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Article (Accepted Version)

Disney, Richard, Miller, Helen and Pope, Thomas (2019) Firm-level investment spikes and aggregate investment over the Great Recession. *Economica*, 87 (345). pp. 217-248. ISSN 0013-0427

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

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September 20, 2018

Abstract

It is widely accepted that firm-level investment is characterised by periods of low investment punctuated by ‘spikes’ but widely debated whether such lumpiness matters for aggregate investment. We provide new empirical evidence that variation in UK aggregate investment is driven by variation in the number of firms undertaking investment spikes; this pattern holds for all sectors and across the business cycle. We set out and estimate a tractable firm-level model of the timing of investment spikes that incorporates the effect of specific macroeconomic factors and aggregates to match observed variation in aggregate investment. Using simulations, we establish that low demand growth was the dominant factor inhibiting UK firms’ investment spikes immediately following Great Recession, while heightened uncertainty prolonged low investment and prevented a ‘v-shaped’ economic recovery. We use the Great Recession as a source of exogenous variation with which to study heterogeneity in response to aggregate shocks. We find that the minority of firms operating with persistently high-debt levels - and therefore with balance sheets more exposed to the costs of financial distress - were significantly less likely to undertake an investment spike following the recession.

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.

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1 Introduction

It is well documented that non-convex capital adjustment costs (such as fixed costs) and indivisibility of investment projects lead to firm-level investment profiles 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), Caballero (1999), Cooper et al. (1999), Nilsen and Schiantarelli (2003), Cooper and Haltiwanger (2006)). But while the prevalence of lumpiness is well-established, there remains a debate in macroeconomics on whether this microeconomic feature matters for aggregate investment (Bachmann et al. (2013)) and within microeconomics there is limited evidence on how specific macroeconomic factors affect firm-level investment spikes. Applied microeconomic work has also made limited progress in incorporating heterogeneity in firms’ responses to aggregate shocks.

The contribution of this paper is twofold. First, we use a large panel of UK company accounts for the period 1995 to 2011 to show that changes in the number of firms undertaking investment spikes account for the majority of variation in *aggregate* investment. This significantly extends a small empirical literature by showing that the importance of firms investment spikes for aggregate investment hold in services (as well as manufacturing) sectors and during both a period of stability (the ‘great moderation’ of the early 2000s) and a large recession (the financial crisis of 2008-09). Second, we set out and estimate a tractable firm-level model of the timing of investment spikes that links microeconomic investment behaviour to aggregate outcomes and allows for heterogeneity in firms’ responses to shocks. We advance previous work by incorporating the effect of specific macroeconomic variables and thereby producing a firm-level model that can be used to assess the relative importance of changes in aggregate demand, uncertainty and the cost of capital in driving firm investment spikes and that, when aggregated, matches observed variation in aggregate investment. Using simulations, we show that low demand growth was the dominant factor depressing the propensity of UK firms to spike immediately following the recession and that increased uncertainty prolonged low investment, preventing the more standard ‘v-shaped’ economic recovery.

We further advance previous work by using the 2008-09 recession as a source of exogenous variation with which to study heterogeneity in firms’ responses to shocks. Specifically, we test whether firms operating with high debt-asset targets - and therefore with balance sheets more exposed to the costs of financial distress - see a larger fall in the propensity to spike following the recession. Most firm characteristics, including capital

structure, are endogenous in a firm-level model of investment and standard instrumenting techniques are not applicable to a discrete choice setting (i.e. the choice of whether to undertake an investment spike).¹ We study heterogeneity by considering the interaction between a firm’s debt-asset ratio (measured across all years and relative to firms in the same industry) and the change in spike propensity post-recession. Identification requires that, after controlling for age, size and industry, there are no unobserved factors that differentially affect the investment response of high-debt firms to the recession. We are the first - that we know of - to incorporate capital structure into an empirical firm investment hazard and thereby contribute to a substantial literature - stemming from Bernanke (1981) - on the importance of balance sheet factors following recessions. We find that those firms that persistently operate with high debt-asset ratios saw a significantly greater fall in the probability of undertaking an investment spike between 2007 and 2009. Using counterfactual simulations we show that 20% of the observed fall between 2007 and 2009 in the share of firms spiking is attributable to the direct effect of operating with high debt. We conclude that, at least following a financial crisis, capital structure is important for understanding both the scale of the fall in aggregate investment and the heterogeneity in responsiveness across otherwise similar firms. More broadly, we conclude that macroeconomic factors are important drivers of firm-level outcomes and that a microeconomic model that incorporates lumpiness in investment can be used to replicate aggregate investment outcomes.

This paper speaks to the 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)). The debate rests heavily on the calibration of adjustment costs and price responses in DSGE models since these factors drive different predictions.² 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. A small complimentary

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¹The difficulty of incorporating heterogeneity in discrete choice settings is one reason that applied work often models firm-level investment as continuous (e.g. Melolinna et al. (2018)). Models that effectively 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 often perform poorly in explaining large investment fluctuations observed in the short-run (Baumann and Price (2007)).

²For example, Gourio and Kashyap (2007) show that the distribution of fixed costs matters in DSGE models because a more compressed distribution means that a shock is more likely to move many firms across the threshold from not investing to investing and the resulting synchronization results in an important role for the firm-level extensive margin.

literature seeks to provide empirical evidence on how changes in the timing of firm-level spikes affect aggregate investment. Cooper et al. (1999) show that ‘investment activity at the extensive margin plays a major role in aggregate investment behavior’ for US manufacturing in the period 1972-91. Gourio and Kashyap (2007) decompose variation in the aggregate investment rates of USA and Chile manufacturing firms in the 1980s and 1990s and show that the majority is due to variation in the number of firms undertaking spikes. We conduct an equivalent empirical exercise and show that not only does this result hold in the UK, it extends to service industries and to an economic downturn (the Great Recession) as well as the relatively stable period of the early 2000s. The dominant role of the extensive margin of firm-level spikes during a recession is consistent with a set of large shocks acting to synchronise firms’ actions and not being offset by aggregate price changes. We find that the magnitude of spikes and the amount of investment happening outside of spikes vary very little over the economic cycle. We interpret this evidence as supporting the conclusion of Caballero (1999) that the dynamic behaviour of aggregate investment is shaped by coordination of lumpy firm-level profiles.

Cooper et al. (1999) emphasise that microeconomic lumpiness can also have aggregate implications as shocks act to change the cross-sectional distribution of the age of the capital stock. For example, a recession that reduces the propensity of firms to invest necessarily shifts the distribution capital age which, all else equal and if the probability of a spike is increasing in capital age (i.e. the investment hazard is upward sloping), increases the proportion of firms likely to invest in future periods. The importance of this effect is an empirical question. We find that the UK’s cross-sectional distribution of capital stock age was stable throughout the 2000s and not therefore explaining movement in aggregate investment. However, average duration increased significantly in the 3 years following the recession, suggesting that this will be a channel through which microeconomic lumpiness affects aggregate investment in future years (outside our period of observation).

We follow Cooper et al. (1999) and subsequent work (including Nilsen and Schiantarelli (2003) and Whited (2006)) in studying firm-level spikes by estimating an investment hazard, which describes the probability that a firm undertakes an investment spike in a given year conditional on firm characteristics and duration since the previous spike.³ An empirical investment hazard can be motivated from a flexible model of firms

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³A 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 evidence of non-convexities as a starting point and develop an empirical model of firm investment in this setting.

facing non-convex capital adjustment costs and making a choice each period 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)).⁴ An investment hazard framework is well suited to studying the timing of investment spikes. However, previous work has been silent on which aggregate factors affect firm-level investment spike timing and have faced a common difficulty of incorporating firm heterogeneity into this discrete choice framework. We overcome these drawbacks by estimating an empirical hazard that includes measures of the aggregate environment (rather than simply allowing the annual variation to be captured by year dummies) and by using the exogenous variation provided by the Great Recession to incorporate an important dimension of firm heterogeneity in response to shocks.

In considering firm heterogeneity, we focus on capital structure, and specifically debt levels, due to its import link to investment financing and, potentially, to how different types of firms are affected by a financial crisis. 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), Whited (2006)).⁵ Yet, the ‘financial accelerator’ originally set out by Bernanke (1981) describes how an endogenous worsening of credit market conditions can amplify real adverse economic shocks. In short, shocks that 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. These potential ‘financial distress’ costs associated with high debt are seen as a key factor in determining debt-asset ratios 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

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⁴Caballero 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).

⁵Gilchrist and Zakrajšek (2012) use firm specific corporate bond spreads to assess the role of credit during the US 2008 recession, 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.

payments) against the risk associated with having a high debt level when a negative shock arises.⁶ We are able to test whether those firms that were more exposed to financial distress because they operated with persistently high debt-to-asset ratios relative to industry norms 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 method we use - i.e. exploiting the recession as a form of experiment - could in principle be used to study other forms of heterogeneity in response to shocks.

The remainder of 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 investment hazard framework, our empirical specification and baseline results. Sections 4 and 5 set out, respectively, results on the role of aggregate fluctuations in driving investment and the role of capital structure in explaining heterogeneity in response to the recession. 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. For each firm, i , we measure the year-on-year change in the tangible fixed assets stock (ΔK_i), which will capture the net effect of gross investment, disposals and 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

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⁶There 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.

⁷We 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.

⁸Depreciation refers to accounting depreciation. It will capture any revaluation of assets that are recorded on the accounts, although 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.

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) and can 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 UK firms; of the remainder, about half are part of UK headquartered groups.

Figure 2.1 compares aggregate net investment (measured by annual change in the aggregate capital stock) in our sample ('Firm Accounts') and the UK national accounts. We do not expect our series to completely replicate aggregate national accounts data given that our measure is based on the historic book value of tangible assets, we do not have a fully representative sample (we exclude some small and very large firms) and the firm accounts measure will capture some asset revaluation and sale of assets between firms.¹⁰ However, our series tracks the turning points in the aggregate series; net investment was growing in the period from 2004-2007, fell substantially during the recession and had started to rebound in 2011. This gives us confidence that our sample of firms and measure of net investment is relevant for considering the factors that drive changes in the aggregate capital stock over the economic cycle.

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.¹¹

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⁹The data are drawn from balance sheets and available commercially from Bureau Van Dijk (Amadeus). Our sample covers firms that were active at some point between 2009 and 2013, a choice driven by data availability. As such, we cannot comprehensively measure births and deaths. We exclude firms that are small, defined by Bureau van Dijk 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 from unconsolidated accounts, allowing us to isolate UK activity and avoid double counting. We check all results using a balanced panel of 21,508 firms that are present from 1995 onwards.

¹⁰If the purchase of land or capital by one firm from another UK firm (including mergers or acquisitions) is not fully reflected in the measured fall in capital of the other firm, we would overestimate aggregate capital stock growth.

¹¹This 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.

Figure 2.1: *Comparison of net investment in firm-level data and national accounts*

Notes: Net investment is measured as the change in net capital stock and 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.

For the empirical work we require a definition of which investment episodes are ‘spikes’. We follow previous studies 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 $\Delta K_{it} > 20\%$.¹² The aim is to capture those investment decisions that will have been affected by non-convex costs and that lead to a substantial increase in productive capacity. We confirm that spikes are an important driver of increases in capital stocks (more on this below) and that they are (statistically significantly) correlated to increases in employment, implying an association between spikes and increased productive capacity.¹³

¹²We clean the definition of spike to remove those net investments that are greater than 20% but preceded or proceeded by large falls in the asset stock; we assume these represent accounting, rather than genuine economic, adjustments. A 20% cut-off is used by Cooper et al. (1999) and Nilsen and Schiantarelli (2003). While they use a measure of gross investment (rather than change in net capital stock), we find a similar proportion of investment events are spikes. We test robustness of our results to alternative absolute spike definitions (15% and 30%) and to a relative firm-level measure. An alternative, used by Lettierie and Pfann (2007) and Lettierie et al. (2010), is to use a structural model to endogenously identify those investment events that are subject to non-convex costs.

¹³Details are provided in Appendix A, where we also show that ‘false’ spike events are not associated with increases in employment.

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 usually 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,¹⁴ 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). For a sub-sample of 9,547 firms for which we observe depreciation, spikes, on average account for 70% of firm’s total investment. 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 in 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. Specifically, we document the following two empirical findings: the majority of variation in aggregate investment is driven by variation in investment that happens as part of spikes; variation in investment that happens as part of spikes is driven by the extensive margin (the change in the capital weighted number of firms spiking) and not the intensive margin (the size of spikes).

The correlation between the aggregate investment rate ($\frac{I}{K_{t-1}}$) and total investment that takes place as part of spikes ($\frac{I^s}{K_{t-1}}$), when both series are linearly detrended, is 0.96; that is, aggregate investment is larger when the amount of investment taking place as part of spikes is larger.¹⁵ Following an approach akin to

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¹⁴27.5% 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.

¹⁵The correlation is 0.98 if the series are not detrended.

Gourio and Kashyap (2007), we decompose variation in the aggregate investment rate $\frac{I}{K_{t-1}}$ into variation that occurs as part of spikes $\frac{I^s}{K_{t-1}}$ and variation that occurs as part of other events $\frac{I^{ns}}{K_{t-1}}$.¹⁶ We conduct this decomposition for the sub-sample of firms for which we observe gross (of depreciation) investment.¹⁷ The share of variation in aggregate investment accounted for by variation in investment that takes place as part of spikes, measured as $Cov(\frac{I}{K_{t-1}}, \frac{I^s}{K_{t-1}})/Var(\frac{I}{K_{t-1}})$, is 79%.¹⁸ This result is in line with that of Gourio and Kashyap (2007), who decompose variation in aggregate manufacturing investment in Chile and the US and find covariance terms of 86% and 97% respectively.

Figure 2.2: *Decomposition of investment that happens as part of investment spikes*

Notes: Decomposition described in equation 2.1.

¹⁶'False spikes' (see footnote 11) are classified in the non-spike 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.

¹⁷Using a measure of net investment mechanically understates the role of spikes because the absence of a spike appears as a fall in investment (i.e. absent any investment we observe a depreciation of the capital stock rather than no change), such that variation driven by the propensity to spike will in part be attributed to variation in negative investment.

¹⁸The contribution of $\frac{I^s}{K_{t-1}}$ and $\frac{I^{ns}}{K_{t-1}}$ sum to 1 by construction. This method attributes the covariance terms between the investment of the two groups equally to each group (i.e. $Cov(\frac{I}{K_{t-1}}, \frac{I^s}{K_{t-1}})/Var(\frac{I}{K_{t-1}}) = (Var(\frac{I^s}{K_{t-1}}) + Cov(\frac{I^s}{K_{t-1}}, \frac{I^{ns}}{K_{t-1}}))/Var(\frac{I}{K_{t-1}})$). The full decomposition into variance and covariance terms is: $Var(\frac{I}{K_{t-1}}) = Var(\frac{I^s}{K_{t-1}}) + Var(\frac{I^{ns}}{K_{t-1}}) + 2Cov(\frac{I^s}{K_{t-1}}, \frac{I^{ns}}{K_{t-1}})$. The share of total variance accounted for by the covariance between spike and non-spike events, i.e. $Cov(\frac{I^s}{K_{t-1}}, \frac{I^{ns}}{K_{t-1}})/Var(\frac{I}{K_{t-1}})$, is small (-6%).

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

$$\frac{I^s}{K_{t-1}} = \frac{I^s}{K_{t-1}^s} \frac{K_{t-1}^s}{K_{t-1}} \quad (2.1)$$

These series are plotted in 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 ($\frac{I^s}{K_{t-1}^s}$) or extensive ($\frac{K_{t-1}^s}{K_{t-1}}$) 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. 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). While the average investment rate conditional on spiking is relatively stable over time, the extensive margin tracks with the aggregate rate.

Our results support the conclusion of Gourio and Kashyap (2007) and Bachmann et al. (2013) that aggregate investment is largely driven by the extensive margin decision over whether to undertake an investment spike and extend that finding to services sectors and to a period that includes both a great moderation (the early 2000s) and a large financial crisis (2008-09). We conclude that understanding variation in aggregate investment requires understanding firms' propensity to perform spikes.

3 Firm-level investment hazards

3.1 Empirical specification

We explore what explains variation in investment across firms and time by modelling 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). 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.¹⁹ 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 procyclical, such that the probability of a spike increases when profitability is higher.²⁰

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 ($\theta(\cdot)$) of the form:

$$\theta(t, X) = v_i \theta_0(t) \exp(\beta' X) \quad (3.1)$$

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. v_i represents unobserved firm-level heterogeneity. Previous work has differed mainly in the specification of X and the assumed functional form of v_i .

We follow this approach in estimating 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 undertake more than one spike event, s .²¹ We assume that time is discrete and parameterize the hazard as a logistic function. The probability (hazard rate) that the length

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¹⁹The 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).

²⁰The 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.

²¹Allowing 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.

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 (v_i) is therefore:

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

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 $v_i \sim \mathcal{N}(0, 1)$ (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.

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:

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

where t_i and $\bar{t}^i$ reflect the first and last year respectively for which a firm is in the estimation sample. 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).

Table 3.1: *Estimation sample summary*

	Mean	SD	P10	P90
Main 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: The estimation sample excludes (from the full sample used in Section 2) firms that never spike. The debt sample includes only firms in the balanced panel (present from 1995 onwards) with debt-asset information in all years and no year in which the debt-to-asset ratio exceeds 200%. The statistics are measured over the years 1998-2011, which we take as our estimation sample (there are very few firms for which duration can be measured before 1998). Aggregate variables are from the following 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).

3.3 Baseline hazard

Table 3.2 shows the baseline results. The coefficients are odds ratios. The hazard is upward sloping once unobserved heterogeneity is controlled for (column 2).²² 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 indicate the durations at which the increase in the probability of a spike is statistically significant.²³

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 find no evidence that the *slope*, rather than the level, of the hazard differs significantly across these characteristics. Year dummies capture substantial annual variation in the proportion of firms undertaking and investment spike 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) similarly 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.²⁴

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²²In all specifications the probability of spike is highest at duration equals 1 (i.e. in the period immediately after a spike). Large investment episodes may be spread across multiple periods, explaining this result.

²³We conduct a series of F-tests of whether a given duration dummy is statistically significantly higher than all previous dummies. The grouping in column 3 of Table 3.2 and Figure 3.1 represent the result that the coefficient on D_4 is the first that is statistically significantly higher than D_2 ; D_5 is higher than D_4 ; D_{13} is higher than D_5 . We show groupings only to illustrate that significance tests confirm that the hazard is upward sloping; we do not use groups in any subsequent analysis.

²⁴Firms 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 to define a spike; results shown in Table C.1 in the Appendix.

Table 3.2: *Baseline main*

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

Notes: Hazards drawn for a manufacturing firm in the 5th size decile, 30 years old and incorporated between 1980-89. The solid (dashed) lines are based on the specification in column 2 (3) of Table 3.2. The grouped dummies indicate the durations at which the increase in the probability of a spike is statistically significant.

4 Variation over the business cycle

Our first contribution to the investment hazard literature is to allow the hazard to vary with measures of 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.²⁵

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 ‘Great 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

²⁵The previous literature on investment hazards was mainly interested in identifying a hazard slope and captured annual variation through the use of year dummies.

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.²⁶ The variables are summarised in Table 3.1. In estimation we transform variables to have zero mean and unit standard deviation such that the coefficients can be interpreted as 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 for most firms, while the cost of capital may matter more for the size of spike (the intensive margin). There is also likely to be substantial heterogeneity in the effect of finance costs across firms - while the cost of capital may not have a large effect on the timing of spikes for most firms, it may be very important for subsets of 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

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²⁶It 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)).

cost of capital leads to a 9% reduction in spike probability.²⁷ 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).²⁸

Table 4.1: *Model with aggregate variables*

	(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: The specification underlying column 1 is the same as the baseline except year dummies are replaced by aggregate variables. Column 2 adds an interaction between aggregate variables and an indicator for firms incorporated after 2000 (a 'new' firm). Column 3 excludes firms incorporated after 2000. The three aggregate variables are transformed by subtracting the mean and dividing by the standard deviation. These specifications include the full set of variables (other than year dummies) included in column 2 of table B.1. A subset of coefficients are shown for brevity, but all remain largely unchanged from the baseline specification.

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

²⁷The 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

²⁸There may also be idiosyncratic changes to the cost of finance that are important for firms decisions. 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 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.

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.²⁹

4.1 Simulations of aggregate investment from firm hazards

We 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 aggregate 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 is relevant for studying 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 firm will spike. Based on this we recalculate the subsequent path of firm-level duration and repeat the exercise for each following year.³⁰ Panel A of Figure 4.1 shows the actual spike frequency (i.e. the proportion of firms that we observe undertaking a spike 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.

We also use simulations to demonstrate which of the aggregate variables was most important in driving the aggregate trend.³¹ 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 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.

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²⁹Results of robustness checks are available on request.

³⁰For 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.

³¹Changes in the aggregate environment, combined with the estimated coefficients, describe which changes were most important in driving the post-2007 investment slump. The reduction in investment was most severe in 2009 and 2010. Our measure of uncertainty was 0.5 (2.1) standard deviations above the mean in 2009 (2010), the weighted average cost of capital was 1.0 (1.4) standard deviations above the mean in 2009 (2010) and GDP growth was 3.3 (less than 0.1) standard deviations below the mean in 2009 (2010).

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, simulations are re-run with each of the cost of capital, GDP or uncertainty held at their pre-recession sample mean.

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 undertake a spike in a year 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 that we observe.³² Common shocks (whether captured through year dummies or aggregate variables) are significantly more 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).

³²As 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.

5 Firm investment heterogeneity and capital structure

5.1 Capital structure, financial distress and investment

There was substantial heterogeneity in firm-level investment during and immediately following the crisis. We consider whether part of this variation can be explained by firms' capital structure. Specifically, we test 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).³³

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).³⁴ The premium on external finance may increase by more for firms with high debt if adverse financial conditions are accompanied by a "flight to quality", whereby investors and banks prefer lower return, safer assets (Bernanke et al. (1996)). One would expect these 'financial distress' costs to be more pronounced for firms operating with higher debt-to-assets ratios.³⁵

There is no consensus view on how capital structure relates to investment; the two main competing theories of capital structure - the pecking order theory and trade-off theory (Harris and Raviv (1991) describe)

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³³See also Bernanke (1983), Bernanke and Gertler (1989), Bernanke et al. (1996) and Kiyotaki and Moore (1997).

³⁴In 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 internal resources.

³⁵For 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 of 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. Within our sample of firms, which excludes large publicly traded firms, differences in creditworthiness are likely to be less pronounced.

- have both been shown to match data poorly.³⁶ 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 of 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.³⁷ 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 (the benefits of debt finance) 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 current and non-current loans and liabilities owed to creditors to total fixed assets). This is despite the fact that a spike implies a substantial increase in the denominator of the ratio. Periods of investment inaction are characterised, in general, by falling or static debt-to-asset ratios. The 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).

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³⁶A 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)).

³⁷DeAngelo 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.

Table 5.1: *Investment and capital structure*

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 the balanced panel with information on debt and no year in which the debt-asset ratio is greater than 200%.

5.2 Classifying firms as high-debt

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).³⁸

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.

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

³⁸The 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.

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 (63.2%) are in the lowest quintile at least once and half (50.9%) are in the highest quintile at least once (Table 5.3).³⁹

We class as high-debt those firms with a debt-to-asset ratio that is in the top 60% of the industry-year distribution in all years. We consider this an indication of firms that operate with a high debt target. This group represents 23.3% 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%.

Table 5.2: *Debt quintile transitions*

Debt quintile (t)	Debt quintile (t+1)					Total
	1	2	3	4	5	
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.

5.3 Estimating the role of capital structure

We test whether high-debt firms are less likely to undertake an investment spike in the post recession period by interacting year dummies with the indicator of whether a firm has been classified high-debt. We are using (what we argue is) exogenous variation caused by the Great Recession to study the differential response

³⁹35% 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.

of firms with differing capital structures. Table 5.4 sets out the results. High-debt firms are statistically significantly more likely to undertake a spike in general (column one) but are statistically significantly less likely to undertake a spike following the recession (column two).

We cannot interpret these results as the causal effect of operating with high-debt on investment.⁴⁰ We can interpret the interaction between the indicator of whether a firm is high-debt and the recession year dummies (i.e. ‘constant high-debt*09’) as showing the causal impact of the financial distress costs of the recession on investment under the assumption that there are no unobserved factors that are correlated with how a high-debt firm responds to the recession and how likely they are to undertake a spike. This identification assumption, which we think reasonable, is significantly weaker than would be needed to identify the direct effect of capital structure on spike propensity. One type of concern is that changes in the aggregate environment (for example in demand) may have affected high-debt firms more because such firms were on average also more likely to be in a particular industry or at a point in their life cycle. The large number of controls included in the hazard regression (including those for industry, age and size) help mitigate such concerns.⁴¹ The results - which are also presented in Figure 5.1 - show that the probability of a high-debt target firm undertaking a spike fell by 8 percentage points between 2007 and 2009, compared with only 5 percentage points for other firms. The interpretation of this difference as the direct effect of being 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 is supported by the finding that the effect is strongest in 2009, which was the year in which commercial interest rates and our measure of the weighted average cost of capital were highest.

In columns 3 and 4 of Table 5.4 we show that this result is robust to including a contemporaneous measure of a firm’s debt rank (within an industry) and the interaction of the contemporaneous measure with year dummies. Again, these variables are endogenous (such that we cannot separately identify investment dynamics from any direct effects of contemporaneous debt levels on investment choices), but their inclusion addresses a possible concern that the result in column 2 is driven by those firms that had high debt in the years directly preceding the recession. If this were the case, we may be capturing any interactions between

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⁴⁰The debt target of the firm (and whether a firm is in the group we define as ‘high-debt’) may be correlated with a range of unobserved firm characteristics. For example in the dynamic trade-off theory of capital structure 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).

⁴¹The finding that high debt firms fare worse in 2009 is robust to the inclusion of interaction terms between the 2009 year dummy and the set of baseline covariates (for age, size and industry).

investment dynamics (as captured by temporarily high debt) and the recession rather than the effect of operating with persistently high debt. Adding contemporaneous measures leaves the estimated coefficients on the interactions between constant high-debt and the recession unchanged. That is, the effect is not simply driven by the contemporaneous debt position.

Column 5 shows that the point estimate on the interaction between high-debt and the 2009 dummy is very similar if we instead define high-debt firms as those always operating in the top 40% of their industry debt-asset distribution, although the share of the sample that have high debt using this definition is much lower and the result no longer statistically significant.⁴² The results are also robust to categorising firms as high-debt based only on data from the pre-recession years (i.e. not on all years as in the main results), which addresses the concern that by requiring that firms have high-debt levels both before and during the recession we capture only those firms that were unable to reduce their debt levels when the recession hit. We also 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 being driven by the way in which we define high debt firms.

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 percentage points higher (12.5% vs 11.9%), which accounts for 20% of the observed reduction in spike probability between 2007 and 2009.⁴³

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⁴²Table C.4 in the Appendix presents results for additional alternative definitions of ‘high-debt’.

⁴³Simulations 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)	(5)
2008	0.66***	0.66***	0.66***	0.66***	0.66***
2009	0.44***	0.46***	0.46***	0.52***	0.49***
2010	0.47***	0.48***	0.48***	0.48***	0.47***
Constant high debt	1.11***	1.13***	1.16***	1.16***	1.19***
Constant high debt*08		1.01	1.01	1.01	1.00
Constant high debt*09		0.80***	0.80***	0.76***	0.83
Constant high debt*10		0.92	0.92	0.92	0.96
Debt/Assets below 20th percentile			0.97	0.98	0.96*
Debt/Assets in 20-40th percentile			0.98	1.00	0.98
Debt/Assets in 60-80th percentile			0.98	0.98	0.99
Debt/Assets in 80th-90th percentile			0.92**	0.92**	0.92**
Debt/Assets above 90th percentile			0.90***	0.90***	0.88***
Debt/Assets below 20th*09				0.88	0.93
Debt/Assets in 20th-40th*09				0.73**	0.77*
Debt/Assets in 60th-80th*09				0.89	0.86
Debt/Assets in 80th-90th*09				0.99	0.97
Debt/Assets above 90th*09				0.97	0.95
N	201280	201280	201280	201280	201280
N (high debt)	46645	46645	46645	46645	19659

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. In columns 1-4, a firm is defined as constant high debt if their debt to asset ratio is in the top 3 quintiles of their industry in every year. 3,898 of the 16,745 firms in the sample (23.3%) are classified as high debt. Column 5 presents results where constant high debt firms are required to have a debt to asset ratio always in the top 2 quintiles of their industry.

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. We take as a starting point the body of evidence that firm-level 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 use exogenous variation provided by the Great Recession to study the role of firm capital structures in driving heterogeneous responses to the crisis.

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 cyclicalities in aggregate investment. In particular, variation in aggregate investment is driven by the frequency rather than the magnitude of investment spikes. This finding generalises previous results to the UK, but also to services sectors and to an economic downturn. Using a firm-level duration model, 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 find 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 distress 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. We present a firm-level investment hazard with aggregate characteristics as 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.

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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. In support of this, Table A.1 shows that firms are less likely to reduce employment and more likely to increase the size of their workforce in years in which they undertake an investment spike (relative to years in which no spike occurs). This is an indication that spikes are associated with genuine increases in productive capacity. We estimate probit models to confirm that these differences are statistically significant.

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

Investment rate (%)	Employment			Total %
	Negative change %	No change %	Positive change %	
>20 (Spike)	23.2	10.5	66.3	100.0
>20 (False)	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.

Table A.1 distinguishes between ‘false’ spikes and other spikes. A spike is deemed false 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 an increase in the capital stock of at least 20%. 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. False spikes are no more likely to result in an increase in employment than smaller positive investment events.

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.

C

Additional robustness results

Tables C.1, C.2 and C.3 show the robustness of results to changes in the definition of a firm-level investment spike. In each of the three tables, the first column repeats the main result from the paper, in which an investment spike is defined as an investment rate greater than 20%. Columns 2 and 3 use alternative absolute cut-offs ($I_i/K_i > 15\%$ and $I_i/K_i > 30\%$ respectively) and column 4 presents a firm-specific cut-off, defined as the larger of 2.5 x the firm's median investment or 10%. We favour using an absolute over a relative cut off because it is more robust to two issues: (i) when a firm is observed for a short time there is relatively little information to calculate what is normal for a firm and therefore what constitutes a spike; (ii) median firm level (net) investment is usually negative (the capital stock is usually depreciating between spikes) and we would not want to call any positive investment a spike.

Table C.1: *Baseline hazard robustness to alternative definitions of an investment spike*

	(1)	(2)	(3)	(4)
j=2	0.53***	0.51***	0.54***	0.68***
j=3	0.53***	0.52***	0.55***	0.71***
j=4	0.56***	0.53***	0.57***	0.73***
j=5	0.59***	0.56***	0.61***	0.75***
j=6	0.57***	0.55***	0.58***	0.71***
j=7	0.55***	0.53***	0.60***	0.66***
j=8	0.58***	0.55***	0.58***	0.65***
j=9	0.59***	0.55***	0.59***	0.62***
j=10	0.58***	0.53***	0.62***	0.62***
j=11	0.54***	0.57***	0.56***	0.63***
j=12	0.59***	0.54***	0.58***	0.60***
j=13	0.68***	0.60***	0.64***	0.60***
j=14	0.60***	0.52***	0.60***	0.56***
j=15	0.66***	0.52***	0.52***	0.38***
j=16	0.80	0.71*	0.62*	0.61*
j=17	0.40	0.45	0.62	0.44
incorp 1980-89	1.01	0.99	1.04	1.01
incorp 1990-99	1.22***	1.18***	1.29***	1.07***
incorp 2000-09	1.58***	1.50***	1.69***	0.89***
Age	1.00***	1.00***	1.00***	1.00
Administrative	0.96	0.97	0.90***	0.90***
Agriculture	0.91**	0.95	0.83***	0.91***
Arts and Entertainment	0.83***	0.83***	0.83***	0.85***
Education	0.85***	0.87***	0.81***	0.93**
Electric,Gas and Steam	1.37***	1.34***	1.39***	0.98
Finance and Insurance	0.67***	0.65***	0.66***	0.71***
Human Health	0.81***	0.82***	0.79***	0.85***
Information and communication	0.88***	0.88***	0.86***	0.85***
Manufacturing	0.89***	0.92***	0.85***	0.94***
Other Services	0.82***	0.83***	0.78***	0.84***
Professional	0.84***	0.85***	0.80***	0.87***
Public Admin	0.77	0.78	0.80	0.86
Transportation and storage	1.10**	1.14***	1.01	1.02
Water supply and sewerage	1.52***	1.59***	1.37***	1.08
Wholesale and Retail trade	0.84***	0.86***	0.81***	0.88***
Size decile: 20	0.78***	0.80***	0.74***	0.84***
Size decile: 30	0.64***	0.66***	0.58***	0.68***
Size decile: 40	0.57***	0.60***	0.52***	0.59***
Size decile: 50	0.52***	0.55***	0.46***	0.53***
Size decile: 60	0.48***	0.51***	0.40***	0.47***
Size decile: 70	0.40***	0.45***	0.33***	0.42***
Size decile: 80	0.32***	0.36***	0.26***	0.35***
Size decile: 90	0.31***	0.35***	0.24***	0.34***
Size decile: 100	0.29***	0.34***	0.23***	0.32***
1999	0.88***	0.86***	0.88***	0.85***
2000	0.81***	0.79***	0.83***	0.77***
2001	0.74***	0.72***	0.80***	0.71***
2002	0.69***	0.67***	0.71***	0.63***
2003	0.69***	0.67***	0.71***	0.62***
2004	0.72***	0.71***	0.75***	0.67***
2005	0.73***	0.72***	0.76***	0.68***
2006	0.72***	0.70***	0.75***	0.67***
2007	0.74***	0.72***	0.77***	0.69***
2008	0.66***	0.64***	0.69***	0.64***
2009	0.46***	0.44***	0.48***	0.42***
2010	0.49***	0.48***	0.52***	0.45***
2011	0.60***	0.58***	0.64***	0.52***
N	395291	414693	358913	427099
Exponentiated coefficients				
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$				

These results are the analogue to column 2 of of Table 3.2 in the main paper. Coefficients reported as odds ratios. The base option is a firm at duration 1 incorporated before 1980 in the first decile, in the Accommodation and food sector in 1998.

Table C.2: *Model with aggregate variables: robustness to alternative definitions of an investment spike*

	(1)	(2)	(3)	(4)
Incorporated 1990-1999	1.16***	1.12***	1.23***	1.02
Incorporated post-2000	1.46***	1.40***	1.57***	0.84***
Electric,Gas and Steam	1.37***	1.33***	1.39***	0.98
Finance and Insurance	0.67***	0.65***	0.66***	0.71***
Manufacturing	0.89***	0.92***	0.85***	0.94**
Transportation and storage	1.10***	1.14***	1.01	1.03
Water supply and sewerage	1.52***	1.59***	1.36***	1.09
Wholesale and Retail trade	0.85***	0.86***	0.81***	0.88***
Size decile: 50	0.52***	0.55***	0.46***	0.52***
Size decile: 100	0.30***	0.34***	0.23***	0.31***
Annual GDP growth	1.09***	1.09***	1.08***	1.08***
Policy uncertainty	0.92***	0.92***	0.93***	0.89***
Weighted average cost of capital (t-1)	0.97***	0.98***	0.95***	1.00
N	395291	414693	358913	427099

Exponentiated coefficients

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

These results are the analogue to column 1 of Table 4.1 in the main paper. Coefficients and base option as in Table C.1. A subset of coefficients on firm characteristics and duration are recorded for brevity, but all remain broadly unchanged from the baseline specification.

Table C.3: *Debt and the recession: robustness to alternative definitions of an investment spike*

	(1)	(2)	(3)	(4)
2008	0.66***	0.65***	0.69***	0.65***
2009	0.52***	0.47***	0.52***	0.48***
2010	0.48***	0.48***	0.51***	0.48***
Constant high debt	1.16***	1.15***	1.17***	1.18***
Constant high debt*08	1.01	1.01	0.97	0.99
Constant high debt*09	0.76***	0.79***	0.78**	0.84**
Constant high debt*10	0.92	0.91	0.87	0.91
Debt/Assets below 20th percentile	0.98	0.97	0.95*	0.97
Debt/Assets in 20-40th percentile	1.00	1.00	0.97	1.00
Debt/Assets in 60-80th percentile	0.98	0.97	0.97	1.00
Debt/Assets in 80th-90th percentile	0.92**	0.91***	0.95	0.92***
Debt/Assets above 90th percentile	0.90***	0.87***	0.88***	0.89***
Debt/Assets below 20th*09	0.88	0.94	0.93	0.92
Debt/Assets in 20th-40th*09	0.73**	0.76**	0.68**	0.84*
Debt/Assets in 60th-80th*09	0.89	0.96	0.96	0.97
Debt/Assets in 80th-90th*09	0.99	0.96	0.84	0.93
Debt/Assets above 90th*09	0.97	1.05	1.03	0.99
N	201280	212791	180099	221934

Exponentiated coefficients

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

These results are the analogue to column 4 of Table 5.4 in the main paper. Coefficients and base option as in Table C.1

Table C.4 provides further robustness to the results on high debt firms and the recession (Table 5.4). The first five columns of Table C.4 shows robustness of results to changes in the definition of which firms are deemed to be ‘constant high-debt’. The first column replicates the result from the main paper (column 4 of Table 5.4), where a firm is deemed high-debt if the debt-to-asset ratio is in the top 3 quintiles of the industry-year distribution in every year. The definitions of ‘constant high debt’ used in the following columns

are as follows: (2) debt-to-asset ratio in the top 2 quintiles of the industry-year distribution in every year; (3) the firm's modal industry-year quintile is the top quintile; (4) equivalent to the baseline definition, but with criteria based only on the pre-recession years (1995-2007); (5) the set of firms in the baseline group and for which the modal industry-year quintile is the top quintile.

The sixth column of Table C.4 allows for differential impacts of the recession based on observables. Specifically, we interact the full set of firm-level controls in our baseline specification with the 2008, 2009 and 2010 year dummies. The results are unchanged, so the coefficient on our 'Constant high-debt*09' dummy variable is not being driven by observable compositional differences between high debt and other firms.

Table C.4: *Debt and the recession: robustness to alternative definitions of 'high-debt' and differential recession trends*

	(1)	(2)	(3)	(4)	(5)	(6)
2008	0.66***	0.66***	0.66***	0.65***	0.66***	0.65***
2009	0.52***	0.49***	0.49***	0.51***	0.49***	0.71
2010	0.48***	0.47***	0.48***	0.48***	0.47***	0.72
Constant high debt	1.16***	1.19***	1.32***	1.11***	1.25***	1.15***
Constant high debt*08	1.01	1.00	1.01	1.03	1.02	1.01
Constant high debt*09	0.76***	0.83	0.92	0.80**	0.90	0.79**
Constant high debt*10	0.92	0.96	0.92	0.93	1.00	1.01
Debt/Assets below 20th percentile	0.98	0.96*	0.96*	0.98	0.96*	0.98
Debt/Assets in 20-40th percentile	1.00	0.98	0.98	1.00	0.98	1.00
Debt/Assets in 60-80th percentile	0.98	0.99	0.99	0.99	1.00	0.98
Debt/Assets in 80th-90th percentile	0.92**	0.92**	0.85***	0.93**	0.90***	0.92**
Debt/Assets above 90th percentile	0.90***	0.88***	0.78***	0.91***	0.85***	0.90***
Debt/Assets below 20th*09	0.88	0.93	0.92	0.88	0.92	0.83*
Debt/Assets in 20th-40th*09	0.73**	0.77*	0.77*	0.74**	0.77*	0.74**
Debt/Assets in 60th-80th*09	0.89	0.86	0.84*	0.88	0.84*	0.88
Debt/Assets in 80th-90th*09	0.99	0.97	0.96	0.98	0.95	0.98
Debt/Assets above 90th*09	0.97	0.95	0.95	0.95	0.93	0.95
N	201280	201280	201280	201280	201280	201280
N (high debt)	46645	19659	35171	52930	19334	46645

Exponentiated coefficients

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

The full set of baseline covariates are included, but not shown. N (high debt) shows the number of observations associated with high debt firms under each of the definitions.