possible that the coefficient on the WACC could be biased downwards by measurement error. Our estimation sample is somewhat smaller than other studies. But we also use a different and more comprehensive measure for the cost of capital and this could be another reason why our estimates are different.

each firm. Finally, by combining the results for all the firms, we calculate the median impact and the dispersion around that impact across all firms.

Chart 10 shows the distribution of these impacts across firms on contemporaneous investment rates. The chart shows that a 1 standard deviation increase in the WACC has a smaller effect than a similar increase in the hurdle rate or hurdle premia. The dispersion of outcomes is much greater, too. For example, a 1 standard deviation increase in the hurdle rate lowers investment ratios by up to 0.3% while for the WACC this is up to 0.1%. The median impact of the SVU measure on investment is similar in magnitude to the hurdle rate and hurdle premia effects, but there is a longer tail where some firms' investment ratios are up to 0.4% lower.

This is an immediate impact of a change in different explanatory variables. But these effects will change investment ratios in the future as well, as firms adjust to an increase in uncertainty, for example. Since the models in Table 4 are dynamic we can show how an increase in an explanatory variable affects investment in the future. Using the coefficient on lagged investment in Model 4 and the means of the contemporaneous shocks presented in Chart 10, we can calculate how the effect of the shock, on average, declines over time. Chart 11 shows that the impact of a 1 standard deviation increase affects investment ratios fairly quickly. The effect is halved after one year and does not affect investment ratios after around 5 years. As might be expected, the WACC has a fairly small impact when compared to the effect of uncertainty.

Chart 10: Distribution of a 1 standard deviation change in explanatory variables on firm-specific investment ratios

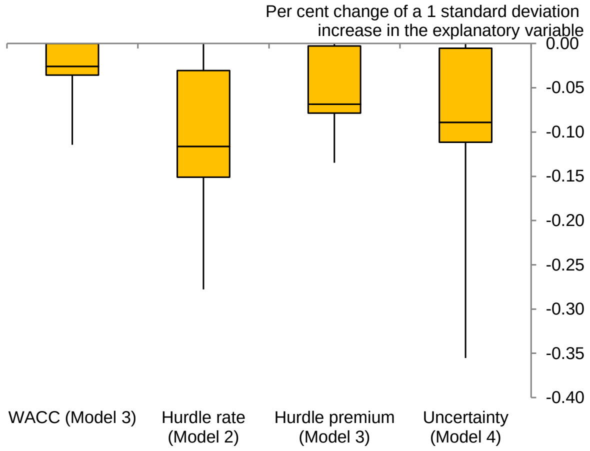


Chart 11: Dynamic impact of a 1 standard deviation increase in explanatory variables on investment ratios

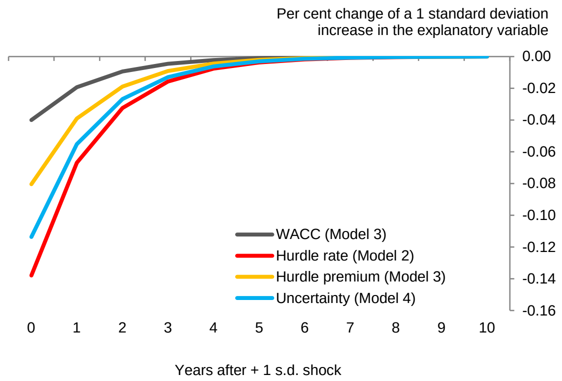


Table 5 shows robustness checks with other specifications of the dynamic model. Columns (5), (6) and (7) replace the WACC with firm-level cost of debt. The coefficients are negative but are not statistically significant. This suggests that it is important to move beyond simple measures of the cost of current debt. Our measure of credit spreads is shown in columns (8) and (9). The coefficient is statistically significantly negative, suggesting that variation in firms' debt cost relative to a risk-free rate (which provides a measure of the riskiness of a firm's project) has explanatory power for firm-level investment dynamics.

Table 5: Firm-level panel regression results – dynamic model extensions

DEPENDENT VARIABLE investment to capital ratio						
INDEPENDENT VARIABLES	(5)	(6)	(7)	(8)	(9)	(10)
inv to capital ratio (lag 1)	0.508***	0.522***	0.541***	0.488***	0.516***	0.525***
	(0.0718)	(0.0641)	(0.0651)	(0.0605)	(0.0679)	(0.0554)
sales to capital ratio	0.120***	0.0857**	0.105***	0.0927**	0.103***	0.102***
	(0.0462)	(0.0369)	(0.0363)	(0.0368)	(0.0349)	(0.0337)
hurdle rate					-1.685***	-0.985**
					(0.579)	(0.502)
hurdle premium			-0.966***			
			(0.319)			
stock-price uncertainty		-0.422***		-0.393***		-0.382***
		(0.0902)		(0.0982)		(0.0877)
cost of debt (firm-level)	-0.104	-0.0744	-0.0815			
	(0.0859)	(0.0656)	(0.0759)			
cost of debt - 10yr Gilt yield				-0.0827***	-0.0987***	
				(0.0290)	(0.0289)	
Observations	1,213	1,213	1,213	1,213	1,213	1,213
Pseudo R-squared	0.505	0.509	0.521	0.498	0.509	0.515
Number of firms	159	159	159	159	159	159
No of instruments	144	187	187	187	187	187
AR1 p-value	0	0	0	0	0	0
AR2 p-value	0.370	0.368	0.374	0.319	0.317	0.379
Hansen p-value	0.134	0.852	0.799	0.875	0.861	0.845

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

All variables are assumed endogenous and are instrumented with the first and second lags of their own levels in the difference equation and the first-difference in the levels equation. The Arellano-Bond tests for first and second order autocorrelation are based on the null hypothesis of no autocorrelation. The models are estimated using forward orthogonal differences and Windmeijer's finite-sample correction for the two-step covariance matrix.

Firm-level uncertainty, as measured by the SVU, is very significant in all specifications (and is much larger in the dynamic than the static specification). Gilchrist et al. (2014) find for the US that uncertainty decreases in significance when credit spreads are introduced into the same equation as changes in uncertainty are transmitted mainly through changes in credit spreads. However, we find that for our sample of UK firms, the uncertainty variable does not decrease in significance when credit spreads are introduced into the same equation (column (8)). The SVU measure is also significant when it is introduced in the same regression with the hurdle rate (column (10)), possibly because it is picking up different aspects of uncertainty than hurdle rates. Hence, there appears to be an important role for uncertainty as a driver of firm-level investment decisions in the UK, irrespective of the cost of capital measure used.

Table 6 reports the results for a subset of the dynamic models to examine whether the HFM measure of aggregate uncertainty is also significant for firm-level investment decisions. The results suggest aggregate uncertainty is a statistically significant driver of investment. Hence, the models appear to be relatively robust to our preferred measures of both aggregate and firm-level uncertainty.[34] We also experimented with another popular measure of aggregate uncertainty used in the literature, namely the Economic Policy Uncertainty (EPU) index introduced by Baker et al. (2015).[35] Using separately a UK EPU (to account for uncertainty in the UK) and US Equity Market EPU (to account for general financial market uncertainty), we do not find either of these measures to be significant drivers of investment in our dynamic panel regressions. Overall, it appears that firms pay attention to both idiosyncratic as well as aggregate uncertainty when making investment decisions, although the latter does not seem to be related to general uncertainty about economic policy.

[34] One caveat on the interpretation of the models with aggregate uncertainty is that because the time fixed effects need to be excluded from the regression, the aggregate uncertainty variable may be capturing other common time-varying effects on investment, to the extent that these effects are not captured by other variables in the model.

[35] The EPU Index attempts to measure economic uncertainty in terms of, for example, newspaper references and dispersion of macroeconomic forecasts of key variables. For more details, see Baker et al. (2015). The data is available at http://www.policyuncertainty.com/index.html.

Table 6: Firm-level panel regression results – dynamic model, aggregate uncertainty

DEPENDENT VARIABLE investment to capital ratio			
INDEPENDENT VARIABLES	(1)	(2)	(3)
inv to capital ratio (lag 1)	0.505***	0.543***	0.522***
	(0.0645)	(0.0702)	(0.0672)
sales to capital ratio	0.194***	0.132***	0.133***
	(0.0412)	(0.0416)	(0.0375)
WACC (firm-level)	-0.147***		
	(0.0438)		
aggregate uncertainty	-0.0381**	-0.0692**	-0.111***
	(0.0194)	(0.0278)	(0.0237)
cost of debt (firm-level)		-0.0489	
		(0.0732)	
cost of debt - 10yr Gilt yield			-0.0961***
			(0.0215)
Observations	1,213	1,213	1,213
Pseudo R-squared	0.476	0.472	0.462
Number of firms	159	159	159
No of instr	158	158	158
AR1 p-value	0	0	0
AR2 p-value	0.145	0.107	0.0879
Hansen p-value	0.502	0.531	0.567

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

All variables are assumed endogenous and are instrumented with the first and second lags of their own levels in the difference equation and the first-difference in the levels equation. The Arellano-Bond tests for first and second order autocorrelation are based on the null hypothesis of no autocorrelation. The models are estimated using forward orthogonal differences and Windmeijer's finite-sample correction for the two-step covariance matrix.

We also explored the robustness of our results to different controls for fundamentals in the model. A model that includes a measure on the market value of assets in relation to their book value – Tobin's Q – appears to be particularly relevant for our approach involving financial account data.[36] The idea of this approach is to take into account the financial position of the firm using Tobin's Q as an indicator of expected future profitability of the firm. The higher the Tobin's Q, the better the prospects and the higher current investment should be (see, for example, Abel and Blanchard (1986), Chirinko (1993) and Bond et al. (2004)). In Table 7, we replicate the relevant dynamic specifications using a Tobin's Q measure instead of the sales variable. These are best viewed as robustness checks for the significance of the uncertainty variables presented above. In general, the benchmark results on uncertainty hold if we use the Tobin's Q variable; credit spreads and uncertainty measured by SVU and hurdle rate/premia are still significant drivers of investment.

[36] It is worth noting that this robustness check cannot be used to say anything about the robustness of the WACC, given that the WACC and Tobin's Q are partly driven by the same underlying factors, and are negatively correlated.

Table 7: Firm-level panel regression results – dynamic model with Tobin's Q

DEPENDENT VARIABLE investment to capital ratio					
INDEPENDENT VARIABLES	(1)	(2)	(3)	(4)	(5)
inv to capital ratio (lag 1)	0.457***	0.495***	0.508***	0.498***	0.415***
	(0.0611)	(0.0591)	(0.0566)	(0.0574)	(0.0633)
Tobin's Q	0.350***	0.305***	0.297***	0.200***	0.228***
	(0.0760)	(0.0741)	(0.0762)	(0.0728)	(0.0765)
WACC (firm-level)	-0.0568		-0.0502	-0.0380	
	(0.0380)		(0.0384)	(0.0342)	
hurdle rate		-1.287**			
		(0.562)			
hurdle premium			-0.642*		
			(0.379)		
stock-price uncertainty				-0.307***	-0.289***
				(0.0975)	(0.0948)
cost of debt - 10yr Gilt yield					-0.0968***
					(0.0321)
Observations	1,213	1,213	1,213	1,213	1,213
Pseudo R-squared	0.468	0.481	0.490	0.487	0.453
Number of firms	159	159	159	159	159
No of instr	144	144	187	187	187
AR1 p-value	0	0	0	0	0
AR2 p-value	0.443	0.413	0.480	0.433	0.258
Hansen p-value	0.121	0.135	0.862	0.864	0.879

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

All variables are assumed endogenous and are instrumented with the first and second lags of their own levels in the difference equation and the first-difference in the levels equation. The Arellano-Bond tests for first and second order autocorrelation are based on the null hypothesis of no autocorrelation. The models are estimated using forward orthogonal differences and Windmeijer's finite-sample correction for the two-step covariance matrix.

It is possible that the effects of financial costs and uncertainty are not constant over time. We allow the effects to vary before and after the financial crisis by including a post-crisis dummy variable and interacting it with the relevant measures of the cost of capital and uncertainty. The main results of this analysis are reported in Table 8. Column (1) suggests that the effect of the WACC is statistically significantly negative throughout the period, but the effect is substantially larger before the financial crisis than after it. That is, it appears that investment has been much less responsive to changes in the WACC since the financial crisis. Column (3) suggests that the opposite is true for the stock price uncertainty variable. It is statistically significantly negative only since the crisis. The lack of significance for the hurdle rate variable in column (2) is probably due to the fact that it is a mixture of uncertainty and interest rate effects.

Table 8: Firm-level panel regression results – dynamic model with post-crisis dummy

DEPENDENT VARIABLE investment to capital ratio			
INDEPENDENT VARIABLES	(1)	(2)	(3)
inv to capital ratio (lag 1)	0.463***	0.514***	0.487***
	(0.0691)	(0.0642)	(0.0585)
sales to capital ratio	0.183***	0.138***	0.160***
	(0.0450)	(0.0362)	(0.0395)
WACC (firm-level)	-0.336***		-0.317***
	(0.101)		(0.111)
WACC*post-crisis dummy	0.170*		0.167*
	(0.0969)		(0.0972)
hurdle rate		-0.914	
		(0.722)	
hurdle rate*post-crisis dummy		-1.327	
		(0.995)	
stock-price uncertainty			-0.0661
			(0.111)
stock-price uncertainty*post-crisis dummy			-0.381***
			(0.136)
Observations	1213	1213	1213
Pseudo R-squared	0.517	0.513	0.518
Number of firms	159	159	159
No of instr	145	145	189
AR1 p-value	0	0	0
AR2 p-value	0.473	0.390	0.470
Hansen p-value	0.121	0.156	0.892

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

All variables are assumed endogenous and are instrumented with the first and second lags of their own levels in the difference equation and the first-difference in the levels equation. The Arellano-Bond tests for first and second order autocorrelation are based on the null hypothesis of no autocorrelation. The models are estimated using forward orthogonal differences and Windmeijer's finite-sample correction for the two-step covariance matrix.

Overall, we conclude the following from the firm-level regression results. First, investment, as measured with financial account data, is relatively persistent from one year to another, and is affected by economic fundamentals as well as our measure of the firm-level WACC. Second, firm-level uncertainty is a significant driver of investment, with hurdle rates and hurdle premia having a similar sized impact to the SVU uncertainty measure. This result is robust to the different specifications of the model. Third, higher riskiness and risk aversion, as measured by credit spreads, have a negative effect on investment. Finally, the WACC has a small effect on firms' investment rates. But the WACC had much more of an effect on investment before the financial crisis than after it, while the opposite is true for firm-level uncertainty.

5. Conclusions

This paper presents firm-level analysis of factors that have driven business investment in the UK in the recent past, using a new dataset on different cost of capital and uncertainty measures. In general, we find that macroeconomic fundamentals, cost of capital and uncertainty have all been important drivers of investment.

Our estimates of the elasticity of investment with respect to changes in the cost of capital are relatively low compared to previous literature, and for some cost measures they are not statistically significant. In contrast, our main measure of firm-level uncertainty (based on stock price volatility) is strongly significant, suggesting that firm-level uncertainty shocks have been important drivers of investment dynamics in the UK. On the other hand, the cost of capital, while significant, seems to have a smaller impact on firms' investment. However, our analysis shows that our preferred cost of capital measure had much more of an effect on investment before the financial crisis than after it, while the opposite is true for firm-level uncertainty. These results could have significant policy implications, especially in the current uncertain post-EU referendum environment. Although our dataset is too small for wide-ranging aggregate-level conclusions to be drawn, it does appear possible that macroeconomic policies helping to alleviate investment uncertainty could have more traction than previously appreciated. At the same time, firms' investment decisions may be reacting more sluggishly to traditional monetary policy measures than theory and historical estimates suggest.

Our analysis necessarily comes with caveats and suggestions for further research. The data required for the analysis, especially one that is based on firm-level measures of the cost of capital and uncertainty, means that the sample we use is relatively small. However, we show that there is substantial variation at the firm level that is important for understanding investment patterns. Enhancing data availability and expanding firm-level surveys on investment is clearly a key area of further practical development. Investigating the plausibility of alternative models of business investment that can explicitly incorporate the non-convex adjustment costs that will matter for short-run dynamics, while being tractable enough to estimate with firm-level data, is another important avenue of further work.

Appendix 1

This appendix sets out details of the uncertainty variables used in the analysis.

A1.1 Estimation details and variables used in hurdle rate models

Our choice of variables in the hurdle rate models follows the same strategy as Jagannathan et al. (2011) and Jagannathan et al. (2016). The basic idea is to link certain financial account variables to a firm's hurdle rate, with *a priori* theoretical signs for the coefficients depending on how uncertainty is expected to affect the variables. Then, to construct hurdle rate time series, these coefficients are linked to a time series of the relevant variables of a sample of firms for which the financial account data is available.

More specifically, the estimation of hurdle rates time series proceeds in two stages:

1) First, we link cross-sectional hurdle rate data to financial account data of the firms surveyed in the FID survey. For this, based on the survey responses, we are able to use hurdle rate data from 459 firms and match them to (in most cases) firm-specific financial account data, using the Capital IQ database. In addition, we use the firm-level WACC estimates as defined in the main text. This allows us to compute hurdle premia (hurdle rate minus WACC) for the sample of firms, and then regress these hurdle premia on the relevant financial account explanatory variables in the spirit of Jagannathan et al. (2011).

2) In the second step, we generate a time series proxy for the hurdle rate. To do this, we select 626 firms from the Capital IQ database[37], filtering out firms for which the relevant financial account variables from step 1) are not available over a sufficiently long time horizon. Then, applying the coefficients from the hurdle rate regression in step 1) to the financial account data of the 626 firms for annual data between 1996 and 2015, we have a sample of 2,970 observations, from which we can calculate aggregate-level *imputed* hurdle rate/premia proxies over time.

We experimented with various different specifications of the cross-sectional hurdle rate regressions in step 1. The results are shown in Table A1 (for definitions and intuition for the choice of variables, see below). In general, the explanatory variables have the expected

[37] The vast majority of the 300,000 firms in the Capital IQ database are not included in our analysis because the financial account data required for the analysis is not available/applicable.

signs and they are statistically significant. The only exception is the industry returns variable (Industry_r), for which the sign is ambiguous. This leads us to discard models (1) to (3). We then include different combinations of the remaining four variables in models (4) to (7), whilst always keeping at least two firm-specific variables (i.e., two of the first three variables) in the model. Sales growth, the Z-score and the Industry R^2 appear to be the most robust variables, so ideally we would like to keep all of these in our preferred model. However, as it turns out, the Z-score availability severely restricts the size of the sample in stage 2) and hence, we end up using model (5) as the preferred one.

The results for the models in Table A1 nevertheless suggest that the hurdle rate estimates are relatively robust to the choice of variables, as long as we keep two of the most significant variables in the model specification. Hence, the three models produce relatively similar estimates of the aggregate hurdle rate over time. The endpoint of the hurdle rate estimate for 2015 is also very close to the average of the hurdle rate from the survey responses. This implies that the benchmark results presented in the main text are qualitatively similar for hurdle rate models (4) to (6).

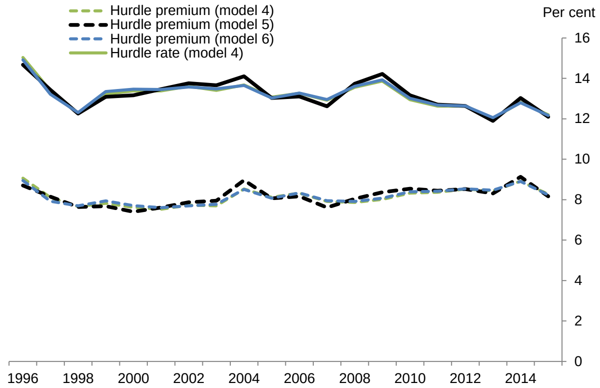
Table A1: Cross-sectional hurdle rate models

LHS VARIABLE							
hurdle premium							
RHS VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
salesgr	0.00634**	0.00829***	0.00648**	0.00708***	0.0115***	0.00699***	
	(0.00275)	(0.00261)	(0.00275)	(0.00269)	(0.00172)	(0.00226)	
cashratio	0.0136	0.0101			0.0168	0.0114	0.0147
	(0.0174)	(0.0171)			(0.0171)	(0.0177)	(0.0179)
azscore	0.0140**	0.0162***	0.0144**	0.0142**		0.0138***	0.0260***
	(0.00584)	(0.00609)	(0.00583)	(0.00586)		(0.00525)	(0.00348)
Industry_r	-0.00801	0.00279	-0.00755				
	(0.00547)	(0.00401)	(0.00541)				
Industry_rsq	0.0530**		0.0515**	0.0296*	0.0428***	0.0298**	0.0447***
	(0.0224)		(0.0223)	(0.0160)	(0.0164)	(0.0149)	(0.0142)
Observations	459	459	459	459	459	459	459
Adjusted R-squared	0.771	0.769	0.771	0.771	0.768	0.771	0.766

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

The resulting hurdle rates from the preferred models are presented in Chart A1. It shows a time series for hurdle rates based on the coefficients estimated in our three main models ((4) to (6)) and firm-level data at each point in time.

Chart A1: Imputed hurdle rates and hurdle premia over time



The chart shows time series estimates of imputed hurdle rate and premia, based on the panel regression from step 2 for models 4, 5 and 6 (see main text for definitions).

The variables used in the hurdle rate models, with the rationale for the signs, are detailed below.

Altman's Z-score

The Z-score is a measure of a firm's financial riskiness, developed originally by Altman (1968) and used extensively by financial market participants. There are different versions of the formula, but we stick with the original formulation as reported by the Capital IQ database. The Z-score is defined as follows:

$$Z = 1.2 * \left[\frac{Working\ capital}{Total\ assets}\right] + 1.4 * \left[\frac{Retained\ earnings}{Total\ assets}\right] + 3.3 * \left[\frac{Earnings\ before\ interest, taxes}{Total\ assets}\right] + 0.6 * \left[\frac{Market\ value\ of\ equity}{Book\ value\ of\ liabilites}\right] + 1.0 * \left[\frac{Sales}{Total\ assets}\right]$$

Based on empirical work on the likelihood of bankruptcy in the original paper, the Z-score is further divided into three categories for an indicator variable (Zi) used in our analysis:

Zi=1 if Z<1.81 (high risk of bankruptcy)

Zi=2 if 1.81≤Z<2.99 (moderate risk of bankruptcy)

Zi=3 if Z≥2.99 (low risk of bankruptcy)

The correlation between the Z-score and hurdle rates is expected to be positive. This is because low-risk firms typically have better growth prospects, which means that the option value (and hence hurdle premium) of waiting for new investment projects is higher.

Cash/assets ratio

This is calculated as a firm's cash position divided by its total assets. This is expected to have a positive sign in the hurdle rate model, as a larger cash position is assumed to give the firm more investment opportunities in future, and hence the option to wait has a higher value.

Sales growth/employee

This is calculated as a firm's year-on-year change in revenue divided by the number of employees (for the purposes of our analysis, this is further divided into 10 categories of indicator variables depending on distance from firm-wide average in the sample). High-growth firms are likely to have more investment opportunities in future, and hence the value of the option to wait and the hurdle rate is higher.

Industry R

This is a sectoral measure of industry returns, based on monthly stock market data. If a firm belongs in a high-return sector, the growth prospects are generally higher and the value of the option to wait and hurdle rate is expected to be higher as well.

Industry R-square

This is a sectoral measure of the correlation between sector and market stock price returns (in a capital asset pricing model (CAPM) relationship) calculated from daily returns of the stock prices of the firms included in the sample. The correlation between the R-square and hurdle rates is ambiguous. On the one hand, the higher the correlation, the higher the beta in the CAPM and the uncertainty related to future returns of the sector, and hence, firms in the sector should require higher hurdle rates to compensate for the wider range of expected future return outcomes. On the other hand, for a given beta, the lower the R-square is, the higher the dispersion of returns in the sector is, and hence, the higher the value of option to wait.

A1.2 Stock price volatility based uncertainty measure

The SVU measure is based on a three-step procedure of firm-level stock price data, based on Gilchrist et al. (2014). First, we estimate the following CAPM type relationship on daily returns of individual stock prices:

$$\left(R_{itd} - r_{td}^{f}\right) = a_i + b_i R_{mtd} + u_{itd} \tag{A1}$$

where R_{itd} is the daily return on stock i in day d of quarter t, r_{td}^{f} is the risk-free rate (3-month Libor), R_{mtd} is the daily market (FTSE250) return and u_{itd} is the error term, reflecting idiosyncratic returns. The model is estimated with a sample from January 1995 to December 2015 with 622 firms.

In the second step, the quarterly firm-specific standard deviation of daily idiosyncratic returns is calculated according to:

$$\sigma_{it} = \sqrt{\left\{\left[\frac{1}{D_t}\right]\sum_{d=1}^{D_t}(\hat{u}_{itd} - \bar{u}_{it})^2\right\}} \tag{A2}$$

where $\hat{u}_{itd}$ denotes the residual from equation (A1), $\bar{u}_{it}$ is the sample mean of daily idiosyncratic returns in quarter t, and D_t is the number of trading days in quarter t. Thus, σ_{it} is an estimate of time-varying equity price volatility for firm i, purged from forecastable variation in the expected market return. This is defined as our firm-level uncertainty measure.

Finally, to transform this firm-level measure to aggregate level, we assume that the firm-level measure follows an autoregressive process of the form:

$$\log \sigma_{it} = y_i + p \log \sigma_{it-1} + v_t + e_{it} \tag{A3}$$

where y_i denotes firm fixed effects that controls for cross-sectional heterogeneity inσ_{it}, and v_t (time fixed effects) is our proxy measure of aggregate level uncertainty[38].

[38] The estimate for the coefficient p from the regression is 0.41, suggesting that uncertainty tends to be persistent at firm level (and in line with the results of Gilchrist et al. (2014) for the US), while the R^2 of the regression is 0.39.

A1.3 A hybrid uncertainty measure based on a simple factor model

The hybrid factor model of aggregate uncertainty combines different measures into one in a state space framework, with the aim of purging idiosyncratic volatility and preserving the underlying uncertainty in the different uncertainty measures. The state space framework is a flexible tool, also with the advantage of accommodating missing values and ragged edges in the data.

The state space form gathers the structure of the model into a form consisting of a measurement equation and a state equation:

$$\begin{aligned} Y_t &= C'X_t + V_t & \qquad V_t &\sim N(0, R) \\ X_t &= AX_{t-1} + W_t & \qquad W_t &\sim N(0, Q) \end{aligned}$$

where the first, measurement equation contains the observable variables in Y_t, the factor in X_t and C and V_t are parameters to be estimated. The second, state equation contains the dynamics of the factor, where A and W_t are parameters to be estimated.

The current set-up for uncertainty is fairly simple, with 3 observable variables (i.e., Y_t is a (3x1) vector), with a (1x3) coefficient vector C_t, (3x1) error term vectors V_t and W_t, variance-covariance matrices R and Q, and scalar transition coefficient A. The three observable variables are the aggregate hurdle rate, aggregate SVU and FTSE100 3-month implied volatility (see main text). The estimation of the model is carried out with the Kalman filter, using the Matlab Iris Toolbox[39]. A Bayesian Metropolis-Hastings algorithm is used to optimise the likelihood function of the model. Flat priors were used for the parameter estimates.

[39] J. Benes, M. K. Johnston, and S. Plotnikov, IRIS Toolbox Release 20150318 (Macroeconomic modelling toolbox). The software is available at http://www.iris-toolbox.com

Appendix 2

Finance and Investment Decisions Survey

The Finance and Investment Decision (FID) survey was a follow up on the Bank of England's Discussion Paper on finance for productive investment (see Bank of England (2016)). The Discussion Paper concluded that overall there was no compelling evidence of investment deficiency in the UK, and that in aggregate the availability of finance did not appear to be a constraint on investment although there did appear to be variability across businesses. The FID survey explored the relationship between finance and investment in more detail and at the level of the firm (Saleheen et al. (2017)).

The FID survey was carried out from the population of Bank's Agency contacts over the period 1-18 November. The survey was sent to around 4,600 firms in the private sector (excluding agriculture, mining and utilities), and 1,220 firms (or 26%) responded. This response rate is higher than similar past surveys. For a large number of respondents, the survey was filled out by CEOs and CFOs, so we believe we have good quality responses.

Overall, the survey was broadly representative of all industries, firm sizes and UK regions (Tables A-B). There are some small differences between our sample and the population of UK businesses, for instance, our sample underrepresents the service sector and small firms. In addition, our survey does not really capture young firms although these firms are generally difficult to survey. But these differences are small, and we are able to correct for these imbalances by weighting the results by a sector and firm size weights. All results reported should be thought of as being representative of the UK population of businesses.

Table A	Survey composition by industry, firm size[(a)] (by employment) and sector GVA[(b)]							
	Small		Medium		Large		Total (GVA share)	
	Sample (per cent)	Population (per cent)	Sample (per cent)	Population (per cent)	Sample (per cent)	Population (per cent)	Sample (per cent)	Population (per cent)
Manufacturing	3.5	3.9	12.9	3.3	9.8	6.1	26.2	13.3
Construction	2.2	4.8	3.4	1.1	3.2	1.9	8.8	7.8
Finance	2.3	1.2	3.0	0.9	2.7	7.7	8.0	9.8
Market services	5.9	10.7	10.7	3.1	14.9	14.8	31.6	28.6
Business services	9.0	14.9	8.9	6.4	7.6	19.2	25.5	40.5
All sectors	23.0	35.5	38.8	14.8	38.3	49.7	100.0	100.0

(a) Small businesses are defined as firms that have fewer than 50 employees. Medium-size businesses are those that have between 50–249 employees. Large businesses are those that have more than 249 employees.
(b) GVA is gross value added. It measures the contribution to the economy of each individual producer, industry or sector in the United Kingdom.

Sources: Bank of England Finance and Investment Decisions Survey, BEIS Business Population Estimates and ONS National Accounts.

Table B	Survey composition by region and age	
Region		
	Sample (per cent)	Population (per cent)
England	79.3	86.2
Wales	6.9	4.1
Scotland	6.1	7.1
Northern Ireland	7.7	2.5
Total	100.0	100.0
Age		
	Sample (per cent)	Population (per cent)
Less than two years	0.8	16.8
Two to ten years	6.0	38.9
Ten or more years	93.2	44.3
Total	100.0	100.0

Sources: Bank of England Finance and Investment Decisions Survey, BEIS Business Population Estimates and ONS National Accounts.

The survey asked firms about hurdle rates in a couple of questions. We use the question that directly asked firms about what their hurdle rate is. More specifically, this was question 12 in the survey (see below).

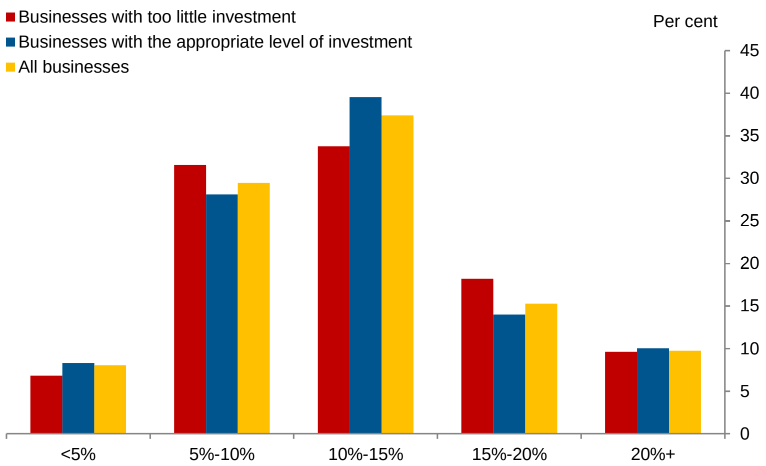
12) If you set an investment hurdle rate (or target rate for the *total* rate of return required on investment expenditure), what is it?

The total rate of return on investment includes all costs of funds and depreciation. An approximate answer is fine.

Less than 5%	5 to<10%	10 to <15%	15 to <20%	20% or more
☐	☐	☐	☐	☐

The weighted average hurdle rate across UK businesses was 12%. The distribution of hurdle rates in the survey is shown below.

Chart A2: Hurdle rates



Source: Bank of England Finance and Investment Decisions Survey.

(a) Question 7: 'Do you feel your business has made the appropriate level of investment over the past five years?' and Question 12: 'If you set an investment hurdle rate, what is it?'

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