Institute for Fiscal Studies

Firm-level investment spikes and aggregate investment over the Great Recession

IFS Working Paper W18/03

Richard Disney
Helen Miller
Thomas Pope

E·S·R·C
ECONOMIC
& SOCIAL
RESEARCH
COUNCIL

Firm-level investment spikes and aggregate investment over the Great Recession

Richard Disney[*], Helen Miller[†], Thomas Pope[‡]

January 31, 2018

Abstract

Firm-level investment paths are commonly characterised by periods of low or zero investment punctuated by large investment 'spikes'. We document that such spikes are important for understanding firm and aggregate level investment in the UK. We show that annual variation in aggregate investment is driven by variation in the number of firms undertaking investment spikes rather than in the size of spikes or in investment outside of spikes. Our main contribution is to set out and estimate a firm-level model of the timing of investment spikes that: (i) incorporates measures of macroeconomic conditions and can be used to replicate movements in aggregate investment; (ii) incorporates a role for firm capital structure, which we demonstrate explains part of firms' heterogeneous investment responses to the Great Recession. We find an important role for low demand growth in depressing investment in the recession and for ongoing uncertainty in prolonging investment weakness in later years. The minority of firms that persistently operate with high debt levels were significantly less likely to undertake an investment spike after the recession, which is consistent with them having been more exposed to financial distress.

Keywords: Business investment; adjustment cost; recession; hazard functions; capital structure
JEL classification: C41 D22 E22 E32 G31 G32 L25

Acknowledgements: We thank The Leverhulme Trust for financial support (RPG-2015-428) and the Economic and Social Research Council (ESRC) for financial support under the Centre for the Microeconomic Analysis of Public Policy (CPP) at the Institute for Fiscal Studies (ES/H021221/1). The authors thank Rachel Griffith, Orazio Attanasio and Peter Egger, as well as participants at seminars/conferences in Dublin, Zurich, Nevada, Munich and Manchester for useful comments.

[*]Institute for Fiscal Studies, University College London and University of Sussex
[†]Corresponding author. Institute for Fiscal Studies, 7 Ridgmount Street, London, WC1E7AE. E-mail: helen_m@ifs.org.uk; Telephone: +44 207 291 4800.
[‡]Institute for Fiscal Studies

1 Introduction

It is well documented that firm-level investment profiles can be characterised by periods of low or zero investment, punctuated by large discrete changes, commonly referred to as 'spikes' or 'lumps' (Doms and Dunne (1998), Cooper and Haltiwanger (1993), Cooper et al. (1999), Nilsen and Schiantarelli (2003)). This pattern of intermittent investment has been linked both theoretically and empirically to the presence of non-convex capital adjustment costs (such as fixed costs) and indivisibility of investment projects (Caballero (1999), Cooper and Haltiwanger (2006)) Accounting for these features of firm-level capital adjustment is important for explaining fluctuations in firm-level investment.[1]

In this paper, we show that accounting for intermitancy in firm-level investment is also important for explaining short-term fluctuations in *aggregate* investment. Building from this observation, we set out and estimate a firm-level model of the timing of investment spikes. Using simulations of the firm-level model, we show that the predicted proportion of firms undertaking investment spikes each year matches the observed aggregate. We argue that a micro-founded model of investment that explicitly incorporates the role of non-convex firm-level adjustment costs and of common aggregate shocks is important for the study of aggregate investment dynamics. We also show how such a model can be used to study firm-level heterogeneity in investment responses to the Great Recession. We apply this to the UK, which saw a large fall in aggregate investment after the 2008 financial crisis but with significant heterogeneity across firms. Our empirical results show that firm's capital structure before the recession helps to explain part of that heterogeneity.

Specifically, we use a large panel of UK company accounts for the period 1995 to 2011 to show that discrete firm-level changes in capital stocks (henceforth 'spikes') are important for explaining variation in investment at both the firm and aggregate UK levels. Spikes are relatively rare, but most firms undertake them at some point and, when they do, they are very important for determining the size of the capital stock over long periods. This finding represents new evidence for service sector industries (previous studies have focused almost exclusively on manufacturing firms) and the UK. We provide empirical evidence that spikes are central to understanding variation in aggregate investment; the majority of annual variation in aggregate UK investment, including over the Great Recession, is explained by variation in the proportion of firms undertaking spikes. The magnitude of spikes themselves and the amount of investment happening

[1] Models that assume convex adjustment costs perform fairly well in explaining firm-level investment over longer time periods, especially with respect to the user cost of capital, but they perform poorly in explaining large investment fluctuations commonly observed in the short-run (Baumann and Price (2007)).

outside of spikes play only a minor role. This need not have been true; we could have found that the size of firm-level investment spikes or of investment outside of spikes were more important for aggregate variation. There is an ongoing debate in macroeconomics over whether microeconomic investment lumpiness has implications for how aggregate shocks affect aggregate investment (as argued by Caballero and Engel (1999) and Bachmann et al. (2013)), or whether adjustment in output and factor prices partially or wholly offset the effect of discreteness at the firm-level (as argued by Thomas (2002), and Khan and Thomas (2008)).[2] While different DSGE models can produce different predictions, there is some empirical evidence that changes in the frequency of firm-level spikes matter for variations in aggregate investment; Cooper et al. (1999) and Gourio and Kashyap (2007) show this for the USA and the USA and Chile respectively. Our results contribute to this empirical evidence. We conclude that understanding short run fluctuations in investment (at the firm and aggregate levels) requires an understanding of what drives the timing of firm-level investment spikes.

Our main contribution is to estimate a firm-level investment hazard, which describes the probability that a firm undertakes an investment spike in a given year conditional on firm characteritics and duration since the previous spike.[3] Intuitively, in each period, the firm optimisation problem for the choice of capital stock can be characterised as a choice between investing today (and bearing the associated costs in return for a larger, and possibly higher quality, capital stock) and not investing (and allowing the capital stock to depreciate for an additional period) (Bond and Van Reenen (2007)). A duration model captures the idea that immediately following a spike, a firm's capital stock should be at (or close to) the desired level. As time passes, a number of factors, including the depreciation of the capital stock, any technological advances embodied in new capital equipment, and the accumulation of (persistent) productivity and demand shocks increase the probability that the benefit from investment now outweighs the non-convex capital adjustment costs (i.e. the hazard is upward sloping). In using this framework, we are building on Cooper et al. (1999), which motivates an empirical investment hazard from a flexible model of firms facing non-convex capital

[2] In the DSGE models on which this debate is built, much rests on the calibration of adjustment costs and price responses. Bachmann et al. (2013) present evidence that micro-level adjustment costs (alongside general equilibrium effects) are necessary to match the patterns seen in US data, including the procyclical sensitivity of aggregate investment to shocks.

[3] A large literature has sought to test which types and size of non-convexity or asymmetry in adjustment costs can best explain observed firm investment (e.g. Bertola and Caballero (1994) and Cooper and Haltiwanger (2006)). We take evidene of non-convexities as a starting point and develop an empirical model of firm investment in this setting.

adjustment costs and applies it to US manufacturing firms.[4] Our paper is related to Nilsen and Schiantarelli (2003) and Whited (2006), which estimate investment hazards for Norway and the USA respectively.

Our specification and use of a firm-level hazard is novel relative to the current literature in two main ways. First, we estimate an empirical hazard that includes measures of the aggregate environment. Previous papers have showed that the hazard is pro-cyclical by allowing the average spike propensity to vary with year dummies. By explicitly including measures of the aggregate environment we can show which types of common shock are affecting investment outcomes. We use simulations of firm-level investment spikes to show that the inclusion in the hazard of three simple, easily available measures of the aggregate environment - aggregate demand growth, uncertainty and the cost of capital - can do a very good job of replicating the fluctuations in aggregate investment. We are also able to quantify how important these factors are in driving aggregate investment, both in general and during the Great Recession.

Second, we incorporate an important dimension of firm heterogeneity. In empirical work to date, the level of the hazard has been allowed to vary with a limited set of fixed firm characteristics, but they have had no bearing on the response of hazards to shocks. One major difficulty is that time-varying firm characteristics are endogenous to investment decisions and therefore non-trivial to include in investment hazards. We exploit the Great Recession as a form of experiment to test whether firms that differ before the recession (in ways that are predicted to be correlated with how they respond to shocks) differ in their investment patterns after the recession. Specifically, we incorporate capital structure (measured by firms' debt holdings) into the firm-level hazard in order to explain (at least part of) the heterogeneous response of firms to the Great Recession. Balance sheet factors have received relatively little attention in empirical models of investment and - to our knowledge - have not been considered in the context of investment hazards; the effects of the cost of capital and financial constraints on investment are more commonly studied (Bond and Van Reenen (2007)).[5] Yet, the 'financial accelerator' originally set out by Bernanke (1981) describes how an endogenous worsening of credit market conditions can act to amplify real adverse economic shocks. In short, shocks that

[4]Caballero et al. (1995) and Caballero and Engel (1999) develop the concept of the gap between a firm's actual and desired capital stock. A structural investment model can be used to estimate the gap, allowing the drivers of the gap to be empirically estimated. This alternative method is less attractive in our setting since it would require accurately estimating the (possibly substantially changed) desired capital stock in the wake of the recession. Non-convexities have also been studied in the context of a Q model; see, for example, Abel and Eberly (1994) and Abel et al. (1996).

[5]Gilchrist and Zakrajšek (2012) use firm specific corporate bond spreads to assess the role of credit during the recession in the US, while Franklin et al. (2015) use information on firms' pre-recession banking relationships to identify the effects of credit on firm performance and productivity in the UK. Benito and Young (2002) find a significant effect of financial pressure, defined as the ratio of interest payments to profits, in reducing investment.

reduce asset values can render a firm less able to service a (nominal) debt. This can depress investment directly as firms divert resources away from investment towards paying down the debt and indirectly as the weakened financial position leads to an increased cost of external finance. The potential 'financial distress' costs associated with high debt levels are seen as a key factor in determining debt levels in theories of capital structure that posit a trade-off between the costs and benefits of holding debt (Bradley et al. (1984) reviews). That is, firms will weigh the benefits of holding debt (notably the tax deductions associated with interest payments) against the risk associated with having a high debt level when a negative shock arises.[6] The Great Recession led to a reduction in the net present value of assets for many firms. We test whether those firms operating with high debt-to-asset ratios before 2008 - and therefore more exposed to financial distress in the wake of a financial crisis - responded differently following the recession. We present evidence that the probability of undertaking a spike post-2008 fell substantially more for the minority of firms that operate with high debt than for other firms. The key assumption behind this approach is that firms did not foresee the particular 2008 crisis in the prior decade.

The paper is structured as follows. Section 2 describes the data, documents firm-level investment patterns and presents evidence on the role of firm-level investment spikes in driving aggregate investment. Section 3 sets out the hazard framework, our empirical specification and baseline results. Sections 4 and 5 set out our results on aggregate fluctuations and capital structure respectively. A final section concludes and comments on the implications of our results for policy.

2 Data and the description of investment spikes

We use data from the financial accounts of a large, unbalanced panel of UK firms in the years 1995 to 2011. These data cover firms from across the economy.[7] To date, much of the empirical work on investment has considered firms in the manufacturing industry, which in the UK accounts for just 10% of national output. Our interest is in considering changes in capital stocks. For each firm, we measure the year-on-year change in the tangible fixed assets stock (ΔK), which will capture the net effect of gross investment, disposals and

[6] There are other costs and benefits associated with debt contracts. For example, debt allows the firm to retain control over decisions but also incorporates an obligation that the sum be repaid on the agreed terms.

[7] We exclude the following industries, which either have frequent and dramatic swings in capital stocks or often have zero capital stock: Construction, Mining, Real Estate, head office services and activities of households as employers.

the depreciation of assets. We will refer to this as (net) investment. A year in which no new investment occurs will usually appear as a small fall in the capital stock as a result of ongoing depreciation.[8]

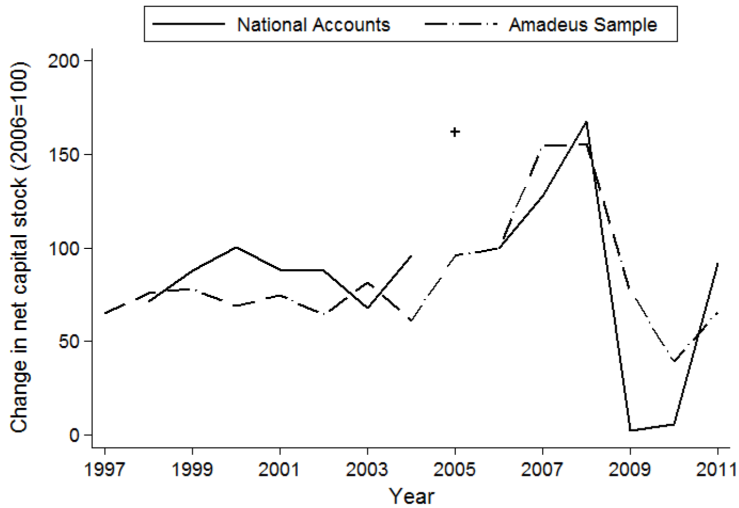
We work with a sample of 54,998 UK firms (655,168 observations) that file unconsolidated accounts, are not defined as small (based on their assets, employment or turnover) and have complete data on tangible fixed assets.[9] To prevent our analysis being skewed by extreme outliers, we remove firms that have an absolute change in tangible assets that is in the top or bottom 0.02% in any year. On average, firms in the sample have £3.13 million of fixed assets (the standard deviation is £24.48 million). Firms in our sample can, on average, be thought of as large enough to have access to bank credit but not so large as to have easy access to large equity markets. The very largest, often publicly traded, firms that file consolidated accounts are not in the sample, although their UK subsidiaries will be where there are available unconsolidated accounts. 65.2% of firms in the sample are standalone firms and not part of a larger group; of the remainder, about half are UK headquartered.

Figure 2.1 shows the aggregate capital stock in our sample compared to the national accounts aggregate. We do not expect our series to completely replicate aggregate data given that our measure is based on the book value of historic capital costs and we do not have a fully representative sample. However, our series tracks the turning points in the aggregate series, giving us confidence that our sample of firms and capital stock measure is relevant for considering the factors that drive changes in the aggregate capital stock over the economic cycle. We see that capital was growing in the period from 2004-2007, fell substantially during the recession and had started to rebound in 2011.

[8]Depreciation refers to accounting depreciation. It will capture any revaluation of assets that are recorded on the accounts but this happens infrequently. For a subset of firms we directly observe depreciation and therefore $I_{it} - D_{it}$. From this we verify that changes in net investment are driven by acquisitions and disposals rather than varying depreciation rates.

[9]The data are drawn from balance sheets and profit and loss accounts and available commercially from Bureau Van Dyke (Amadeus). Our sample covers all firms that were active at some point between 2009 and 2013, a choice driven by data availability. We exclude firms that are small, defined by Bureau van Dyke as those with fewer than 15 employees, turnover of less than €1 million and total assets of less than €2 million. These firms account for a very small proportion of capital. We use information on firms that file unconsolidated accounts, allowing us to isolate UK activity and avoid double counting. We check all results using a balanced panel of 21,508 firms which are present from 1995 onwards.

Figure 2.1: *Change in capital stock*



Notes: Change in net capital stock is calculated using comparable industries (Mining, real estate and construction removed) Source: Authors' calculations using Amadeus and Net capital stocks series from ONS capital stocks and consumption of fixed capital, 2015. There is an irregularity in the recording of ONS capital stock data in 2005.

2.1 Firm level investment spikes

In line with the results of previous papers (including Doms and Dunne (1998), Gourio and Kashyap (2007) and Nilsen and Schiantarelli (2003) for the US, US and Chile and Norway respectively), we find that large investments are important for driving growth in UK firms' capital stocks. For example, for 41% of firms, a single investment episode in the years 1995-2011 accounts for at least 50% of the sum of net increases in the capital stock over that period.[10]

For the empirical work, we require a definition of which investment episodes count as spikes. We follow previous empirical work by defining investment 'spikes' as events in which the net investment rate (i.e. ΔK_{it}) is above an absolute cut off. In our main results we use $\Delta K_{it} > 20\%$.[11] The aim is to capture those investment decisions that will have been affected by non convex costs and that will thereby lead to

[10]This calculation only includes events with positive net investment so as not to overestimate the role of large investments, and only includes firms that have at least 3 such events.

[11]A 20% cut-off is used by Cooper et al. (1999) and Nilsen and Schiantarelli (2003). While they use a measure of gross investment, our data uses net investment based on a book value capital stock measure. We find that the proportion of investment events that are spikes is similar in our sample to these papers. Furthermore, we ensure that our results are robust to alternative absolute spike definitions (15% and 30%) and a relative firm-level measure, which defines the spike threshold as the greater of 2.5 times the median investment for the firm or 10%. An alternative, used by Letterie and Pfann (2007) and Letterie et al. (2010), is to use a structural model to endogenously identify those investment events that are subject to non-convex costs.

a substantial change in productive capacity. We confirm that not only are such spikes an important driver of increases in capital stocks (more on this below), they are also (statistically significantly) correlated to increases in employment, implying an association between spikes and increased productive capacity.[12]

We establish four notable features of UK firms' investment patterns. First, most firms undertake investment spikes, but they are relatively rare: 81% of all firms, and 92% of firms that we observe from 1995 onwards, have at least one spike, but spikes account for just 20.3% of firm year observations. Second, between spikes capital stocks are often depreciating, indicating little or no gross investment. 62% of firm-year observations that are not spikes involve a (mostly small) negative change in the capital stock. Excluding spikes that occur in consecutive periods,[13] on average capital stocks decrease by 18% between spike events. Third, spikes are important for individual firms' capital stock growth. Among the firms that have at least one spike, changes in net capital stock that occur in spiking episodes on average account for more than 100% of the total change (across all years) in net capital stock (due to the presence of negative capital stock changes in our data).[14] Fourth, there are notable differences in the propensity to spike across firms. Of the firms that have at least one spike, 25% spike only once, while 15% spike 5 times or more. Spike propensity also varies by industry, both in terms of level and volatility across years. For example, business and consumer service companies are (statistically significantly) more likely to spike than manufacturing companies.

2.2 Investment spikes and aggregate investment

There is ongoing interest and debate about the extent to which firm-level investment spikes impact on aggregate investment. We examine empirically how much of the annual variation in aggregate UK investment (as measured from our sample of company accounts) is explained by variation in firm-level investment spikes. We follow an approach similar to that of Gourio and Kashyap (2007), who provide evidence for firms in Chile and the US and conclude that "aggregate investment is largely driven by investment spikes". We find very

[12]In the spirit of identifying substantial changes in productive capacity, we do not classify as spikes events which are either preceded or proceeded by large falls in the asset stock, which we assume represent accounting, rather than genuine economic, adjustments. In the analysis that follows, we classify these 'false' spike events as small positive investments. Details are provided in Appendix A, where we also show that these events are not associated with increases in employment. In so far as these events do represent genuine increases in productive capacity, our analysis will understate the role of spikes.

[13]27.5% of spikes in our data are followed by another spike in the next period. This is likely due to our data being observed at annual intervals, while large investment events may span multiple accounting periods.

[14]For a subsample of 9,547 firms for which we observe depreciation, we calculate net investment gross of depreciation. At the mean, spikes account for 70% of a firm's total investment by this measure.

similar evidence for the UK both before and during the Great Recession. Specifically, we document three new empirical findings.

1. The amount of investment that happens as part of firm-level investment spikes is important for the *level* of the aggregate UK capital stock growth.

2. The annual variation in aggregate UK investment is mostly driven by variation in investment spikes. This is particularly notable in the period of the Great Recession from 2008-2011.

3. This annual variation occurs largely through the extensive margin (the change in the capital weighted number of firms spiking) and not the intensive margin (the size of spikes).

The first two facts are demonstrated in the first panel of Figure 2.2. We decompose the rate of change in the total aggregate capital stock (I/K_{t-1}) into four groups according to whether changes at the firm-level represent: a spike in the investment rate of greater than 20% (s); a positive change of between 5% and 20% (p); a small change between plus and minus 5% (0); a negative change of at least -5% (n) (equation 2.1).[15]

$$\frac{I}{K_{t-1}} = \frac{I^s}{K_{t-1}} + \frac{I^p}{K_{t-1}} + \frac{I^0}{K_{t-1}} + \frac{I^n}{K_{t-1}} \tag{2.1}$$

The category containing spikes (s) need not dominate the level of aggregate investment by construction. This is because spikes are defined as investments that are large for the firm (i.e. they don't necessarily measure investments that are large in absolute terms). It is also not the case that spikes will necessarily explain the majority of *variation* in aggregate investment. Nonetheless, we find both to be the case.

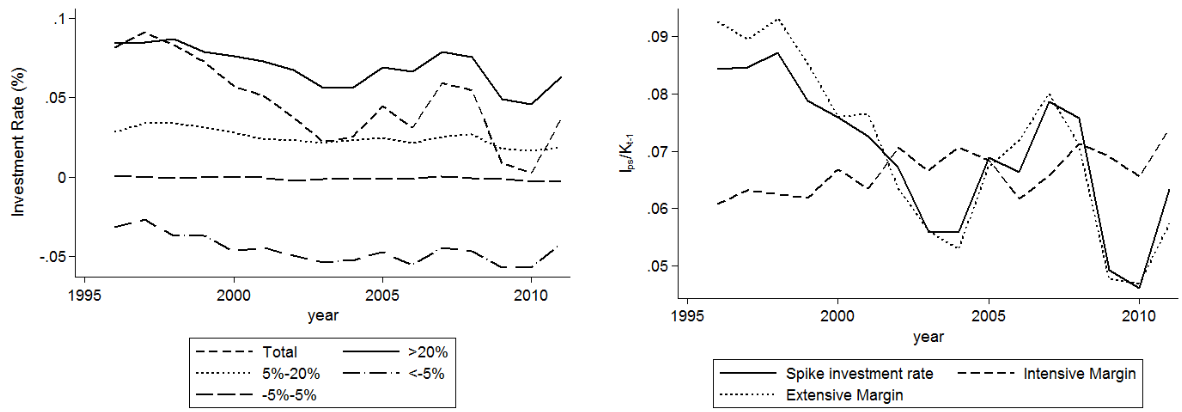
We quantify how important spikes are for changes in aggregate investment by decomposing variation in the aggregate investment rate (I/K_{t-1}). Details are provided in Table 2.1. The share of variance accounted for by variation in the investment rate of firms conducting spikes is 48%, rising to 56% in the years 2008-2011 (despite accounting for only 18.3% of observations over this period.) Looking at net investment inclusive of depreciation understates the importance of these events in increasing the capital stock, however.[16] For

[15]'False spikes' (see section 2.1 for details) are classified in the 5% to 20% category despite having an investment rate over 20%. To the extent that these events are increases in productive capacity, we will understate the role of spikes.

[16]In particular, the importance of negative net investment events may be overstated at the expense of the role of spikes. If negative net investment events arise mostly as a result of depreciation, a reduction in the number of spikes that occur (alongside a corresponding increase in negative net investment events) will reduce overall investment, but the effect on net investment will be attributed both to a reduction in spikes and an increase in negative net investment.

the subsample of firms for which we can calculate net investment gross of depreciation, spikes account for substantially more of the variation, and negative investment events are less important.

Figure 2.2: *Decompositions change in capital stock*



Notes: Decompositions described in equations 2.1 and 2.2 for two panels respectively.

Table 2.1: *Decomposition of variation in aggregate investment rate (as measured by company accounts)*

	Main sample		Depreciation subsample	
Investment rate (%)	1995-2011	2008-2011	1995-2011	2007-2011
>20 (I^s/K_{t-1})	0.48	0.56	0.68	0.72
5-20 (I^p/K_{t-1})	0.17	0.17	0.24	0.40
-5-5 (I^0/K_{t-1})	0.03	0.01	0.02	-0.01
<-5 (I^n/K_{t-1})	0.33	0.26	0.06	-0.11

Notes: Categories based on size of firm-level investment rate as in equation 2.1. For the sub-sample of firms with depreciation information, we decompose net investment gross of depreciation, but maintain classifications of investment events based on the net investment rate. The share of total variation accounted for by each category, I^x/K_{t-1} is measured as $cov\frac{I^x}{K_{t-1}}/var\frac{I}{K_{t-1}}$. This method attributes the covariance terms between the investment of two groups equally to each group. Columns sum to 1 by construction.

Variation in the investment that takes place as part of spikes will be driven by both an extensive margin - the number of firms undertaking a spike - and the intensive margin - the average size of the spike. We quantify the contribution of the intensive and extensive margins by decomposing (in logs) $\frac{I^s}{K_{t-1}}$ into the average investment rate of spiking firms (intensive margin), $\frac{I^s}{K^s_{t-1}}$, and the capital weighted number of firms spiking (extensive margin), $\frac{K^s_{t-1}}{K_{t-1}}$ (equation 2.2).

$$\frac{I^s}{K_{t-1}} = \frac{I^s}{K^s_{t-1}} \frac{K^s_{t-1}}{K_{t-1}} \tag{2.2}$$

These series are plotted in the second panel of Figure 2.2. The figure shows the counterfactual paths for the overall spike investment rate ($\frac{I_s}{K_{t-1}}$) if only one of the intensive ($\frac{I^s}{K^s_{t-1}}$) or extensive ($\frac{K^s_{t-1}}{K_{t-1}}$) margins had varied while the other was held at its sample mean. It is clear from the Figure that the variation in I^s/K_{t-1} is explained by movements in the extensive margin. While the average investment rate conditional on spiking is relatively stable over time, the extensive margin tracks with the aggregate rate. The covariance between the extensive margin and the overall investment of spiking firms ($\frac{I^s}{K_{t-1}}$) is greater than 1 (the contributions of the intensive and extensive margins sum to 1 by design), showing that the trend is driven by the number of firms spiking and not the size of those spikes (the basis for fact three above). This finding corroborates the evidence of Gourio and Kashyap (2007) and Bachmann et al. (2013), who similarly found a dominant extensive margin, but in a new geographical (the UK), industrial (the whole economy rather than just manufacturing) and macroeconomic (a recession) setting.

In summary, we show that variation in aggregate investment is driven by the amount of investment that takes places as part of a spike, which in turn is driven by the number of spikes that take place. We conclude that understanding variation in aggregate investment requires understanding firms' propensity to perform spikes.

3 Firm-level investment hazards

3.1 Empirical specification

In order to consider what explains variation in the propensity to spike across firms and time and, in particular, in response to the Great Recession, we model the probability that a firm undertakes an investment spike in a given year conditional on firm characteristics and the duration since the last spike (an investment hazard). Intuitively, we control for duration to capture the investment dynamics created by non-convex adjustment costs. Immediately following a spike, a firms' capital stock should be at (or close to) the desired level but as time passes the old capital stock depreciates and it becomes more likely that the benefits of investment (from, for example, technological advances embodied in new capital or the ability to satisfy increases in demand) outweighs the costs. More formally, Cooper et al. (1999) motivate the estimation of an investment hazard from a ('machine replacement') model in which firms make a discrete choice each period as to whether to replace an item of capital stock while facing non-convex adjustment costs (their specification can be seen as a specific example of the more general firm optimisation problem set out in Bond and Van Reenen (2007)). The productivity of the capital stock is affected by the age of the equipment and any shocks to profitability. There is a gain to capital replacement both because old capital depreciates and new capital embodies new technology. Firms weigh the benefits from a more productive capital stock against the (non-convex) costs of replacement.[17] When adjustment entails fixed costs and profitability shocks are sufficiently serially correlated, the probability that a spike occurs is increasing in the time since the last spike (i.e. the hazard is upward sloping). Under these conditions, the hazard is also expected to be procylical, such that the probability of a spike increases when profitability is higher.[18]

There is a small literature estimating investment hazards, mainly aimed at testing whether hazard functions are upward sloping as evidence of non-convex capital adjustment costs. Cooper et al. (1999) and Nilsen and Schiantarelli (2003) find evidence (for at least some types of capital) of upward sloping hazards for US and Norwegian plants respectively. Whited (2006) find evidence of an upward sloping hazard and use a sample-splitting approach to identify the effects of credit constraints. Broadly, the empirical approach taken in all of these papers is based on a proportional hazard function ($\theta(.)$) of the form:

$$\theta(t, X) = \upsilon_i \theta_0(t) exp(\beta' X) \tag{3.1}$$

where $\theta_0(t)$ is the baseline hazard at time t that is common across spike events, X is a vector of covariates (including the duration since the previous spike) that shift the hazard and β are the corresponding parameters. υ_i represents unobserved firm-level heterogeneity. Previous work has differed mainly in the specification of X and the assumed functional form of υ_i.

We follow this approach in estimating an investment hazard for UK firms. Specifically, we estimate the probability (hazard) that a firm, i, undertakes an investment spike conditional on the duration (measured in years, t) since the last spike. In estimation we allow firms' durations to be right censored and firms to

[17] The costs comprise an opportunity cost proportional to output (representing the diversion of resources away from production towards adjustment) and a fixed cost proportional to capital (representing a direct loss of output during investment).

[18] The hazard need not be procyclical. If investment entails a diversion of resources from current production, a recession can be a good time to undertake investment (Aghion and Saint-Paul (1998)). This effect can be offset by the desire to invest when demand is strong if shocks are expected to be sufficiently correlated over time.

undertake more than one spike event, s.[19] We assume that time is discrete and parameterize the hazard as a logistic function. The probability (hazard rate) that the length of an event s (of firm i) - T_s - is equal to j, conditional on the time since the last spike, a set of covariates (X_{it}) and a firm specific effect (υ_i) is therefore:

$$h(j, X) = P_{isjt} = [1 + exp(-\Sigma_{j=1}^{J} \gamma_j D_j - \beta' X_{it} + \upsilon_i)]^{-1} \tag{3.2}$$

where D_j is a dummy for each possible duration, J is the maximum observed duration and γ_j are the associated coefficients. We use dummies to capture duration dependence in order not to impose functional form assumptions. In X_{it} we include year dummies and firm characteristics (firm age, decade of incorporation, size and industry) that may be related to adjustment costs or expected shocks. Including a measure of firm size also allows us to control for the possibility that our measure of spikes will not be comparable across firms that differ in how aggregated their capital stocks are across assets. The model is identified from variation across firms that are at different points in their investment durations at different points in time, and from variation across time within firms that undertake multiple spikes.

We explicitly control for unobserved heterogeneity, assuming $\upsilon_i \sim \mathcal{N}(0, 1)$ (this is equivalent to a random effect). Failure to control for unobserved heterogeneity across individuals in duration models is known to lead to a downward bias in the hazard function (Lancaster (1992)). In the context of investment spikes, firms may, for example, differ in their (unobserved) fixed cost of adjustment. If firms with lower costs replace their capital more frequently, then considering a cross section of firms may lead us to conclude that the hazard is downward sloping, even if it is upward sloping for any given firm. Effectively, we would have a sample selection problem at high values of duration: only firms with more durable capital will remain, leading to a lower probability of spike relative to lower values of duration. We expect the observed firm-level characteristics to reduce but not remove heterogeneity.

[19] Allowing only one spike event per firm would reduce the number of censored observations (spells that reach the end of the sample without a spike), which tends to bias the hazard upwards. This problem is more severe if censored observations are excluded, or firms are only included if they spike more than once.

3.2 Estimation

We define a dichotomous indicator variable, Y_{it}, that equals 1 if firm i has an investment spike in year t and 0 otherwise. P_{isjt} in equation 3.2 denotes the conditional probability that $Y_{it} = 1$. The log-likelihood function for a sample of N firm-events can therefore be written as:

$$\log L = \sum_{i=1}^{N} \sum_{t=t_i}^{\bar{t}^i} \left(\log[1 - P_{isjt}] + y_{it} \log[\frac{P_{isjt}}{1 - P_{isjt}}] \right) \tag{3.3}$$

where t_i and $\bar{t}^i$ reflect the first and last year respectively for which a firm is in the estimation sample.[20] As set out above, P_{isjt} is a function of covariates for firm i at duration j and time t. Our data includes spells that can last up to 17 years. We estimate the specification using maximum likelihood.

Table 3.1 summarises the sample of 42,508 firms used in estimation. A firm enters the estimation sample when we observe its first spike (as we cannot measure duration before this point) and therefore the estimation sample excludes firms that never spike. Firm size is measured using lagged fixed assets and categorized into deciles in each year. Each firm belongs to one of 16 industries. We include dummies for the decade of firm incorporation and a measure of age in years (these effectively allow a non-linear affect of firm age on investment).

3.3 Baseline hazard

Table 3.2 shows the baseline results. The coefficients are odds ratios. The hazard is upward sloping at high durations once unobserved heterogeneity is controlled for (column 2).[21] This is in line with the previous investment hazard literature, which also finds that accounting for unobserved heterogeneity is important. The shape of the hazard can be seen more clearly in Figure 3.1, where we also illustrate results from a specification using grouped dummies. The groups are chosen to indicate the durations at which the probability of a spike is statistically significantly higher than at the previous duration.

We find heterogeneity in spike propensity based on size, age and industry: smaller firms, younger firms and those in utilities and business services are more likely to spike. We found no evidence that the *slope*, rather than the level, of the hazard differed significantly across these characteristics. Year dummies capture

[20] In the absence of unobserved heterogeneity, this is equivalent to a standard binary logit model.

[21] In all specifications we have run, the probability of spike is highest at duration equals 1 (i.e. in the period immediately after a spike). Large investment episodes may often be spread across multiple periods, explaining this result.

substantial annual variation in the proportion of firms spiking and show that the hazard is procyclical. The probability of spiking was substantially reduced in the years 2009-2011 relative to the pre-recession years (Figure 3.1 shows the comparison between 2007 and 2009). Nilsen and Schiantarelli (2003) also found that the hazard for Norwegian plants was higher in years associated with strong economic performance.

These results are robust to estimation on a balanced panel of just under 17,000 firms and to alternative definitions of an investment spike.[22]

Table 3.1: *Estimation sample summary*

	Mean	SD	P10	P90
Estimation sample (42508 firms)				
Tangible Fixed Assets (£000s)	2,965	16,291	26	4,132
Change in Assets (%)	57	2,467	-25	59
Age (years)	23	19	6	48
Duration (years)	4	3	1	8
Debt sample (16745 firms)				
Tangible Fixed Assets (£000s)	3,373	18,060	44	4,664
Change in Assets (%)	42	1,921	-24	44
Age (years)	31	20	13	57
Duration (years)	4	3	1	9
Debt to asset ratio (%)	25	28	0	66
Aggregate variables				
Annual GDP growth (%)	2.0	2.1	-0.6	3.5
Policy uncertainty	1.1	0.6	0.5	2.3
Weighted average coc (%)	5.3	0.4	4.9	6.1

Notes: Statistics are measured over the years 1998-2011. The estimation sample excludes (from the full sample used in Section 2) firms that do not spike. The debt sample includes only firms in the balanced panel (present from 1995 onwards) with full capital structure information and no year in which the debt-to-asset ratio exceeds 200%. Sources: Policy Uncertainty from Baker et al. (2015), GDP growth from Office for National Statistics (Series ABMI), Cost of capital from Oulton and Wallis (2015).

[22] Firms in the balanced panel tend to be larger, older and less likely to spike than firms in the main sample but the shape of the estimated hazard is not significantly different. Results are robust to using 15% or 30% investment rate cut-offs or a firm specific relative measure, where a spike is defined as 2.5 times the median firm investment rate, or 10%, whichever is larger.

Table 3.2: *Baseline main*

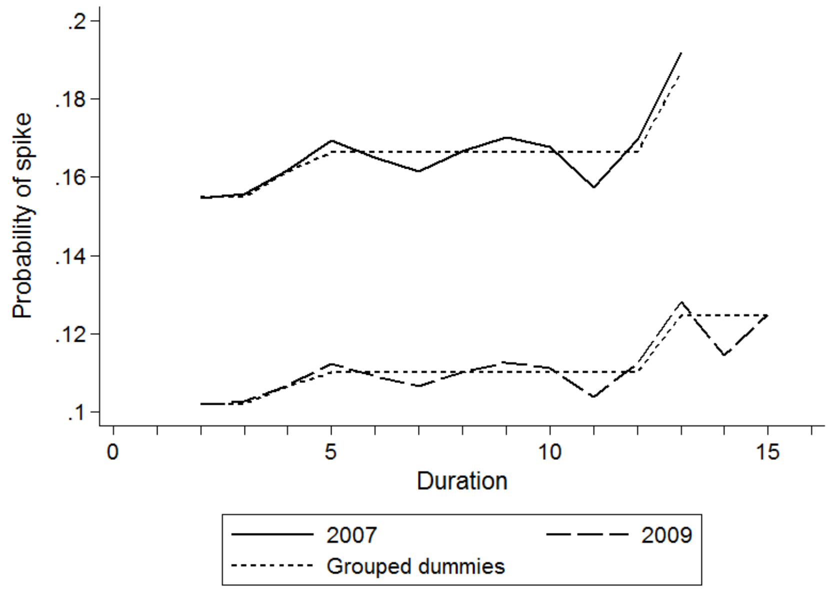
	(1)	(2)	(3)
j=2	0.513***	0.527***	0.529***
	(0.006)	(0.007)	(0.006)
j=3	0.506***	0.531***	
	(0.007)	(0.007)	
j=4	0.518***	0.555***	0.556***
	(0.008)	(0.009)	(0.009)
j=5	0.535***	0.587***	0.575***
	(0.009)	(0.011)	(0.008)
j=6	0.508***	0.569***	
	(0.010)	(0.012)	
j=7	0.485***	0.554***	
	(0.011)	(0.014)	
j=8	0.494***	0.575***	
	(0.013)	(0.017)	
j=9	0.496***	0.590***	
	(0.015)	(0.020)	
j=10	0.478***	0.580***	
	(0.017)	(0.023)	
j=11	0.435***	0.538***	
	(0.019)	(0.025)	
j=12	0.468***	0.588***	
	(0.024)	(0.032)	
j=13	0.530***	0.682***	0.662***
	(0.032)	(0.044)	(0.031)
j=14	0.454***	0.600***	
	(0.038)	(0.052)	
j=15	0.500***	0.663***	
	(0.054)	(0.073)	
j=16	0.601***	0.802	
	(0.090)	(0.122)	
j=17	0.295**	0.396	
	(0.139)	(0.188)	
Manufacturing	0.907***	0.887***	0.887***
	(0.020)	(0.021)	(0.021)
Electric,Gas and Steam	1.331***	1.371***	1.372***
	(0.104)	(0.118)	(0.118)
Finance and Insurance	0.703***	0.672***	0.672***
	(0.024)	(0.025)	(0.025)
Wholesale and Retail trade	0.867***	0.843***	0.843***
	(0.019)	(0.020)	(0.020)
Size decile: 50	0.566***	0.517***	0.516***
	(0.010)	(0.011)	(0.011)
Size decile: 100	0.341***	0.293***	0.293***
	(0.007)	(0.007)	(0.007)
Incorporated 1990-1999	1.207***	1.220***	1.220***
	(0.022)	(0.025)	(0.025)
Incorporated post-2000	1.501***	1.576***	1.578***
	(0.035)	(0.040)	(0.040)
2007	0.782***	0.737***	0.736***
	(0.020)	(0.019)	(0.019)
2009	0.492***	0.457***	0.456***
	(0.013)	(0.012)	(0.012)
N	395291	395291	395291

Exponentiated coefficients

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

Notes: Coefficients reported are odds ratios. A subset of coefficients are shown here; for full list see table B.1. In the third column, duration dummies 2 to 3, 5 to 12 and 13 and above are grouped. The coefficients listed refer to the grouped dummies. Standard errors reported in parentheses. The base option is a firm at duration 1 incorporated before 1980 in the first size decile, in the Accommodation and Food sector in 1998.

Figure 3.1: *Baseline hazard*



Hazards drawn for a manufacturing firm in the 5th size decile, 30 years old and incorporated between 1980-89. The solid lines are based on the specification in column 2 of Table 3.2. The dashed lines are based on the specification with grouped dummies in column 3 of Table 3.2. The grouped dummy specifications represent the duration levels at which the spike probability significantly differs from the previous duration.

4 Variation over the business cycle

We are interested in explaining common (across firms) annual variation in spike propensity. This is in contrast to the previous literature on investment hazards, which has captured annual variation through the use of year dummies (as their interest was in identifying a hazard slope, and therefore controlling for aggregate variation, rather than explaining it). To this end, our first contribution to the investment hazard literature is to allow the hazard to vary with measures of the aggregate economic conditions in order to better understand *why* the hazard is varying year-on-year and what drives the procyclicality of spikes shown above.

We expect the propensity to undertake a spike to vary across the business cycle as a result of changes in the economic environment that firms face. The 2008 recession entailed (possibly idiosyncratic) negative demand shocks. Lower demand would be expected to induce firms to reduce their desired capital stocks and therefore their demand for investment. This in turn might lead firms to delay or cancel planned investment 'spikes' and possibly to reduce their capital stock. The 2008 recession was also accompanied by a large increase in uncertainty over both the path of the recovery and economic policies (Baker et al. (2015), Haddow et al. (2013)). Uncertainty creates a real option value to waiting until more information is available (Dixit and Pindyck (1994), Bloom et al. (2007)) and therefore provides an incentive for firms to delay investment decisions and postpone entering new markets (Bloom (2009), Disney et al. (2003)). Finally, the cost of capital (both debt and new equity) increased substantially at the start of the recession. A higher cost of capital lowers the net benefit of undertaking an investment and is therefore expected to reduce investment.

Motivated by these factors (and the large underlying literature on how economic conditions affect investment incentives across the business cycle), we include three time varying macroeconomic variables in the hazard function (in X_{it}, instead of year dummies): annual GDP growth (a measure of aggregate demand), policy uncertainty (from Baker et al. (2015)) and a measure of the weighted (across debt and equity finance) average cost of capital (Oulton and Wallis (2015)). We enter the later with a one year lag. The effects of these aggregate variables are identified from variation in the average spike propensity over time.[23] The variables are summarised in Table 3.1. In estimation we adjust the variables to approximate the standard normal distribution such that the coefficients show the impact of a one standard deviation change in the variable.

Table 4.1 presents the results. The signs are as expected: higher GDP growth is associated with a greater spike propensity, while greater uncertainty or finance costs reduce the probability of a spike. A one standard deviation fall in GDP growth leads to a 9% reduction in spike probability. The equivalent effects of a one standard deviation increase in uncertainty or in the weighted average cost of capital are a 8% and 3% reduction respectively.

These results imply that variation in the cost of capital is less important than demand or uncertainty in driving investment over the cycle. This may be because demand and uncertainty are more important for determining the timing of spikes than the cost (which may matter more for the size of the spike at the intensive margin). It may also reflect that there is greater heterogeneity in the effect of finance costs across

[23]It would be preferable (from an identification point of view) to use measures that varied at the firm-level. However, even where available, firm specific measures (such as sales growth, cash flows or the cost of capital) are endogenous to the investment decision. The discrete choice hazard framework does not lend itself to the instrumenting strategies (including system-GMM, see Arellano and Bond (1991)) commonly used in linear investment models or to many of the techniques used to try to estimate financial constraints (Bond and Van Reenen (2007)).

firms (the estimates will capture average effects across firms). In column 2 of Table 4.1, we present some evidence for this. The spike probability for a younger firm (defined as a firm incorporated after 2000) is more responsive to the cost of capital than other firms. For this group, a one standard deviation increase in the weighted average cost of capital leads to a 9% reduction in spike probability.[24] In column 3 we exclude new firms from the sample and find no significant effect from the cost of capital. These results are consistent with previous evidence that finance is especially important for young firms (Brown et al. (2009) and Rajan and Zingales (1998) among others). This does not, of course, rule out that that there are idiosyncratic changes to the cost of finance that are important for firms decisions.[25]

Table 4.1: *Aggregate results*

	(1)	(2)	(3)
Incorporated 1990-1999	1.16***	1.16***	1.18***
Incorporated post-2000	1.46***	1.40***	
Electric,Gas and Steam	1.37***	1.37***	0.95
Finance and Insurance	0.67***	0.67***	0.66***
Manufacturing	0.89***	0.89***	0.89***
Transportation and storage	1.10***	1.10***	1.10**
Water supply and sewerage	1.52***	1.52***	1.48***
Wholesale and Retail trade	0.85***	0.85***	0.84***
Size decile: 50	0.52***	0.52***	0.52***
Size decile: 100	0.30***	0.30***	0.30***
Annual GDP growth	1.09***	1.09***	1.09***
Policy uncertainty	0.92***	0.92***	0.92***
Weighted average cost of capital (t-1)	0.97***	0.98*	0.99
Weighted average cost of capital * new firm		0.93***	
Annual GDP growth * new firm		0.97**	
Policy uncertainty * new firm		1.01	
N	395291	395291	346898

Exponentiated coefficients

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

Notes: 1. Specification as in baseline results with year dummies replaced by aggregate variables. 2. Additional interaction between aggregate variables and an indicator for firms incorporated after 2000 (a 'new' firm). 3. As in 1 but excluding firms incorporated after 2000. The three aggregate variables are transformed by subtracting the mean and dividing by the standard deviation. A subset of coefficients on firm characteristics are shown for brevity, but all remain largely unchanged from the baseline specification.

[24] The overall effect of the weighted average cost of capital on new firms is given by the exponent of the sum of the logs of the coefficients in the Table. 4.1

[25] Whited (2006) studies financial constraints in a hazard framework using a sample splitting approach (firms are split into groups that are similar in all dimensions except how likely they are to face financial constraints) and provides evidence that firms that are less likely to have internal resources (and therefore more likely to be constrained) have lower investment hazards. We do not follow this approach here because (i) we are not confident that there is a selection criteria that produces sub-samples of firms that differ only in their financial conditions (Kaplan and Zingales (1997) critiques this method) and (ii) characteristics used to determine whether firms have access to external finance in normal times will not necessarily capture those firms who experience a worsening in credit conditions during the recession.

This approach has the benefit of being simple and easy to implement using readily available measures of the aggregate environment. However, one may be concerned that the simple aggregate measures are endogenous. Most notably, a measure of aggregate GDP will in part be capturing aggregate investment. To address this we repeat the exercise with a number of alternative variables, including growth in only consumer spending or an industry level measure of downstream demand (as used in Shea (1993))in place of aggregate GDP. The pattern of the results are broadly unchanged.[26]

4.1 Simulations of aggregate investment from firm hazards

Using the specification that includes aggregate measures, we can conduct a dynamic simulation of firm-level investment spikes and show that the resulting sum of firm-level spikes in a given year matches the observed pattern. Given that the movements in aggregate UK investment are driven predominately by the number of firm-level investment spikes (shown in Section 2), we conclude that our model can be used to replicate the pattern of aggregate UK investment.

Specifically, in the first year that a firm enters the sample we use the estimated parameters (column 1 from Table 4.1) to calculate the probability that that firm will spike. Based on this we recalculate the subsequent path of firm-level duration and repeat the exercise for each following year.[27] Figure 4.1 shows the actual spike frequency (i.e. the proportion of firms that we observed spiking each year) and the simulated frequency of firms that undertake an investment spike. The simulated frequency matches the actual pattern, and in particular the turning points around the recession, very well. With year dummies this would be trivially true (the dummies ensure that the model predicts the correct proportion of spiking firms each year), but this is not the case with the aggregate variables; the turning points need not necessarily be matched.

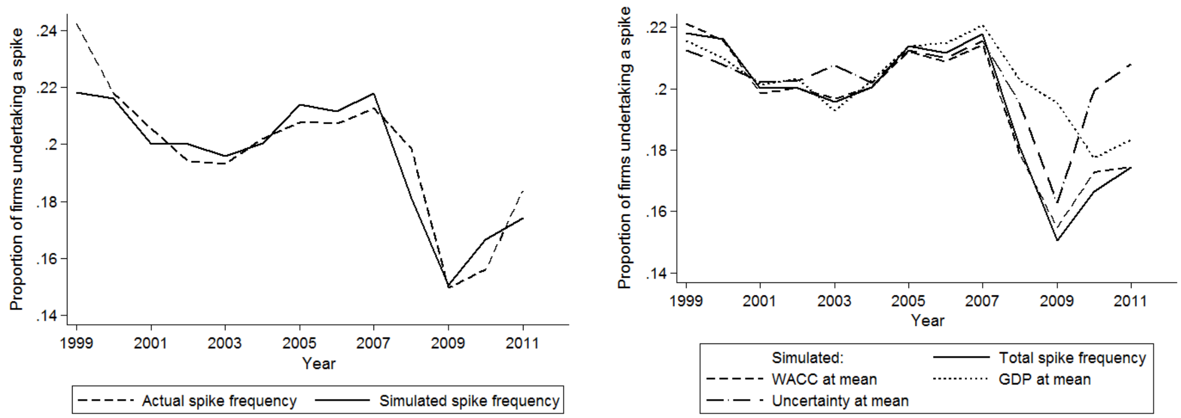
Simulations can also be used to demonstrate which of the aggregate variables was most important in driving the aggregate trend, especially during the recession.[28] Figure 4.1 panel B shows the simulated counterfactual paths for the proportion of spikes per year if each of the three aggregate variables were held

[26] Results of robustness checks are available on request.

[27] For each firm-year we compare the predicted hazard rate to a random number between 0 and 1 drawn from a uniform distribution. We say that a (simulated) spike has occurred if the hazard rate is greater than the random number. This process is repeated for each year with the duration since the last spike continuously updated based on simulated spikes.

[28] Our measure of uncertainty was 0.5 standard deviations above the mean in 2009, and 2.1 in 2010 (the two years in which the reduction in investment was most severe), the weighted average cost of capital was 1.0 standard deviations above the mean in 2009 and 1.4 in 2010, while GDP growth was 3.3 standard deviations below the mean in 2009, though less than 0.1 standard deviations below the mean in 2010. These changes in the aggregate environment, combined with the estimated coefficients, describe which changes were most important in driving the investment slump that occurred post 2007.

Figure 4.1: *Aggregate variables. Panel A: Model fit; Panel B:The role of GDP growth and uncertainty*



Notes: Simulations are generated based on the coefficients in column 1 of Table 4.1. In Panel B, we hold each of the cost of capital, GDP and uncertainty at their pre-recession sample mean and re-run simulations.

at their pre-recession sample mean. This shows that the fall in investment would have been substantially less sharp if GDP growth had not fallen in 2009; in 2009 the proportion of firms spiking would have been almost 4% higher had GDP growth remained at its pre-recession sample mean and only uncertainty and the cost of capital had deteriorated. The recovery would have been quicker were it not for the effect of ongoing uncertainty, especially in 2010, but little would have changed had the cost of finance remained at pre-recession levels. In summary, these results imply that the size of the initial fall in aggregate UK investment following the recession was largely attributable to the fall in demand, with high uncertainty prolonging the weakness.

4.2 The role of duration

Simulations can also be used to measure how important changes in the cross-sectional distribution of firm durations are for explaining aggregate investment. In the presence of non-convex capital adjustment costs (and an upward sloping hazard), a shock that increases (decreases) the proportion of firms that spike leads to a fall (increase) in the average duration. This shift in the cross-section of durations can itself affect the path of aggregate investment (because firms at high durations are more likely to invest). We find that changes in the cross sectional distribution of durations explain very little of the movement in aggregate investment.[29] Common shocks (whether captured through year dummies or aggregate variables) are significantly more

[29] As in the simulations described in the main text, one can conduct a simulation where the duration parameters are set to zero (creating a flat hazard) and use this to consider how the inclusion of duration affects the fit of the model.

important. This is in line with the findings of Nilsen and Schiantarelli (2003). However, and as noted by Cooper et al. (1999), changes in the cross-sectional capital stock age (duration) may play a bigger role following large changes in aggregate investment. We expect that to be true for the UK. For most of our sample period, the cross-sectional distribution was relatively stable. Following the recession, the large fall in the frequency of investment spikes in 2009, 2010 and 2011 acted to increase average duration. It is plausible that this move in the cross-sectional distribution towards higher durations will affect aggregate investment in later years (that are outside our period of observation).

5 Firm investment heterogeneity and capital structure

5.1 Capital structure and financial distress

There was substantial heterogeneity in firm-level investment during and immediately following the crisis. We consider whether part of this variation in behaviour across firms during the recession can be explained by their capital structure. Specifically, we ask whether firms that operate with high debt-to-asset ratios were more likely to reduce their investment in response to the recession. The intuition behind this hypothesis is that those firms with relatively high levels of debt are more likely to have experienced financial distress during the financial crisis. They would have been more susceptible to the possibility that an endogenous worsening of credit market conditions acts to amplify real adverse economic shocks; this is the 'financial accelerator' originally set out by Bernanke (1981).[30] Consider a firm that faces a negative demand or productivity shock that in turn reduces cash flows. This renders the firm less able to service a (nominal) debt that is now larger relative to the reduced value of assets. In some cases, the firm may have to sell capital assets at a deep discount in order to service the debt. In less extreme cases, the firm may still have to divert resources away from investment towards paying down the debt and would expect to face a higher cost of external finance for any new debt issued (due to the increase in the default probability and lower levels of collateral).[31] The premium on external finance may increase by more for high debt firms if adverse financial conditions are accompanied by a"flight to quality", whereby investors (and banks) prefer lower return, safer assets

[30] See also Bernanke (1983), Bernanke and Gertler (1989), Bemanke et al. (1996) and Kiyotaki and Moore (1997).

[31] In Bernanke (1981), a reduction in the internal resources in and of itself increases the cost of investment because external finance is assumed to come at a premium to external resources.

(Bemanke et al. (1996)). One would expect these 'financial distress' costs to be more pronounced for firms operating with higher debt-to-assets ratios.[32]

There is no consensus view on how capital structure relates to investment and the two main competing theories of capital structure - the pecking order theory and trade-off theory (Harris and Raviv (1991) describe) - have both been shown to match data poorly.[33] DeAngelo et al. (2011) set out a dynamic trade-off theory that can reconcile the notion that firms are trading off the costs and benefits of holding debt with the empirical regularities on how firms' debt positions evolve. Effectively, by augmenting a static trade-off model with an opportunity cost to taking out debt today and thereby reducing debt capacity in future periods, firm investment policy is made endogenous to the debt decision.[34] This theory predicts that firms operate with a long run debt target that can be thought of as the level of debt that balances the tax shield provided by interest payments with the costs of financial distress and the opportunity cost of borrowing today rather than preserving borrowing capacity. Firms will deviate temporarily and deliberately from this target in response to shocks that increase the incentives to undertake investment. DeAngelo et al. (2011) show theoretically that investment spikes are associated with increases in debt ratios, which then steadily revert back to the firm's target in subsequent periods as firms build debt capacity for future investments.

Following the line of reasoning of a dynamic trade-off theory of capital structure, we expect firms' debt choices to be related to their investment, and in particular to investment spikes, but for debt choices to also vary across firms for other reasons. We confirm the link between debt and investment spikes for firms in our sample. Table 5.1 shows that spikes are associated with increases in debt-to-asset ratios (measured as the ratio of total debt (current and non-current loans and liabilities owed to creditors) relative to total fixed assets).. Periods of investment inaction are characterised, in general, by falling or static debt-to-asset ratios. This is despite the fact that a spike implies a substantial increase in the denominator of the ratio. The

[32]For a given percentage fall in asset value, those firms with high debt-to-asset ratios will face a larger absolute increase in the debt-to-asset ratio, such that, for a given shock, they are further away from their debt target and have more work to do to restore their balance sheets. We assume here that firms with higher debt targets have higher targets due to greater benefits to holding debt (for example, because they are more capital intensive or are more profitable). If differences in debt targets arise from differing costs (for example because some firms are just inherently more 'creditworthy'), we would not necessarily expect high debt firms to be more exposed during the recession. For our sample of firms, that excludes large publicly traded firms, differences in creditworthiness are likely to be less pronounced.

[33]A static trade-off model predicts that firms choose debt to meet a stable target (Bradley et al. (1984)). Criticisms of this model are discussed by Myers (1984) Titman and Wessels (1988) and Rajan and Zingales (1995)). The 'pecking order' theory posits that external funds are raised solely for investment and ranked according to the costs associated with asymmetric information. Neither models' predictions match the observation that debt levels are linked to but not solely driven by investment (Fama and French (2002), DeAngelo et al. (2011)).

[34]DeAngelo et al. (2011) additionally assume a finite debt capacity, motivated by the presence of financial distress costs and the asymmetric information problems that limit creditors' willingness to allow firms to take on large quantities of debt.

differences in mean debt-asset ratio change in Table 5.1 are statistically significant. This evidence suggests that investment spikes are often funded by debt, and so variability in debt ratios for firms over time will be linked to their capital accumulation (i.e. endogenous to investment decisions).

Table 5.1: *Investment and capital structure changes*

Investment Rate (%)	Change in debt-asset ratio			
	Increase	Unchanged	Decrease	Mean change
20	42.0%	24.1%	33.9%	1.66%
5-20	37.0%	22.7%	40.3%	-0.13%
-5 - 5	30.3%	26.1%	43.6%	-0.96%
<-5	32.1%	23.2%	44.8%	-1.40%

Note: Includes firms in our balanced panel with non-missing debt information and no year in which the debt ratio is greater than 2.

5.2 Estimating the role of capital structure

There is substantial variation in debt-to-asset ratios across firms (Table 3.1 summarises). Some firms in some years hold no debt at all while others have debt greater than their assets. In just under 30% of firm-years debt holdings are zero, but only 4.3% of firms never hold debt over the sample period.

If firms' debt choices follow a dynamic trade-off, then in a cross section there will be two types of firms with high debt: those with high debt targets and those at temporarily high levels of debt (above their target). Broadly, the latter are likely to be those firms that have recently undertaken a large investment. As a result, we expect a contemporaneous or lagged measure of a firm's debt position to be endogenous to the decision of whether to undertake an investment spike (even after controlling for duration).[35]

To identify the relationship between capital structure and investment in the post recession period we construct an indicator of those firms that operate with high debt-to-asset ratios in all years. The aim is to distinguish these firms from those that are high debt temporarily as a result of their point in the investment cycle. That is, we seek to overcome endogeneity concerns by exploiting our panel of data to construct a measure of firms' capital positions that can be thought of as a fixed characteristic and that is predicted to be directly related to the probability that a firm suffers financial distress costs following the recession.

[35] The debt-to-asset ratio may contain additional information about a firm's investment intentions over and above the duration since the last spike. For example, a high lagged debt-to-asset ratio may indicate that an investment (but not a spike) took place in the previous year, making a spike less likely in this year. Alternatively, the debt-to-asset ratio may contain information about the size of a previous spike and therefore the likelihood that another spike occurs in subsequent years.

Table 5.2: *Debt quintile transitions*

	Debt quintile (t+1)					
Debt quintile (t)	1	2	3	4	5	Total
1	83.0%	6.0%	5.3%	3.4%	2.3%	100.0%
2	16.9%	58.9%	18.8%	3.6%	1.8%	100.0%
3	8.8%	11.0%	62.1%	15.6%	2.5%	100.0%
4	5.1%	1.7%	15.8%	63.3%	14.2%	100.0%
5	3.4%	0.9%	2.4%	14.3%	79.0%	100.0%

Note: See Table 5.1.

Table 5.3: *Variability of firm capital structure*

Statistic	Q1	Q2	Q3	Q4	Q5
Max quintile	4.3%	5.2%	15.8%	23.9%	50.9%
Min quintile	63.2%	13.5%	13.6%	7.4%	2.3%
Modal quintile	31.9%	8.7%	18.2%	19.2%	22.0%

Note: See Table 5.1.

In constructing a measure of high debt we account for systematic differences in average debt levels across industries. These will arise for a variety of reasons, including, for example, differences in the demand for assets that are more or less suitable as collateral. We do not want to simply measure high (low)-debt firms as those that operate in the utilities (agriculture) sectors. We therefore consider firms' debt positions relative to other firms within the same industry. Specifically, in each year, we classify firms that are observed from 1995-2011 (i.e. those in the balanced panel) into quintiles within broad industry groupings based on their debt-to-assets ratio.Year-on-year, firms tend to make relatively small moves across ranks; debt quintiles are fairly persistent (Table 5.2). Yet, over the 16 years from 1995, almost two thirds of firms are in the lowest quintile at least once and over half are in the highest quintile at least once (Table 5.3).[36]

We class as 'high-debt' those firms that have a debt-to-asset ratio that is in the top 60% of the industry-year distribution in all years. This group can be though of as an indication of firms that operate with a high debt target. In our data, this group represents 23% of firms (the firms with a minimum quintile of 3 or above in Table 5.3) and has an average debt-to-asset ratio of 51%.

[36]35% of the total variance in debt-to-asset ratios is attributable to within-firm, as opposed to between-firm, variation. These patterns are consistent with the dynamic trade-off model, which allows that firms can be above a debt target in years where they are investing and below target in years when they are building capacity.

We test whether high-debt firms are less likely to undertake an investment in the post recession period by allowing year dummies to be interacted with the indicator of high debt firms. Table 5.4 sets out the results. High debt firms are statistically significantly more likely to undertake a spike in general (column one of Table 5.4) but are statistically significantly less likely to undertake a spike following the recession (column two). This effect is shown in Figure 5.1. The spike probability of a high debt target firm fell by 8 percentage points between 2007 and 2009, compared with only 5 percentage points for other firms.

One cannot interpret these results as saying that a high debt target boosts investment. Clearly, the relationship is as likely to run in the other direction (firms may operate with high debt targets if they expect to have high investment demand). More broadly, the debt target of the firm (and whether a firm is in the group we define as 'high debt') will be correlated with a range of firm characteristics. For example, in the dynamic trade-off theory of capital structure set out previously, firms that face a low volatility of shocks to investment opportunities are likely to have higher debt targets (because they place a lower value on the opportunity cost of preserving debt capacity). The coefficient on 'constant high debt' is therefore capturing the average effect of the number of ways in which high debt firms differ. While it is possible that some of these characteristics will affect how firms respond to the recession, we argue that such characteristics do not lead to a systematic positive or negative bias in the coefficient capturing the interaction between the recession and high debt firms. We interpret the latter result as indicative that firms tending to operate with high levels of debt were less likely to invest in the wake of the recession because they were more exposed to the financial costs associated with having a high debt-to-asset ratio at a time when the cost of debt is increasing and credit supply contracting. The fact that the effect is strongest in 2009 supports this interpretation as this was the year in which our measure of the weighted average cost of capital was highest, and the year in which commercial interest rates were highest.

As discussed above, we expect a contemporaneous or lagged measure of a firm's debt rank to be endogenous. It is not possible therefore to separately identify investment dynamics from any direct effects of contemporaneous debt levels on investment choices. We can, however, address the concern that the result in column two is driven by those firms that had high debt in the years directly preceding the recession, which would mean that we are picking up any interactions between investment dynamics (as captured by temporarily high debt) and the recession rather than the effect of operating with persistently high debt. In column three we control for a lagged measure of a firm's rank (within an industry) of the debt-to-asset ratio.

Column 4 additionally interacts a contemporaneous measure with the 2009 year dummy. The coefficient on 'high-debt' is little changed. That is, the effect is not simply driven by the contemporaneous debt position.

The choice of the 'high-debt' firm definition is driven by a desire to avoid our results being driven by mean reversion. As a robustness test to ensure that we are picking up a recession effect, we run a placebo test in which we treat 2005 and 2006 as a 'dummy recession' defining high debt firms based on the years 1995-2007. We do not find any significant effect, implying that our results are picking up a recession effect rather than by the way we define high debt firms. A second concern might be that, by requiring that firms have relatively high debt levels both before and during the recession, we capture only those high debt firms that were unable to reduce their debt levels when the recession hit. However, in a further robustness check we define high debt on the pre-recession period, and this does not materially affect our results.

We conclude that there is evidence that capital structure helps to explain the heterogeneity in firms' responses to the recession. Firms that operate consistently with high debt are a relatively small group (23% of our sample) but they account for a significant share of investment (50% in the years prior to 2008). Running simulations of the kind run in Section 4.1, we find that if high-debt firms were affected by the recession in the same way as other firms (on average), the share of firms spiking in 2009 would have been 0.6 ppt higher (12.5% vs 11.9%), which accounts for 20% of the observed reduction in spike probability between 2007 and 2009.[37]

[37] Simulations are run as before using the results in column 4 of Table 5.4. We compare a simulation based on the actual coefficients to one in which the interaction terms between the constant high debt and recession years are equal to 0. This counterfactual is one in which high debt firms' investment intentions were not differentially affected post recession.

Table 5.4: *The effect of debt during the recession*

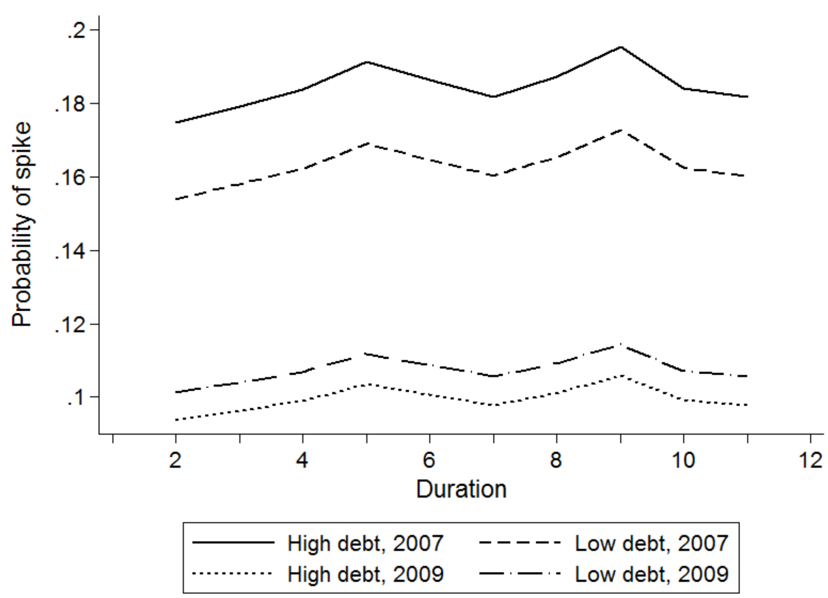
	(1)	(2)	(3)	(4)
2008	0.66***	0.66***	0.66***	0.66***
2009	0.44***	0.46***	0.46***	0.52***
2010	0.47***	0.48***	0.48***	0.48***
Constant high debt	1.11***	1.13***	1.16***	1.16***
Constant high debt*08		1.01	1.01	1.01
Constant high debt*09		0.80***	0.80***	0.76***
Constant high debt*10		0.92	0.92	0.92
Debt/Assets below 20th percentile			0.97	0.98
Debt/Assets in 20-40th percentile			0.98	1.00
Debt/Assets in 60-80th percentile			0.98	0.98
Debt/Assets in 80th-90th percentile			0.92**	0.92**
Debt/Assets above 90th percentile			0.90***	0.90***
Debt/Assets below 20th*09				0.88
Debt/Assets in 20th-40th*09				0.73**
Debt/Assets in 60th-80th*09				0.89
Debt/Assets in 80th-90th*09				0.99
Debt/Assets above 90th*09				0.97
N	201280	201280	201280	201280

Exponentiated coefficients

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

Notes: Results in this table add debt variables to the baseline specification presented in column 2 of Table 3.2. Measures used in columns 3 and 4 are lagged and can be thought of as the debt-to-asset ratio at the start of the year in which a decision over whether or not to spike is being taken.

Figure 5.1: *High debt firms before and during the recession*



Note: Hazard drawn for a manufacturing firm in the 5th size decile, 30 years old and incorporated between 1980-89 based on the results in column 4 of table 5.4.

6 Conclusion

In this paper, we set out and estimate a firm-level model of investment that: (i) incorporates measures of the aggregate economic environment and can be used to replicate aggregate business cycle variation; (ii) incorporates a role for firm capital structure, which we demonstrate helps to explain the heterogeneous response of firms' investment to the Great Recession. We take as a starting point the body of evidence that capital stock adjustment is subject to non-convex costs leading investment to take place intermittently through 'spikes'. Based on this, we develop a duration model in which the firm investment hazard reflects the probability that an investment spike occurs, conditional on the time since the previous spike, the aggregate environment and a range of firm characteristics.

We apply this framework to the UK, which saw a large fall in investment following 2008 and a recovery that differed substantially across firms. We show that spikes are relatively rare at the firm level, but that most firms undertake them and that they are important drivers of the firm-level capital stock growth. We also show that investment that happens as part of spikes drives cyclicality in aggregate investment. In particular, variation in aggregate investment is driven by the frequency rather than the magnitude of investment spikes. This finding generalises a result previously found for the US and Chile to the UK and across many sectors. We show that the probability that a UK firm undertook an investment spike fell substantially after 2008 and we present evidence that this was driven initially by a reduction in aggregate demand and subsequently prolonged through increased uncertainty. We present evidence that firms operating with high levels of debt before the recession were less likely to invest afterwards (all else equal). This finding is consistent with the notion that such firms were more exposed to financial distressed costs associated with having a high debt-to-asset ratio at a time when the value of assets falls, the cost of debt is increasing and the credit supply contracting.

We conclude that in order to understand investment at the firm and/or the aggregate level, one must consider both firm-level factors (such as the presence of non-convex adjustment costs and heterogeneous characteristics such as capital structure) and changes in the aggregate environment. A firm-level investment hazard with aggregate characteristics provides a straightforward and tractable way to incorporate both types of factor.

In the wake of the Great Recession there was much interest, in the UK and elsewhere, in the role that policy could play in fostering a recovery. Our results have two implications for policies aimed at firm investment. First, since aggregate investment is driven predominately by firm-level investment spikes, marginal changes in the cost of capital (resulting from cuts to interest rates) may be less effective in boosting aggregate investment than would be expected if firms faced convex adjustment costs (and therefore smoothly adjusted investment in response to changes in the cost of capital). Second, our results demonstrate that there can be significant heterogeneity across firms. Understanding such firm-level heterogeneity is a precursor to evaluating potential policy responses and for this a micro-founded model is required.

References

Abel, A. B., A. K. Dixit, J. C. Eberly, and R. S. Pindyck (1996). Options, the value of capital, and investment. *The Quarterly Journal of Economics 111*(3), 753–777.

Abel, A. B. and J. C. Eberly (1994). A unified model of investment under uncertainty. *American Economic Review 84*, 1369–1384.

Aghion, P. and G. Saint-Paul (1998). Virtues of bad times interaction between productivity growth and economic fluctuations. *Macroeconomic Dynamics 2*(3), 322–344.

Arellano, M. and S. Bond (1991). Some tests of specification for panel data: Monte carlo evidence and an application to employment equations. *The Review of Economic Studies 58*(2), 277–297.

Bachmann, R., R. J. Caballero, and E. M. Engel (2013). Aggregate implications of lumpy investment: new evidence and a dsge model. *American Economic Journal: Macroeconomics 5*(4), 29–67.

Baker, S. R., N. Bloom, and S. J. Davis (2015). Measuring economic policy uncertainty. Technical report, National Bureau of Economic Research.

Baumann, U. and S. Price (2007). Understanding investment better: insights from recent research. Bank of England Quarterly Bulletin 2007 Q2, Bank of England.

Bemanke, B., M. Gertler, and S. Gilchrist (1996). The financial accelerator and the flight to quality. *The Review of Economics and Statistics 78*(1), 1–15.

Benito, A. and G. Young (2002). Financial pressure and balance sheet adjustment by uk firms. *Bank of England working paper series, No. 168*.

Bernanke, B. and M. Gertler (1989). Agency costs, net worth, and business fluctuations. *The American Economic Review*, 14–31.

Bernanke, B. S. (1981). Bankruptcy, liquidity, and recession. *The American Economic Review 71*(2), 155–159.

Bernanke, B. S. (1983). Nonmonetary effects of the financial crisis in the propagation of the great depression. *The American Economic Review 73*(3), 257–276.

Bertola, G. and R. J. Caballero (1994). Irreversibility and aggregate investment. *The Review of Economic Studies 61*(2), 223–246.

Bloom, N. (2009). The impact of uncertainty shocks. *Econometrica 77*(3), 623–685.

Bloom, N., S. Bond, and J. Van Reenen (2007). Uncertainty and investment dynamics. *The Review of Economic Studies 74*(2), 391–415.

Bond, S. and J. Van Reenen (2007). Microeconometric models of investment and employment. *Handbook of Econometrics 6*, 4417–4498.

Bradley, M., G. A. Jarrell, and E. Kim (1984). On the existence of an optimal capital structure: Theory and evidence. *The Journal of Finance 39*(3), 857–878.

Brown, J. R., S. M. Fazzari, and B. C. Petersen (2009). Financing innovation and growth: Cash flow, external equity, and the 1990s r&d boom. *The Journal of Finance 64*(1), 151–185.

Caballero, R. J. (1999). Aggregate investment. *Handbook of macroeconomics 1*, 813–862.

Caballero, R. J. and E. M. Engel (1999). Explaining investment dynamics in us manufacturing: a generalized (s, s) approach. *Econometrica 67*(4), 783–826.

Caballero, R. J., E. M. Engel, J. C. Haltiwanger, M. Woodford, and R. E. Hall (1995). Plant-level adjustment and aggregate investment dynamics. *Brookings Papers on Economic Activity*, 1–54.

Cooper, R. and J. Haltiwanger (1993). The Aggregate Implications of Machine Replacement: Theory and Evidence. *American Economic Review 83*(3), 360–82.

Cooper, R., J. Haltiwanger, and L. Power (1999). Machine replacement and the business cycle: Lumps and bumps. *American Economic Review 89*(4), 921–946.

Cooper, R. W. and J. C. Haltiwanger (2006). On the nature of capital adjustment costs. *The Review of Economic Studies 73*(3), 611–633.

DeAngelo, H., L. DeAngelo, and T. M. Whited (2011). Capital structure dynamics and transitory debt. *Journal of Financial Economics 99*(2), 235–261.

Disney, R., J. Haskel, and Y. Heden (2003). Restructuring and productivity growth in uk manufacturing. *The Economic Journal 113*(489), 666–694.

Dixit, A. K. and R. S. Pindyck (1994). Investment under uncertainty, 1994. *Princeton UP, Princeton.*

Doms, M. and T. Dunne (1998). Capital adjustment patterns in manufacturing plants. *Review of Economic Dynamics 1*(2), 409–429.

Fama, E. F. and K. R. French (2002). Testing trade-off and pecking order predictions about dividends and debt. *Review of Financial Studies 15*(1), 1–33.

Franklin, J., M. Rostom, and G. Thwaites (2015). The banks that said no: banking relationships, credit supply and productivity in the uk. Technical report, Centre for Macroeconomics (CFM).

Gilchrist, S. and E. Zakrajšek (2012). Credit spreads and business cycle fluctuations. *The American Economic Review 102*(4), 1692–1720.

Gourio, F. and A. K. Kashyap (2007). Investment spikes: New facts and a general equilibrium exploration. *Journal of Monetary Economics 54*, 1–22.

Haddow, A., C. Hare, J. Hooley, and T. Shakir (2013). Macroeconomic uncertainty:what is it, how can we measure it and why does it matter? Bank of England Quarterly Bulletin 2013 Q2, Bank of England.

Harris, M. and A. Raviv (1991). The theory of capital structure. *The Journal of Finance 46*(1), 297–355.

Kaplan, S. N. and L. Zingales (1997). Do investment-cash flow sensitivities provide useful measures of financing constraints? *The Quarterly Journal of Economics 112*(1), 169–215.

Khan, A. and J. K. Thomas (2008). Idiosyncratic shocks and the role of nonconvexities in plant and aggregate investment dynamics. *Econometrica 76*(2), 395–436.

Kiyotaki, N. and J. Moore (1997). Credit cycles. *The Journal of Political Economy 105*(2), 211–248.

Lancaster, T. (1992). The econometric analysis of transition data. Technical report, Cambridge University Press.

Letterie, W., G. A. Pfann, and S. Verick (2010). On lumpiness in the replacement and expansion of capital*. *Oxford Bulletin of Economics and Statistics 72*(3), 263–281.

Letterie, W. A. and G. A. Pfann (2007). Structural identification of high and low investment regimes. *Journal of Monetary Economics 54*(3), 797–819.

Myers, S. C. (1984). The capital structure puzzle. *The Journal of Finance 39*(3), 574–592.

Nilsen, Ø. A. and F. Schiantarelli (2003). Zeros and lumps in investment: Empirical evidence on irreversibilities and nonconvexities. *Review of Economics and Statistics 85*(4), 1021–1037.

Oulton, N. and G. Wallis (2015). Integrated estimates of capital stocks and services for the united kingdom: 1950-2013. Technical report, London School of Economics and Political Science, LSE Library.

Rajan, R. G. and L. Zingales (1995). What do we know about capital structure? some evidence from international data. *The Journal of Finance 50*(5), 1421–1460.

Rajan, R. G. and L. Zingales (1998). Financial dependence and growth. *The American Economic Review 88*(3), 559–586.

Shea, J. (1993). Do supply curves slope up? *The Quarterly Journal of Economics 108*(1), 1–32.

Thomas, J. K. (2002). Is lumpy investment relevant for the business cycle? *Journal of Political Economy 110*(3), 508–534.

Titman, S. and R. Wessels (1988). The determinants of capital structure choice. *The Journal of Finance 43*(1), 1–19.

Whited, T. M. (2006). External finance constraints and the intertemporal pattern of intermittent investment. *Journal of Financial Economics 81*(3), 467–502.

A

The relationship between spikes and employment

As we note in section 2, our definition of spikes is intended to capture increases in productive capacity. As a result, we would expect spikes to be associated with higher employment. Table A.1 shows that this is the case. In spike years, firms are less likely to reduce employment, and more likely to increase the size of their workforce, than any other type of event. This reassures us that our spikes are associated with genuine increases in productive capacity. We also estimate probit models to confirm that these differences are statistically significant.

Table A.1: *Relationship between spikes and changes in employment*

	Employment			
Investment rate (%)	Negative change %	No change %	Positive change %	Total %
>20 (Spike)	23.2	10.5	66.3	100.0
>20 (Discounted)	29.3	16.3	54.4	100.0
5 - 20	37.5	7.0	55.5	100.0
-5 - 5	36.6	12.9	50.4	100.0
<-5	46.8	13.2	40.0	100.0

Note: Includes firms with non-missing employment information (147,905 firm-year observations). A spike is discounted if a reduction in the capital stock in the subsequent period means that the increase in the capital stock no longer represents a 20% increase (allowing for a 10% depreciation rate), or if the spike follows a large reduction in the capital stock and merely works to undo that reduction.

Furthermore, Table A.1 distinguishes between 'discounted' spikes and other spikes. A spike is discounted if it is preceded or proceeded by a fall in the capital stock, such that (after accounting for an assumed 10% depreciation rate), the event no longer represents a substantial enough increase in productive capacity. There are 13,425 such events, accounting for 2% of all observations and a little under 10% of all events with an investment rate greater than 20%. We make this distinction in order to ensure that our spikes are driven by genuine increases in productive capacity, rather than accounting changes that do not represent real economic adjustment. Discounted spikes are no more likely to result in an increase in employment than smaller positive investment events, which we argue justifies this distinction. In our descriptive analysis, we treat discounted spikes as 'small positive investments'. To the extent that these events actually do represent large investments that overcome non-convex costs, our results will understate the importance of spikes in driving aggregate investment.

B

Full table of baseline results

Table B.1: *Main baseline results*

	(1)	(2)	(3)
j=2	0.51***	0.53***	0.53***
j=3	0.51***	0.53***	
j=4	0.52***	0.56***	0.56***
j=5	0.54***	0.59***	0.58***
j=6	0.51***	0.57***	
j=7	0.49***	0.55***	
j=8	0.49***	0.58***	
j=9	0.50***	0.59***	
j=10	0.48***	0.58***	
j=11	0.44***	0.54***	
j=12	0.47***	0.59***	
j=13	0.53***	0.68***	0.66***
j=14	0.45***	0.60***	
j=15	0.50***	0.66***	
j=16	0.60***	0.80	
j=17	0.30**	0.40	
Incorporated 1980-1989	1.01	1.01	1.01
Incorporated 1990-1999	1.21***	1.22***	1.22***
Incorporated post-2000	1.50***	1.58***	1.58***
Age	1.00***	1.00***	1.00***
Administrative	0.98	0.96	0.96
Agriculture	0.92**	0.91**	0.90**
Arts and Entertainment	0.85***	0.83***	0.83***
Education	0.87***	0.85***	0.85***
Electric,Gas and Steam	1.33***	1.37***	1.37***
Finance and Insurance	0.70***	0.67***	0.67***
Human Health	0.83***	0.81***	0.81***
Information and communication	0.90***	0.88***	0.88***
Manufacturing	0.91***	0.89***	0.89***
Other Services	0.85***	0.82***	0.82***
Professional	0.87***	0.84***	0.84***
Public Admin	0.80	0.77	0.77
Transportation and storage	1.11***	1.10**	1.10**
Water supply and sewerage	1.50***	1.52***	1.52***
Wholesale and Retail trade	0.87***	0.84***	0.84***
Size decile: 20	0.80***	0.78***	0.78***
Size decile: 30	0.68***	0.64***	0.64***
Size decile: 40	0.62***	0.57***	0.57***
Size decile: 50	0.57***	0.52***	0.52***
Size decile: 60	0.53***	0.48***	0.48***
Size decile: 70	0.45***	0.40***	0.40***
Size decile: 80	0.36***	0.32***	0.32***
Size decile: 90	0.35***	0.31***	0.31***
Size decile: 100	0.34***	0.29***	0.29***
1999	0.89***	0.88***	0.88***
2000	0.82***	0.81***	0.81***
2001	0.77***	0.74***	0.74***
2002	0.72***	0.69***	0.69***
2003	0.72***	0.69***	0.69***
2004	0.76***	0.72***	0.72***
2005	0.77***	0.73***	0.73***
2006	0.76***	0.72***	0.72***
2007	0.78***	0.74***	0.74***
2008	0.70***	0.66***	0.66***
2009	0.49***	0.46***	0.46***
2010	0.54***	0.49***	0.49***
2011	0.65***	0.60***	0.60***
N	395291	395291	395291

Exponentiated coefficients

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

In the third column, duration dummies 5 to 12 and 13 and above are grouped. The coefficients listed refer to the grouped dummies. Standard errors reported in parentheses.