Expansionary Investment Activities:
Assessing Equipment and Buildings in Productivity

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Abstract:
We study firm-level expansionary investment activities in *both* equipment *and* buildings – so-called investment spikes. Our identification strategy decomposes firm investment spikes into three streams: a spike in equipment only, buildings only or a simultaneous spike. Empirically, we find that the timing and size of investment in equipment and buildings are not independent. Firms conducting a simultaneous spike enhance firm scale more than in the case of a spike in equipment or buildings alone. Employment growth occurs when a firm builds structures. Investment in equipment affects the optimal input mix and high productivity in equipment and buildings provides investment timing signals. In low-tech sectors firm production growth depends on investment in buildings. In contrast, a necessary condition for firms in high-tech sectors to grow their production is investment in equipment.

Keywords: Investment Spikes, Equipment, Buildings, Interrelation, Scale, Productivity, Input Mix, Efficiency, Low- and High-Tech, Labour Intensity

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Introduction

Capital adjustment patterns are lumpy. Generally, annual firm investment activity is low until there is an investment trigger. Then, evidence suggests, firms experience investment spikes (Doms and Dunne, 1998; Cooper *et al*., 1999; Cabellero *et al*., 1995). This investment pattern holds internationally (Nilsen and Schiantarelli, 2003; Letterie and Pfann, 2007) and for expansionary investment and capital replacement (Letterie *et al.*, 2010). Economically, these irregular investment patterns have implications for understanding the dynamic behaviour of micro level investment decisions by firms and may have implications for macroeconomic activity (Cabellero *et al.* 1995; Caballero 1999; Caballero and Engel 1999; Bachman *et al.*, 2013) or not (Thomas, 2002).

A nascent literature investigates investment in equipment to understand its triggers and economic productivity after investment spikes occur. Empirical analysis is consistent with the notion of firm expansion. At the time of an investment burst, both output and the number of employees increase (Sakellaris, 2004; Nilsen *et al.*, 2008). Firms also invest in the latest technologies incorporated in equipment to stave off economic obsolescence (Goolsbee, 1998), to adopt changes in production technology (Klassen and Whybark, 1999), or derive a new optimal mix between labour and capital (Acemoglu, 2015; Dunne *et al.*, 1989; Hémous and Olsen, 2015). Moreover, subsequent to the investment spike, firms may anticipate improved productivity, but quite some economists have found that there is no improvement in labour productivity (Power, 1998; Sakellaris, 2004; Nilsen *et al.*, 2008). This phenomenon may point at a "missing link" between technology, investment and productivity (Power, 1998).

We have learned that microeconomic models of firm behaviour need to incorporate fixed adjustment costs, investment irreversibility and / or indivisibilities to be able to replicate the behaviour observed in firm investment data (Cooper and Haltiwanger, 2007; Bloom, 2009; Asphjell *et al*., 2014). In this way, these studies inform the extensive margin in microeconomic investment. A caveat of this area of research is the sole focus on identifying investment is capital equipment, but not other components of capital that are factors of production.

This paper explores the consequences of firm level investment spikes in productive capital, like equipment, *and* non-productive capital, like buildings. Hence, in our study we also investigate the impact of investment spikes concerning structures. By doing that, we (i) separate expansionary investment from that of replacement – which further calibrates the extensive margin; (ii) identify distinct investment profiles of the firm – in buildings, equipment, or a simultaneous spike of both. Our contribution is to examine how the composition of firms' investment spikes affects the scale of production and employment, productivity, the input mix and operational efficiency.

We begin our analysis by developing a theoretical framework to guide our empirical analysis, which looks at firm investment spikes across time periods and the arbitrary timing in investment spike event patterns across firms to guide our empirical analysis. To operationalize this model, we employ a micro-level panel dataset provided by Dutch Statistics (CBS) covering the period 2000-2008. The dataset contains information concerning investment in buildings and equipmen and firm level investment decisions and production statistics for manufacturing industries in the Netherlands. Firm level data allows us to identify when an investment spike in either equipment or buildings occurs and when a simultaneous spike occurs in both buildings and equipment. Our empirical strategy reveals individual firm's microeconomic activity before and after an episode of intense capital adjustment. To obtain more detailed insight we follow Robertson *et al.*, (2009) and Czarnitzki and Thorwart (2012) in accounting for differences across high- and low-tech sectors. Additionally, we conduct an analysis of firms by cross-sections in labour intensity of industries (Ramirez *et al.*, 2005).

Buildings are an important production factor; they house employees and shield equipment. In our analysis, we investigate whether investment in structures drives employment, production technology and firm capacity in manufacturing industries, and also distinguish industries by research and labour intensity. We find that identifying investment spikes in buildings and equipment has implications for the productivity literature and principally, how we measure the extensive and intensive margins of productivity. Our empirical results document to us that investment in buildings and equipment is interrelated - the timing and size of investment in equipment and buildings are not independent phenomena. We also find that adding investments in buildings to a firm's decision set improves understanding of key firm level performance and production metrics.

Principally, our results point to further investigation of the extensive margin of firm investment activity and production and find that the extensive margin can be decomposed further and shown to understand how we measure productivity. We observe that 14 percent of the datapoints concern spikes related to capital equipment expansion. However, single equipment investment spikes, not coinciding with spikes in buildings, are observed in 11 percent of the observations. Thus, neglecting simultaneity of spikes in buildings and equipment represents inadequately the breadth of the extensive margin. In fact, we show that about twenty percent of the equipment spikes, i.e. those that concur with building spikes, have a very different character according to our empirical results.

Moreover, the decomposition further calibrates an understanding of the intensive margin. A measure of the investment size is more informative when including both expenditures on buildings and equipment. Our empirical results document that firms who signal expansion through simultaneous investment spikes in both buildings and equipment experience a higher post investment expansion in production and number of workers, than firms that experience a spike in either equipment or buildings only. However, the results also reveal that large investments do not improve firm level productivity. Instead high-productivity acts as a signal of when to invest, where before an investment takes place firm productivity is high and afterwards it decreases.

Finally, our empirical study highlights that production process mixes between building and equipment impact productivity and employees different and are fundamentally different across industry sectors. Our results suggest investment in equipment tends to increase the employee wage rate at a firm on average; based on this result we infer that firms buying new machinery display an increase in the skilled worker ratio. Likewise we deduce firms investing in structures hire more unskilled workers. Furthermore, when firms invest in equipment, the labour intensity decreases as well. These latter findings suggest that capital investments also affect the production technology employed by the firm. In addition, we show firm investments affect operational efficiency. Firms in high-tech sectors rely more on investment in equipment to be able to grow, whereas companies in low-tech sectors need investment in buildings to be able to expand.

Our conclusion is that to properly understand firm level production processes one should incorporate investment in buildings. To understand further our analyis, we proceed with providing a theoretical grounding in Section 1. Next, Section 2 describes the data isolating details on firm level panel data and our investment spike identification strategy. We outline our methodology including our model of investment spikes and estimation strategy in Section 3. In Section 4, we report empirical results and in Section 5 an industrial cluster analysis. Finally, we discuss our findings in relation to the investment literature in Section 6.

1. Theoretical Grounding

Few recent studies have analysed firm decisions along more than one dimension when it comes to input demand. Those that have done so usually have focused on two types: investment in equipment and labour (Bloom, 2009; and Asphjell *et al.*, 2014) and investment in equipment and structures (Bontempi *et al.*, 2004; Del Boca et al., 2008). An exception is Ghosal and Nair-Reichert (2009) who distinguish between four categories: investment in mechanical devices, chemical devices, monitoring devices and information technology. Bloom and Asphjell *et al.* conclude that adding a margin to the decision problem of the firm improves the empirical performance of models. Often part of the model relating to a relatively flexible input factor (labour when compared to equipment, or equipment when compared to buildings) gains accuracy in being able to explain the data when analysed jointly with the less flexible factor. This finding reflects the insight by Eberly and van Mieghem (1997) that the adjustment timing of flexible input factors is driven by the fundamentals of the less flexible inputs as well.

We present a simple model to guide our empirical analysis of firm level investment decisions. Consider a firm that at time *t* uses two capital inputs – the stock of buildings is given by K_t^B and the stock of equipment is given by K_t^E - to produce a non-storable output. The firm's objective function is given by:

$$(1) \qquad V_t = E_t \sum_{s=0}^{\infty} \beta^s \left[F\left(A_{t+s}, K_{t+s}^B, K_{t+s}^E\right) - C\left(I_{t+s}^B, K_{t+s}^B, I_{t+s}^E, K_{t+s}^E\right)\right]$$

The term E_t indicates that expectations are taken with respect to information available at time *t*. The discount rate is given by β with $0 < \beta < 1$. The expression $F\left(A_t, K_t^B, K_t^E\right) = p_t Y_t - w_t L_t$ denotes sales minus wage costs. For instance, consider a standard Cobb-Douglas production technology with decreasing returns to scale, $Y_t = \phi_t \left(K_t^B\right)^{\nu} \left(K_t^E\right)^{\mu} \left(L_t\right)^{\kappa}$, where *Y*, *L* and ϕ denote production, labour and a technology parameter respectively and where $0 < \nu, \mu, \kappa < 1$. Labour is a fully flexible factor of production. Let $p_t = \varphi_t \left(Y_t\right)^{-\frac{1}{\varepsilon}}$ denote an isoelastic demand function where $\varepsilon > 1$, then $p_t Y_t - w_t L_t = \varphi_t \left(\phi_t \left(K_t^B\right)^{\nu} \left(K_t^E\right)^{\mu} \left(L_t\right)^{\kappa}\right)^{1-\frac{1}{\varepsilon}} - w_t L_t$. The term $A_t = \varphi_t \phi_t^{1-\frac{1}{\varepsilon}}$ captures randomness in both total factor productivity and demand that the firm is facing.

The firm incurs adjustment costs when investment takes place given by:

(2) $$C\left(I_t^B, K_t^B, I_t^E, K_t^E\right) = \begin{bmatrix} p_t^B I_t^B + \alpha^B \cdot \mathrm{I}\left(I_t^B \neq 0\right) + \frac{b^B}{2}\left(\frac{I_t^B}{K_t^B}\right)^2 \cdot K_t^B \\ + p_t^E I_t^E + \alpha^E \cdot \mathrm{I}\left(I_t^E \neq 0\right) + \frac{b^E}{2}\left(\frac{I_t^E}{K_t^E}\right)^2 \cdot K_t^E \end{bmatrix}$$

The indicator function I(.) takes the value 1 if the condition in brackets is satisfied and equals zero otherwise. As usual the adjustment cost function allows for convex costs. The size of these costs is reflected by the parameters b^B and b^E. Such costs imply a penalty on large capital expenditures and hence induce firms to smooth investment over time. The cost function also allows for non-convexity.[1] For instance, the prices of the input factors are expressed as p_t^B and p_t^E, where for $c \in \{B, E\}$, $p_t^c = p^{c+} \cdot \mathrm{I}\left(I_t^c > 0\right) + p^{c-} \cdot \mathrm{I}\left(I_t^c < 0\right)$. The purchase price for a unit of capital c is p^{c+}, while the value of one unit of sold capital would be p^{c-}. Due to irreversibility of investment decisions, the purchase price of capital is higher than the resale price: $p^{c+} > p^{c-}$. Another non-convexity is due to fixed costs given by α^B and α^E. We assume these to be symmetric by being independent of whether the inputs are positive or negative.

Investment in buildings and equipment is denoted by I_t^B and I_t^E, respectively. By investment the firm decides upon the optimal size of the capital stocks, K_{t+1}^B and K_{t+1}^E. If the parameters δ^B and δ^E measure the rate of capital depreciation of buildings and equipment, respectively, the evolution of capital is governed by

(3) $$K_{i,t+1}^c = \left(1 - \delta^c\right) K_{i,t}^c + I_{i,t}^c$$

where $c \in \{B, E\}$. To obtain the optimal values for I_t^B and I_t^E equation (1) is optimized with respect to these decision variables subject to equation (3). The variables λ_t^B and λ_t^E are the shadow values of an additional unit of capital. Their formal expression for $c \in \{B, E\}$ is

(4) $$\lambda_t^c = E_t \sum_{s=0}^{\infty} \left(1 - \delta^c\right)^s \beta^{s+1} \left[\frac{\partial\left(F\left(A_{t+s+1}, K_{t+s+1}^B, K_{t+s+1}^E\right)\right)}{\partial K_{t+s+1}^c} - \frac{\partial\left(C\left(I_{t+s+1}^B, K_{t+s+1}^B, I_{t+s+1}^E, K_{t+s+1}^E\right)\right)}{\partial K_{t+s+1}^c}\right]$$

[1] Such costs may be skipped when the level of aggregation is high (see for example Groth, 2008). However, we use plant level data featuring lumpy capital adjustment patterns.

They measure how the value of the firm changes if the constraints in equation (3) are relaxed or equivalently, if capital is increased by one unit. The shadow values represent the expected present discounted value of the marginal profit of capital minus the marginal adjustment costs in future periods. For $c \in \{B, E\}$ the first order condition for capital adjustment is given by:

$$(5) \qquad \lambda_t^c - p_t^c - b^c\left(\frac{I_t^c}{K_t^c}\right) = 0$$

In line with Abel and Eberly (1994) and Eberly (1997) optimal factor demand adjustment equals:

$$(6) \qquad \frac{I_t^c}{K_t^c} = \left(\frac{\lambda_t^c - p_t^c}{b^c}\right)$$

The equation determining whether to change the stock of capital for $c \in \{B, E\}$ is given by

$$(7) \qquad \lambda_t^c I_t^c \geq C\left(I_t^c, K_t^c\right)$$

The left hand side of equation (7) measures the expected benefits of investing. The right hand side denotes the cost associated with the firm's decisions.[2] Using equation (6) it can be shown that equation (7) holds if $\frac{1}{2b^c}\left(\lambda_t^c - p_t^c\right)^2 K_t^c \geq \alpha^c > 0$. Hence, the sufficient condition for changing the amount of capital $c \in \{B, E\}$ is:

$$(8) \qquad \left|\lambda_t^c - p_t^c\right| > \sqrt{\frac{2b^c\alpha^c}{K_t^c}} \equiv A^c$$

Equation (8) shows that if the net benefits of adjusting capital do not exceed a certain minimum threshold, the firm decides to abstain from adjusting. The thresholds are also caused by the presence of the fixed adjustment costs α^B and α^E. With larger fixed costs, the threshold will increase. Hence, investment becomes less likely, all else equal. In addition, we observe that with larger fixed costs, once the firm decides to invest, the size of the investment will be larger, because with a larger threshold the left hand side of equation (8) must be higher and this

[2] The expression $\lambda_t^c I_t^c$ approximates the benefits allowing for a closed form solution. In a continuous time framework with one production factor a similar expression holds exactly.

expression drives the size of investment as can be seen from equation (6). Hence, fixed costs largely explain the phenomenon of investment spikes as mentioned before.

If the evolution of input factors is characterized by the occurrence of spikes we expect that the production level of the firm will increase substantially upon large investment, especially if more types of capital goods are adjusted at the same time. The Cobb-Douglas production technology depicted previously, i.e. $Y_t = \phi_t \left(K_t^B\right)^{\nu} \left(K_t^E\right)^{\mu} \left(L_t\right)^{\kappa}$, yields this prediction.

We also expect that if investment in equipment and stuctures is interrelated and if at least one of them is subject to fixed adjustment costs, other input factors will display a lumpy adjustment pattern as well (Abel and Eberly, 1998). It is likely that if the firm buys capital the number of workers will increase. With a higher level of capital present in the firm, the (expected) marginal profit of labour is increasing, assuming the production technology has not changed, inducing the firm to hire more workers while investing in capital. This can be seen as follows. Assuming labour is a flexible input factor, the optimal number of employees L_t is determined by maximizing $p_t Y_t - w_t L_t = \varphi_t \left(\phi_t \left(K_t^B\right)^{\nu} \left(K_t^E\right)^{\mu} \left(L_t\right)^{\kappa}\right)^{1-\frac{1}{\varepsilon}} - w_t L_t$. The first order condition is given by:

$$(9) \qquad \kappa\left(1-\frac{1}{\varepsilon}\right)\varphi_t \left(\phi_t \left(K_t^B\right)^{\nu} \left(K_t^E\right)^{\mu}\right)^{1-\frac{1}{\varepsilon}} \left(L_t\right)^{\kappa\left(1-\frac{1}{\varepsilon}\right)-1} = w_t,$$

where $\kappa\left(1-\frac{1}{\varepsilon}\right) = \kappa\left(\frac{\varepsilon-1}{\varepsilon}\right) < 1$. So with higher stocks of capital, the stock of labour needs to increase as well to restore equality of the first order condition.

Buildings and equipment are also interrelated through the production technology. Suppose the firm invests in equipment, while it abstains from investing in buildings. In that case the shadow value of buildings - λ_t^B - tends to increase, because in equation (4) the term

$$(10) \qquad \frac{\partial\left(F\left(A_{t+s+1}, K_{t+s+1}^B, K_{t+s+1}^E\right)\right)}{\partial K_{t+s+1}^B} = \nu\left(1-\frac{1}{\varepsilon}\right)\varphi_t \left(\phi_{t+s+1} \left(K_{t+s+1}^E\right)^{\mu} \left(L_{t+s+1}\right)^{\kappa}\right)^{1-\frac{1}{\varepsilon}} \left(K_{t+s+1}^B\right)^{\nu\left(1-\frac{1}{\varepsilon}\right)-1}$$

will rise as well. Hence, it becomes more likely to observe a firm investing in buildings.

Power (1998) investigated whether investment affects productivity of a firm. When investment embodies more recent technology available in the market one would expect that over time productivity will increase (Jovanovic and Nyarko, 1994). There may be a delay in improved productivity in that firms need to learn about the new technology. Technology specific human capital may be lost when new machines are present.

Results by Abel and Eberly (1998) imply that factor productivity is a signal for a firm of when to invest. If productivity is high, meaning that the level of input (capital) is low relative to the level of output, this signals the firm is running at high capacity and that it may be sensible to start investing. This can also be seen from equation (4) depicting the shadow values of investment. It shows that investment in buildings is also determined by the marginal profit given by $\frac{\partial\left(F\left(A_{t+s+1}, K^B_{t+s+1}, K^E_{t+s+1}\right)\right)}{\partial K^B_{t+s+1}}$. With the production and demand function we used above in this section, this expression equals

$$(11) \qquad \nu\left(1-\frac{1}{\varepsilon}\right)\frac{\varphi_t\left(\phi_{t+s+1}\left(K^B_{t+s+1}\right)^{\nu}\left(K^E_{t+s+1}\right)^{\mu}\left(L_{t+s+1}\right)^{\kappa}\right)^{1-\frac{1}{\varepsilon}}}{K^B_{t+s+1}}=\nu\left(1-\frac{1}{\varepsilon}\right)\frac{p_{t+s+1}\cdot Y_{t+s+1}}{K^B_{t+s+1}}.$$

This means investment in buildings is driven by expectations about its future productivity reflected by $\frac{Y_{t+s+1}}{K^B_{t+s+1}}$. Hence, investment tends to become more likely if the firm expects higher future productivity. If current productivity is high and also transmits into high future productivity, for instance due to persistent technology shocks ϕ_t being governed by an autoregressive process, current productivity acts as a signal for a firm of when and how much to invest. Obviously, immediately after investment productivity will be lower. For this reason it may be difficult to investigate investment causing productivity.

We investigate the dynamics of productivity surrounding major investment events at the firm level to determine whether productivity acts as a signal for the firm of when to invest or whether it is possible to see improvements in productivity after investments. Note that our framework discriminating between buildings and equipment is more suitable to do that. We will be able to separate expansionary from replacement investment, assuming that investing in equipment alone represents replacing older with newer technology. In addition, we distentangle operating expenditures in buildings from that of large scale capital expenditures or new development.

Investment may not only affect the scale of a firm's operations or firm productivity. It may also imply production technology changes when new capital enters the firm (Acemoglu, 2015; Dunne *et al.*, 1989; Hémous and Olsen, 2015). For instance, upon investment the parameters ν, μ and κ of the Cobb-Douglas production function depicted above may be altered, which potentially affects the optimal mix of input factors. In our study we explore this issue in two different ways. First, we aim to analyze whether upon investment the firm requires a different skill set from its employees by investigating the development of average wage costs. Second, we assess how investment types affect capital intensity of firms. The final issue we address in our study is whether major investment episodes affect the cost efficiency experienced by firms.

2. Data Description

Statistics Netherlands (CBS) annually collects data on production statistics and investment figures at the firm level. Specifically, a random selection of all Dutch companies employing less than 50 people is sent questionnaires and all Dutch firms with 50 or more employees receive a survey.[3] We merge the annual data sets on production statistics and investments of the manufacturing sector using a firm specific identifier, resulting in a panel for 2000 to 2008. Importantly, we aim to capture regular firm investment intensity dynamics and not extreme events like divestments or mergers. To do so, we analyze a balanced set of panel data (cf. Letterie *et al.*, 2004). In this way, the balanced panel conservatively controls for firm entry and exit, major (dis)investment decisions like mergers, acquisitions, bankruptcies and/or geographic relocations. Moreover, as we want to assess empirical data, imputed observations are deleted. The panel data set isolates investment behaviour for a nine year period, concerning 652 firms and for a total of 5868 yearly investment observations.[4]

Identifying Investment Spikes

[3] Detailed information (in Dutch only) on sampling strategies and collection methods of Statistics Netherlands can be retrieved from http://www.cbs.nl/nl-NL/menu/themas/industrie-energie/methoden/dataverzameling/korte-onderzoeksbeschrijvingen/productie-statistiek.htm
[4] To prevent potential contamination of our findings by extreme outliers, we decided to remove the 1% largest investment ratios to obtain the final data.

Firms have been found to conduct investment in a lumpy fashion. Rather than smoothing investment over time, micro-level data have revealed that investment by firms is often concentrated in short time episodes. In this study we will focus on such bursts of capital adjustment as these events represent major retooling or expansionary efforts of firms (Letterie et al., 2010). To investigate micro-level consequences of such events, various studies have proposed a definition of investment spikes. We identify our spike events following a classification method refered to as a relative spike definition (Power, 1998; Kapelko et al., 2015). In line with the literature, we identify an investment spike as the investment ratio of a firm *i* in year *t*, $\frac{I_{it}^z}{K_{it}^z}$, that exceeds the median investment ratio of that firm by an investment threshold (Power, 1998). An investment spike is identified as follows:

$$(12) \qquad S_{it}^z = \begin{cases} 1 \quad \text{if} \left[\frac{I_{it}^z}{K_{it}^z} > \theta \cdot \underset{\tau}{\text{median}} \left(\frac{I_{i\tau}^z}{K_{i\tau}^z} \right) \text{ and } \frac{I_{it}^z}{K_{it}^z} > \delta^z \right] \\ 0 \quad \text{otherwise} \end{cases},$$

where *I* is the financial capital investment, *K* is the existing physical capital stock of firm *i* for investment in capital type *z*. The variable *z* represents investment in equipment, *E*, or buildings, *B*.[5] Importantly, we exogenously define θ as the investment threshold factor. We set the value of $\theta = 1.75$.[6] Based on the latter, if a firm does not invest at all (i.e., $\frac{I_{it}^z}{K_{it}^z} = 0$) in at least 5 out of 9 observed years t, even a miniscule investment in any of the remaining years will classify as an investment spike, since the median investment rate will be 0. To remain conservative, we therefore incorporate a second condition in our investment spike definition. Specifically, the investment rate should also exceed the depreciation ratio for the asset in casu. The depreciation ratio is denoted by δ^z. A strictly positive number for depreciation tends to limit the number of spikes in buildings because of the restriction $\frac{I_{it}^z}{K_{it}^z} > \delta^z$ in the spike definition. For buildings we set depreciation at 0.02, which is fairly conservative for the commercial building sector in

[5] Appendix A documents our calculations for assessing the initial physical capital stock *K*.
[6] We have tested three values for θ, a low (1.75), medium (2.5) and high (3.25) threshold (cf. Power, 1998). Our empirical results are robust to the θ value.

Europe (Bokhari and Geltner, 2014; Chegut *et al.*, 2014). Following Letterie and Pfann (2007), who also employ Dutch data for equipment, the depreciation rate is set at 0.05.[7]

Investment spikes may signal significant expansion when investment in both buildings and equipment occurs, and may have important consequences in identifying changes in productivity, firm scale, input mix and operational efficiency. To measure significant expansion, we include a simultaneous investment spike variable:

$$(13) \qquad S_{it}^{C} = \begin{cases} 1 & \text{if } \left[S_{it}^{B} = 1 \text{ and } S_{it}^{E} = 1 \right] \\ 0 & \text{otherwise} \end{cases}$$

So, the variable S_{it}^{C} identifies the event of a simultaneous spike.

Table 1 documents the descriptive statistics for the investment spikes in buildings, equipment, or simulatenously in both. We have 5868 observations from general firm investments, representing general capital expenditures on equipment and buildings. This sample is representative of large firms, those with 50 or more employees in the Netherlands and our data has close to 30 percent of the large firm sample.8 According to Table 1 our assumptions imply that the frequency of equipment spikes is somewhat larger than that of the spike frequency of buildings. This is consistent with the notion that equipment is a more flexible input factor than structures. In fact, in our dataset firms abstain from investing in buildings far more often than they refrain from investing in equipment. More specifically, we observe 2896 year observations without building investment (i.e. in roughly 49 percent of the observations) and only 552 year observations without investment in equipment (i.e. about nine percent). In case we also add the simultaneous spikes to the spikes in equipment we observe a ratio of about 14 percent in equipment spikes. Hence, the equipment spike frequency is in line with Power (1998) who observes investment spikes in equipment in 13.6 percent of her observations for a θ of 1.75.[9]

[7] Our depreciation rates for buildings and equipment are consistent with the geometric depreciation approach employed by the US Bureau of Economic Analysis calculating the depreciation rate dividing the declining balance rate by the service life using the information provided by Görzig (2007) and van den Bergen *et al*. (2009).
[8] One limitation of our data is that they do not allow us to disentangle or identify substitution or transfer of activities etc. between plants within one firm.
[9] Various studies have also employed an absolute spike definition. For instance, one may define a spike to realize if the investment rate exceeds 0.2. We have a relative spike definition, because

The average investment rate of firms in buildings is 1.0 percent and for equipment about 5.9 percent. The average investment rate in the single spike regimes is 6.8 percent for buildings and 21.6 percent for equipment. Noticeably, the average rate of investment increases with the occurance of a spike. The occurrence of a simultaneous investment spike in buildings and equipment we observe in 3 percent of the sample. The average conditional investment rates are at their largest across the sample, 7 percent and 24 percent for buildings and equipment, respectively, when simultaneous investments in both buildings and equipment are identified.

*** Table 1 about here ***

Identifying Firm Scale, Productivity and Efficiency

Table 2 documents the mean and standard deviation of firm scale operations, productivity and operational efficiency under the scenarios of (i) all observations, (ii) *no* investment spikes, and in case of (iii) single spikes in buildings, (iv) single spikes in equipment and (v) simultaneous spikes. The variables used in the empirical analysis as dependent variable have received a natural log transformation.

We measure the scale of firm operations by production output (firm revenues) and the number of workers (full time equivalent, i.e. FTE). For estimation, production has been deflated by the producer price index (PPI) for the industrial sector to reflect *real* production.[10] Conditional on firms making an investment spike, the mean statistics for levels and natural logarithms suggest it is larger firms that experience an investment spike involving equipment (a single equipment spike or a simultaneous spike).

Micro-level productivity is measured by dividing output by number of workers, the stock of buildings or the stock of equipment. In the cross-section, we see productivity of equipment and labour conditional on observing an equipment spike is high. We also measure features of the overall production technology, or to put it differently, the mix of physical capital and labour. A number of variables provide information in this respect. Our data do not provide a distinction between various types of workers, but to measure the composition of the work force we employ

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the absolute spike definition is not well suited for capturing spasmodic investment bursts that cannot be seen as large in an absolute sense (Power, 1998).

[10]All these indices were retrieved from the Statistics Netherlands (CBS) Statline online datacenter.

the average real wage per worker of the firm.[11] We expect lower values of this variable to indicate that a firm hires relatively more unskilled employees. We identify the mix between capital and labour by dividing the stock of buildings and the stock of equipment by the number of workers. Table 2 reveals spikes involving equipment are associated with firms paying higher wages on average. The latter observation may hint at relatively more skilled workers employed by firms that increase the stock of equipment (together with structures).

The final variable we analyse accounts for the overall efficiency of the firm: the ratio of total costs to sales. Within the cross-section, the efficiency variable is considerably constant at about -0.07 over the observed period regardless of investment activity. In the next section we depict our methodology by which we can analyse the dynamic consequences of investment activity.[12]

*** Table 2 about here ***

3. Methodology

The goal of this study is to obtain basic facts concerning the dynamics of major investment efforts conducted by firms and understand their impact on productivity. Our analysis is descriptive and non-parametric rather than structural and enables us to observe investment activity across capital types. Our methodology is in line with a common approach in the capital investment literature, when the objective is to obtain descriptive evidence of firm behavior in times of major investment episodes. Hence, we closely follow Sakellaris (2004), Letterie *et al.* (2004) and Nilsen *et al.* (2009) and first identify events of large capital adjustments by firms. We use these events and look into what is happening with firm-level employment, production technology and firm capacity in manufacturing industries in periods surrounding these events. One way of looking at this event type of methodology identified by investment spikes is that such episodes reflect that a firm was hit by a large shock. The investment spike in itself represents the response of the firm to the shock. Alternatively, the firm may have been subject to a series of smaller shocks to which the firm has not responded yet due to the presence of

[11] Labour costs have been deflated by the wage development index for the industrial sector obtained from Statistics Netherlands (CBS) Statline online datacenter.

[12] A table with correlations of variables used in the empirical analysis is available upon request.

fixed capital adjustment costs, for instance. The large investment event reflects that the firm has taken action now (Sakellaris, 2004).[13]

In our analysis of investment spike consequences for some firm level metrics – production and employment scale as well as productivity, the input mix and firm efficiency - as denoted by DV_{it}, we adhere to the following model:

$$(14)\qquad DV_{it} = \mu_i + \alpha_t + \sum_{z\in\{B,E,C\}} \beta_z' X_{it}^z + \varepsilon_{it} \quad ,$$

where μ_i is a firm specific time invariant effect.[14] Furthermore, α_t is a year dummy vector (2001-2008, base year is 2000) that captures potential macro-economic shifts. The idiosyncratic error is given by ε_{it}. Based on earlier work by Sakellaris (2004), Letterie *et al.* (2004) and Nilsen *et al.* (2009), X_{it}^z is an independent variable vector. It identifies the relative position of the firm in a series of annual observations around investment spikes for both capital types (i.e. buildings where *z=B* and equipment where *z=E*), as well as for an event named a simultaneous spike, *z=C*, where a simultaneous investment spike in buildings and equipment takes place (i.e. where $S_{it}^B = S_{it}^E = 1$). It behaves as described below:

$$(15)\qquad \left[X_{it}^B\right] = \begin{bmatrix} X_{1it}^B \\ X_{2it}^B \\ X_{3it}^B \\ X_{4it}^B \\ X_{5it}^B \\ X_{6it}^B \end{bmatrix} = \begin{bmatrix} \left(1-S_{it}^B\right)\left(1-S_{it+1}^B\right)S_{it+2}^B\left(1-S_{it+2}^E\right) \\ \left(1-S_{it}^B\right)S_{it+1}^B\left(1-S_{it+1}^E\right) \\ S_{it}^B\left(1-S_{it}^E\right) \\ \left(1-S_{it}^B\right)S_{it-1}^B\left(1-S_{it-1}^E\right) \\ \left(1-S_{it}^B\right)\left(1-S_{it-1}^B\right)S_{it-2}^B\left(1-S_{it-2}^E\right) \\ \left(1-S_{it}^B\right)\left(1-S_{it-1}^B\right)\left(1-S_{it-2}^B\right)\cdot\max\limits_{\tau\le t-3}\left\{S_{i\tau}^B\right\} \end{bmatrix}$$

[13] Our approach resembles an event study (Wooldrige, 2013) where the goal is to estimate the effect of an event, a policy program for instance, on an outcome variable of interest. Typically, such studies allow for exogenous treatment variables such that causal inferences can be made. In our study the assumption of strict exogeneity of the events, which are identified by the occurrence of investment episodes, is violated. Hence, our estimates should be interpreted carefully with regards to causality. They provide us with a description of dynamic patters of plant-level energy metrics surrounding major capital adjustments in firms.

[14] The fixed effect controls for heterogeneity due to for instance cross sectional variation in managerial ability, local input market conditions and strategic interaction at output markets unobserved to the econometrician.

$$(16)\quad \left[X_{it}^{E}\right]=\begin{bmatrix} X_{1it}^{E} \\ X_{2it}^{E} \\ X_{3it}^{E} \\ X_{4it}^{E} \\ X_{5it}^{E} \\ X_{6it}^{E} \end{bmatrix}=\begin{bmatrix} \left(1-S_{it}^{E}\right)\left(1-S_{it+1}^{E}\right)S_{it+2}^{E}\left(1-S_{it+2}^{B}\right) \\ \left(1-S_{it}^{E}\right)S_{it+1}^{E}\left(1-S_{it+1}^{B}\right) \\ S_{it}^{E}\left(1-S_{it}^{B}\right) \\ \left(1-S_{it}^{E}\right)S_{it-1}^{E}\left(1-S_{it-1}^{B}\right) \\ \left(1-S_{it}^{E}\right)\left(1-S_{it-1}^{E}\right)S_{it-2}^{E}\left(1-S_{it-2}^{B}\right) \\ \left(1-S_{it}^{E}\right)\left(1-S_{it-1}^{E}\right)\left(1-S_{it-2}^{E}\right)\cdot\max\limits_{\tau\le t-3}\left\{S_{i\tau}^{E}\right\} \end{bmatrix}$$

$$(17)\quad \left[X_{it}^{C}\right]=\begin{bmatrix} X_{1it}^{C} \\ X_{2it}^{C} \\ X_{3it}^{C} \\ X_{4it}^{C} \\ X_{5it}^{C} \\ X_{6it}^{C} \end{bmatrix}=\begin{bmatrix} \left(1-S_{it}^{C}\right)\left(1-S_{it+1}^{C}\right)S_{it+2}^{C} \\ \left(1-S_{it}^{C}\right)S_{it+1}^{C} \\ S_{it}^{C} \\ \left(1-S_{it}^{C}\right)S_{it-1}^{C} \\ \left(1-S_{it}^{C}\right)\left(1-S_{it-1}^{C}\right)S_{it-2}^{C} \\ \left(1-S_{it}^{C}\right)\left(1-S_{it-1}^{C}\right)\left(1-S_{it-2}^{C}\right)\cdot\max\limits_{\tau\le t-3}\left\{S_{i\tau}^{C}\right\} \end{bmatrix}$$

For $z\in\{B,E\}$ X_{1it}^{z} takes the value 1 if a spike occurs in year *t+2* for investment in asset *z*, but not a spike of the other kind, and no spikes of asset *z* occur in years *t* and *t+1*. In this case, the variable will be 0 otherwise. For *z* = *C*, X_{1it}^{C} takes the value 1 if a simultaneous spike occurs in year *t+2*, but not in *t* and *t+1*. The variables with the sub-index 2 measure how a dependent variable behaves 1 year before a specific investment spike. X_{2it}^{z}, $z\in\{B,E\}$ takes the value 1 if a spike of the asset *z* (but not of the other kind of asset) occurs in year *t+1*, but not in year *t*; it takes value 0 otherwise. X_{2it}^{C} is 1 if a simultaneous spike occurs in year *t+1*, but not in year *t*. To measure changes in the dependent variable at the time of a spike we define variables with the sub index 3. X_{3it}^{z}, $z\in\{B,E\}$ takes the value 1 if a spike of type *z* occurs in year *t*, and there is no spike of the other kind in *t* and it will be 0 otherwise. If *z* = *C*, X_{3it}^{C} is 1 if a simultaneous spike occurred in year *t*. The variables X_{4it}^{z} and X_{5it}^{z} function like X_{2it}^{z} and X_{1it}^{z}, with the difference that it concerns a spike in year *t-1* (*t-2*) rather than *t+1* (*t+2*). Hence these variables identify what happens one and two years after a spike event, respectively. Finally, X_{6it}^{z} takes the value 1 if a spike took place before year *t-2*, but not in *t-2*, *t-1* and *t*. This last variable therefore captures the effect of investment spikes that occurred at least 3 years and at most 8 years (i.e., in case a firm experiences an investment spike in 2000 and no subsequent spikes are observed for that firm) in the past.

After performing Hausman tests on all models, all dependent variables DV_{it} except for Total Costs / Sales required a fixed effects specification. For comparability reasons, we therefore decided to apply a fixed effects specification for all dependent variables. The models are estimated using fixed effects, within estimators. Time-invariant variables are omitted from the model due to differencing fixed effects. Hence, we abstract from such variables.[15]

In our estimations of equation (3), the regression coefficients β_z obtained for independent variables $X_{it}^z,\ z \in \{B, E, C\}$ identify what happens to any dependent variable DV_{it} for firms i that find themselves in the situation described by the specific variable, relative to firms that do not. Note that due to the fixed effects specification the estimates compare the within variation of the dependent variable across various types of investment experiences of firms. The dependent variables are in natural logarithms. The β_z coefficients thus indicate percentage differences in the dependent variable between firms that are, and firms that are not in situation X_{it}^z. For instance, if the dependent variable is the natural logarithm of production in year t and the parameter estimate for X_{3it}^C receives a value of 0.01, then relative to a firm that does not conduct a (simultaneous) spike, a firm that simultaneously does invest in equipment and structures experiences an output level 1 percent higher than its mean.

4. Empirical Results

In Figure 1 and Table 3 we depict the results of an analysis to determine to what extent investment rates are interrelated.[16] We observe from the figure that at the time of an investment spike in either buildings or equipment the investment rate of the other investment component is significantly higher. Especially at the time of a spike in buildings the rate of investment in

[15] Within estimators in principle should be more efficient than first differencing, assuming that the idiosyncratic error terms ε_{it} are i.i.d.. Since we do not (for example) include any lagged variables in the regression, we think this should be a safe assumption after averaging out the fixed effects. Note, we do not intend to estimate a model obtaining causal insights. We rather aim at obtaining insight of a descriptive nature regarding dynamic patterns of some key firm level variables.

[16] To avoid endogeneity issues in the analysis where investment rates are dependent variables, the vectors X_{it}^B and X_{it}^E have been constructed such that $\left(1-S_{iq}^E\right)=1$ and $\left(1-S_{iq}^B\right)=1$ for $q \in \{-2,...,2\}$ respectively.

equipment is higher by almost 4 percentage points. Strikingly, the figure depicts, that firms on average start to invest in equipment already two years before the firm builds new structures. Perhaps before expanding the firm first replaces older machinery or uses its existing buildings more efficiently. Once the firm is more certain about future growth prospects, it also decides in favor of more risky and larger investments by investing simultaneously in buildings and equipment. These results suggest that investments in equipment and buildings are interrelated in the sense that the timing of these decisions is not independent. Using country level data Garcia-Belenguer and Santos (2013) find evidence of interrelation as well. The firm level data employed in our paper allow identification of a richer dynamic interaction between investment in buildings and equipment.

Our previous discussion of the shadow value of investment in equation (10) is in line with these findings. There we argued that investments are interrelated through the production technology. In fact, investment in one type of capital tends to raise the marginal profit of the other type, making it more likely to conduct simultaneous investment. Or, if the firm invests in only one type, it becomes more likely that in the near future the firm also invests in the other type of capital. Figure 1 confirms these thoughts.

*** Figure 1 about here ***

*** Table 3 about here ***

Empirical results for the estimation of Equation (14) are presented in Table 4. The table reports the coefficients and statistical significance at the one, five and ten percent levels. The dependent variables outlined in section 3 are on the horizontal axis and the independent timing variables are on the vertical axis for buildings, equipment and for simultaneous spikes.

*** Table 4 about here ***

Changes in Scale – Production and Employment

Table 4 documents the differences in production and number of workers – FTE employees - across the investment spike horizon in Columns (1) and (2). Figure 2 depicts these changes – two to one years before an investment spike, the year of the investment spike, one to two years after the investment spike as well as three or more years after the investment spike. First, in Column (1) production increases significantly when a firm invests in both buildings and equipment, in the immediate zero to two year horizons by 8 to 15 percent and an impact on production of about 8 percent after three years. This finding is distinct from firms who invested in equipment or buildings alone where firms saw short-term marginal gains in production of about 0 percent and 8 percent, respectively. Investment in buildings does not yield production changes beyond three years after the spike, but equipment does increase production scale by about 4 percent then. A notable finding is that the production level is highest at the time of the investment spike. The data indicate that once investment payments have been booked, production capacity has increased substantially. In case increased capacity is not fully installed yet a larger demand has been met by increasing factor utilization rates. Altogether, the empirical observation that production increases with higher input levels is in line with a standard production technology like a Cobb-Douglas function.

Second, as expected and highlighted in Column (2), the number of workers increases after an investment in buildings, equipment or a simultaneous investment. In fact, we find that employment may increase by 3 to 15 percent in the short-run. However, only in instances where investment in buildings is involved, a longer-lasting effect on employment is observed represented by a 5 to 7 percent increase.[17] Apparently, it is investment in buildings that increases the marginal profit of labour inducing the firm to attract more workers even after three years.

*** Figure 2 about here ***

Changes in the Mix of Production Factors

Table 4 Column (3) and Figure 2 depict that when the firm experiences a spike in equipment the average wage bill becomes higher three years afterwards, indicating more skilled workers

[17] Using a Wald statistic we have tested whether parameters of the model in equation (11) are statistically different between investment types. For instance we have tested the hypotheses whether for $k \in \{1,...,6\}$ the coefficient of X^B_{kit} equals that of X^E_{kit}, whether the coefficient of X^B_{kit} equals that of X^C_{kit}, and whether the coefficient of X^E_{kit} equals that of X^C_{kit}. For the dependent variable production we find that in general, i.e. for $k \leq 5$, the coefficients relating to the equipment and combination spikes are statistically different. We find the same for the coefficients relating to the building and the combination spikes after the spike occurred, i.e. for $k \geq 3$. For the dependent variable number of workers, coefficients relating to equipment spikes in general, i.e. for $k \geq 2$, are different from those of the combination spikes. Those relating to buildings are generally significantly different from those concerning the equipment spikes, for $k \geq 2$. These test are significant at least at the 10% significance level, but often at 5%. They are not reported in the paper, but are available upon request.

hired by the firm. However, when the firm only invests in buildings, the wage decreases before, during and after the investment spike. This hints at firms hiring relatively more unskilled workers in those instances.[18]

*** Figure 3 about here ***

Table 4, Columns (4) and (5), and Figure 3 reveal that before a spike the firm becomes more labour intensive. The capital intensity for both buildings and equipment drops considerably in anticipation of the investment. The capital intensity for buildings gets back to the pre-spike period, but the equipment intensity increases by 12 percent in the post-spike period when a spike in equipment is involved. These numbers indicate that a change occurs in the input factors' optimal mix.[19] This may be due to capital investment causing a change in the parameters ν, μ and κ of the Cobb-Douglas production function $Y_t = \phi_t \left(K_t^B\right)^{\nu} \left(K_t^E\right)^{\mu} \left(L_t\right)^{\kappa}$ we have discussed previously.

The event order described above is consistent with the real option investment theory (Dixit and Pindyck, 1994). Firms tend to first adjust factors of production that are relatively flexible. Labour is flexible compared to fixed capital assets (Asphjell *et al.*, 2014). Firms adjust inflexible inputs like structures once uncertainty has been resolved to a large extent (Dixit, 1998; Eberly and van Mieghem, 1997).

*** Figure 4 about here ***

Changes in Firm Productivity and Efficiency

Columns (6), (7) and (8) of Table 4 further document, that most often productivity is higher before investment spikes. However, in the years subsequent to the investment spike, productivity gains are lower and even negative in some cases. Figure 4 depicts the sharp contrast in labour, building and equipment productivity pre and post investment, where productivity reaches a summit just as investment occurs.

[18] The Wald test tells that the coefficient of X_{6it}^B is not equal to that of X_{6it}^E.

[19] The Wald test informs that coefficients of X_{kit}^B , where $k \notin \{4,5\}$ do not equal that of either X_{kit}^E or X_{kit}^C,

Our results confirm Power's (1998) finding of a "Missing Link" between technology, investment and productivity. Her conclusion was based on investigating the relationship between the history of large investment outlays and labour productivity. Recalling Figure 2 our two firm scale measures, production and number of workers, display very similar behaviour. Hence, it is not surprising that labour productivity is hardly affected by investment dynamics according to Table 4 and Figure 5.

In line with Abel and Eberly (1998), in section 2 of this paper we have argued that productivity may act as a signal of when to invest. Hence, high productivity should precede investment. We find small labour productivity gains of about 2 to 4 percent in case of investment in equipment after three years. However, productivity from equipment drops by as much as 10 to 12 percent when equipment is involved. At the same time productivity of structures improves beyond three years. In order to be able to understand productivity consequences of capital adjustment, our findings suggest one probably needs to conduct a structural estimation approach identifying the process that generates firm productivity.

*** Figure 5 about here ***

Lastly, we see in Table 4 Column (9) and Figure 5 that there is an impact on firm operational efficiency after investment spikes. Capital expenditures for equipment improve cost efficiency by 1 percent after three years. In contrast, investment in buildings decreases cost efficiency by 1 percent or so. This means there is a small but notable difference in cost efficiency between a single spike in equipment and buildings of about 2 percent after 3 years.[20] One way of interpreting this finding is that firms are operating in a competitive manufacturing environment. Firms in such a competitive market operate efficiently where marginal cost is equal to marginal revenue, and the firms cannot afford to do much worse than their competitors in terms of operating efficiency. Firms undergoing investments in equipment and buildings document little variation in efficiency pre and post investment spike events. Instead, investment tends to increase firm production capacity, as seen previously in Figure 1, by which the firm obtains more production revenues and a larger share of the market place, but its efficiency remains more or less at the same level.

*** Figure 6 about here ***

[20] Interestingly, the Wald test signals that the coefficient of X_{6it}^{B} does not equal that of X_{6it}^{E}.

5. Industry Cluster Decomposition

Recent empirical work argues that firms in high-tech and low-tech are different along various dimensions (Robertson *et al.*, 2009; Czarnitzki and Thorwarth, 2012). To obtain more detailed insight, we run our firm level analysis in Equation (3) by innovation industry clusters as well. In addition, we distinguish industries in terms of labour intensity. We adopt a classification developed by Raymond, *et al.* (2006), which identifies high- and low-tech industry categories for Dutch manufacturing firms. A low-tech firm is categorized by its low propensity to engage in innovation seeking activities, e.g., R&D activities and innovation subsidy achievement.[21] In addition, we employ a Dutch industry grouping established by Ramirez *et al*. (2005) who document labour intensity. Table 5 provides results for our sample's firm industry classification by innovation and labour intensity.[22] High-tech and low-tech sectors account for 39 and 45 percent of the investment sample's sectors, respectively. Innovation intensity in high-tech sectors is observed largely in the Oil and coal, Chemicals, and Machines and apparatuses sector, which also corresponds with low-labour-intensity manufacturing. High-, medium- and low-labour-intensive industries reflect 22, 30 and 49 percent of the investment sample's sectors, respectively. Interestingly, low-labour-intensive industries are split almost evenly between high-tech and low-tech industries.

*** Table 5 about here ***

Figure 6 depicts production and number of employees for high- and low-tech industries. Compared to establishments operating in high-tech industries, low-tech firms tend to expand firm size by adding structures rather than equipment. Instead, high-tech industries need equipment to expand production. Apparently, in the low-tech industries the production process is rather labour intensive. In this way, should a low-tech firm want to grow, it needs to create a workplace for its workers.

*** Figure 7 about here ***

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[21] The model developed by Raymond, *et al.* (2006) identifies three categories of innovation intensity: high-technology, low-technology and wood. Wood is a distinctively non-innovative industry.

[22] We have also estimated Equation (3) for industries separated by employing the two digit SIC classification code. However, we generally find no statistically significant patterns. One reason might be that breaking up by SIC codes yields relatively few observations per industry classification.

Figure 7 graphs the dynamics of production and number of employees in industries distinguished by different levels of labour intensity. Notably, firms in labour intensive industries do not expand production and number of employees by investing in structures or equipment. Production processes in these industries are less dependent on capital inputs overall. Apparently, then the share of capital in the production technology is too small to make capital accounting for variation in firm size measures. We find a more pronounced influence of capital investment on firm size measures in industries characterized by low- and medium-labour- intensity. In particular, simultaneous investment spikes increase production scale and number of workers.

*** Figure 8 about here ***

Our results based on a firm investment panel dataset, presented in the previous section, stress the role of simultaneous spikes in understanding firm growth. In particular, capital intensive industries (i.e. low- and medium-labour-intensive sectors) exhibit features that are common to what we observed for the entire sample. For these industries simultaneous spikes are important to understand both employment and production growth. Firms operating in high-tech industries are more dependent on investment in equipment to increase production volume after three years, but employment growth is established by all investment spike types. To grow in low-tech industries firms build structures. Simultaneous spikes in low-tech industries increase production, whereas in high-tech industries they increase employment.

6. Conclusion

Central to firm production is investment in capital. We find the distinction between productive capital, like equipment, and non-productive capital, like buildings, is critical for understanding the scale and production technology of a firm. This analysis documents the impact of decomposing investment spikes in buildings and equipment on scale, productivity, mix of input factors, and firm efficiency. Firms that invest in buildings, equipment or simultaneously in both obtain different outcomes concerning production technology and performance metrics.

Our results reveal high productivity acts as a signal for firms to invest. Furthermore, firms conducting simultaneous investment spikes experience the largest post investment expansion in production and number of workers. We find employment growth does not come from spikes in equipment only. Especially, when buildings are constructed the number of workers increases. Investments involving equipment affect the optimal input mix. In those instances, labour tends to be substituted by equipment. Additionally, operational efficiency is economically affected by spike investments in equipment.

We also conducted a more fine-grained analysis by type of industry. We distinguished high- and low-tech sectors and employed a classification based on labour intensity. The industry analysis reveals that simultaneous spikes drive firm production growth in capital intensive industries (i.e. low- and medium-labour-intensive sectors) and in low-tech industries. Simultaneous spikes enhance employment in capital intensive industries and in a high-tech environment. In order to grow production a necessary condition for low-tech firms is building structures to house workers. High-tech firms depend more on equipment to be able to grow production. These results tell production processes are different across industries. Furthermore they reveal how revenue and employment growth are advanced in different industrial settings.

For future research we recommend three opportunities. First, production processes are different across sectors. Within sectors processes may alter over time according to our results, possibly depending on technological developments, changes in factor input costs etc. An interesting topic for future research concerns whether, how and with what speed firms are capable of adjusting in response to such developments.

Second, our results based on distinguishing between firm expenses on structures and equipment suggest adding firm level investment dimensions to the micro investment literature is worth the effort. We propose a research agenda resulting in a better understanding of investment in both equipment and buildings. Studies on interrelated factor demand have revealed that models of more flexible input factors need to be complemented with less flexible ones. In particular, Bloom (2009) and Asphjell *et al*. (2014) observed that performance of labour demand models improves by also incorporating the dynamics of investment in equipment. However, models concerning the stock of equipment do not have to include labour demand to be able to match important moments of the data. Likewise, we expect that to properly model the dynamics of equipment accounting for investment in buildings is mandatory.

Third, the distinction between firms' investment choices underscores different expected outcomes for economic growth and macroeconomic activity. Caballero and Engel (1999) document lumpiness in firm investment is critical for understanding macroeconomic activity. Bachman *et al*. (2013) further advance the role of investment lumpiness in impacting business cycle activity. However, other studies inspired by Thomas (2002) are more critical regarding the role of investment lumpiness in driving the business cycle. A more recent strand in the literature suggests it is particularly uncertainty that drives macro economic outcomes through investment (Bloom 2009; Bloom *et al*. 2014), but this can be further amplified by the firm's timing in the business cycle as well as the type of industry that is implementing change (Samaniego and Sun, 2015). Due to irreversibility firms tend to become cautious when experiencing higher uncertainty (Guiso and Parigi, 1999; Ghosal, 2000) and this could especially be the case when investing in buildings (Driver *et al*. 2005). In fact, investment in structures is subject to a larger degree of lumpiness than equipment hinting at fixed adjustment costs or indivisibility. Hence, uncertainty potentially affects investment in structures to an even larger extent than investment in equipment.

Furthermore, distinct capital investments result in specific financing frictions, due to varying degrees of irreversibility. Additionally, capital market stakeholders for buildings and equipment differ (Bayer, 2006). Hence, the timing and size of investment depend on capital type, business cycle properties like uncertainty and access to the capital market (Fiori, 2012). Decomposing investment into structures and equipment will be an important contribution in understanding micro and macro level growth. It will also provide better insight into which policies need to be in place to advance growth and employment at both the national and sectoral level.

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Appendix: Construction of Capital Stock Variables

We construct the starting value of a firm's capital stock for buildings and for equipment as follows. The initial capital stock for a firm is the contemporaneous ratio of firm to industy output multiplied by the industry's capital stock of an asset. More specifically, for a given firm *i* in period *t*, the firm's capital stock, i.e. K_{it}^{c} is calculated using $K_{it}^{c} = K_{jt}^{c} \cdot \frac{Y_{it}}{Y_{jt}}$, where *j* denotes the industry a firm is operating in, Y_{it} (Y_{jt}) depicts output of firm *i* (industry *j*) in year *t*, K_{it}^{c} (K_{jt}^{c}) denotes the capital stock of asset *c* of company *i* (industry *j*) at the beginning of year *t*. The industry level data are obtained from the Statline online datacenter of Statistics Netherlands (CBS). To construct the starting values of the capital stock series, data from the year prior to the start of the sample are collected. Hence, these series start in the year 2000.

The capital stock for the remaining years is determined by the perpetual inventory method. Importantly, in the analysis we employ real investment and capital figures. The nominal numbers have been deflated using producer price indices on buildings or equipment assets. The nominal numbers refer to investments done in the bookyear.

Tables and Figures

Table 1: Descriptive Statistics Investment Rates

Investment rate	Observations	Percentage of total (N = 5868)	Mean	Std. Dev.
All observations:				
Rate buildings	5868	100%	.010	.028
Rate equipment	5868	100%	.059	.105
Building spikes:				
Rate buildings	486	8%	.068	.054
Rate equipment	486	8%	.046	.066
Equipment spikes:				
Rate buildings	651	11%	.004	.007
Rate equipment	651	11%	.216	.171
Simultaneous spikes:				
Rate buildings	155	3%	.070	.047
Rate equipment	155	3%	.240	.199

Notes: Table 1 documents the distribution of investment rates for all observations and spikes in buildings, equipment and simultaneous. Percentage of total is a frequency measure representing the number of data points observed.

Table 2: Firm Activity Descriptive Statistics

	All observations N = 5868		No spikes N = 4576		Building spikes N = 486		Equipment spikes N = 651		Simultaneous spikes N = 155	
Dependent Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Level:										
Production (in 1000's of euro)	58566	208175	56142	215859	42925	63886	83819	239011	73100	94659
Number of Workers (in full time equivalents)	196	236	187	230	199	230	238	253	297	307
Natural Logarithms:										
Production	10.03	1.29	9.95	1.29	9.97	1.19	10.44	1.21	10.58	1.17
Number of Workers	4.79	1.01	4.73	1.01	4.80	1.02	5.09	0.88	5.25	0.97
Productivity Labour	5.23	0.63	5.22	0.63	5.18	0.54	5.35	0.68	5.33	0.57
Productivity Buildings	1.08	0.43	1.06	0.43	1.14	0.42	1.11	0.44	1.18	0.44
Productivity Equipment	0.48	1.50	0.34	1.52	0.31	1.38	1.37	1.09	1.22	1.05
Average Wage	3.61	0.25	3.60	0.25	3.58	0.24	3.65	0.25	3.66	0.21
Capital Stock Buildings / Number of Workers	4.16	0.65	4.16	0.65	4.04	0.58	4.24	0.67	4.14	0.63
Capital Stock Equipment / Number of Workers	4.76	1.42	4.88	1.44	4.87	1.37	3.98	1.05	4.10	1.07
Operational Efficiency (Total Costs / Sales)	-0.07	0.10	-0.07	0.10	-0.08	0.09	-0.06	0.10	-0.07	0.08

Notes: Table 2 documents the descriptive statistics, the mean and standard deviation, of the dependent variables by level and natural logarithm. The variables are decomposed into all observations, general investments – no spikes, investment spikes in buildings, equipment and simultaneous spikes.

Table 3: Interrelated Investment

		(1)	(2)
		$\frac{I^B}{K^B}$	$\frac{I^E}{K^E}$
Vector X_{it}^B	*Buildings*		
X_{1it}^B	Two years before spike		.018***
X_{2it}^B	Year before spike		.020***
X_{3it}^B	Year of spike		.038***
X_{4it}^B	Year after spike		.005
X_{5it}^B	Two years after spike		-.001
X_{6it}^B	At least three years after spike		.001
Vector X_{it}^E	*Equipment*		
X_{1it}^E	Two years before spike	-.002	
X_{2it}^E	Year before spike	.000	
X_{3it}^E	Year of spike	.008***	
X_{4it}^E	Year after spike	.004***	
X_{5it}^E	Two years after spike	.000	
X_{6it}^E	At least three years after spike	.001	

Notes: Table 3 presents the results of the estimation parameters for the impact of investment spikes in equipment and buildings. Dependent variables across regressions are on the horizontal row. Dependent variables: (1) Investment rate of Buildings and (2) Investment rate of Equipment. The vertical axis presents independent variables. The vectors X_{it}^B and X_{it}^E have been constructed such that $\left(1-S_{iq}^E\right)=1$ and $\left(1-S_{iq}^B\right)=1$ for $q \in \{-2,...,2\}$. Parameter estimates, conditioned upon observing an investment spike, are documented by investment spike time and investment type. Statistical significance is reflected by: * $p \leq .10$, ** $p \leq .05$, *** $p \leq .01$.

Table 4: Economic Impact from Investment Spikes in Equipment, Buildings and Simultaneously Both

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		PR	NW	AW	CB/NW	CE/NW	PRL	PRB	PRE	TC/S
Vector X_{it}^{B}	*Buildings*									
X_{1it}^{B}	Two years before spike	.044***	.031**	-.001	-.044***	-.004	.013	.057***	.017	-.005
X_{2it}^{B}	Year before spike	.062***	.055***	-.016*	-.069***	-.020	.007	.076***	.027	-.007
X_{3it}^{B}	Year of spike	.079***	.085***	-.023**	-.089***	-.047*	-.006	.084***	.042	-.004
X_{4it}^{B}	Year after spike	.057***	.073***	-.017**	-.015	-.038	-.016	-.001	.022	.005
X_{5it}^{B}	Two years after spike	.058***	.068***	-.017*	-.017	-.037	-.009	.008	.027	.003
X_{6it}^{B}	At least three years after spike	.022	.051***	-.006	.012	-.029	-.029**	-.041**	-.001	.010**
Vector X_{it}^{E}	*Equipment*									
X_{1it}^{E}	Two years before spike	.009	.007	-.010	-.011	-.087***	.003	.014	.090***	-.004
X_{2it}^{E}	Year before spike	.038**	.020*	-.009	-.019	-.112***	.018	.036**	.129***	-.011**
X_{3it}^{E}	Year of spike	.069***	.049***	-.005	-.051***	-.178***	.019	.070***	.197***	.002
X_{4it}^{E}	Year after spike	.029	.046***	-.009	-.044***	-.002	-.017	.028	-.014	.009*
X_{5it}^{E}	Two years after spike	.020	.031**	.003	-.029**	.026	-.011	.018	-.037*	.014**
X_{6it}^{E}	At least three years after spike	.038**	.010	.014*	-.004	.130***	.028**	.032**	-.102***	-.008*
Vector X_{it}^{C}	*Simultaneous*									
X_{1it}^{C}	Two years before spike	.071**	.034	.007	-.047	-.081***	.037*	.084***	.118***	-.027
X_{2it}^{C}	Year before spike	.104***	.079***	-.003	-.091***	-.156***	.025	.116***	.180***	-.008
X_{3it}^{C}	Year of spike	.150***	.119***	-.003	-.190***	-.192***	.031	.161***	.222***	.002
X_{4it}^{C}	Year after spike	.134***	.101***	-.003	-.049*	.006	.032	.081***	.026	.007
X_{5it}^{C}	Two years after spike	.083***	.082***	-.006	-.023	.031	.001	.024	-.030	.013
X_{6it}^{C}	At least three years after spike	.080***	.067**	-.010	-.003	.132***	.012	.016	-.120***	-.000

Notes: Table 4 presents the results of the estimation parameters for the economic impact of investment spikes in equipment, buildings and simultaneously both. Dependent variables across regressions are on the horizontal row and all dependent variables have received a (natural) logarithmic transformation. Dependent variables: (1) Production (2) Number of Workers (3) Average Wage (4) Capital Stock - Buildings / Number of Workers (5) Capital Stock - Equipment / Number of Workers (6) Productivity Labour (7)

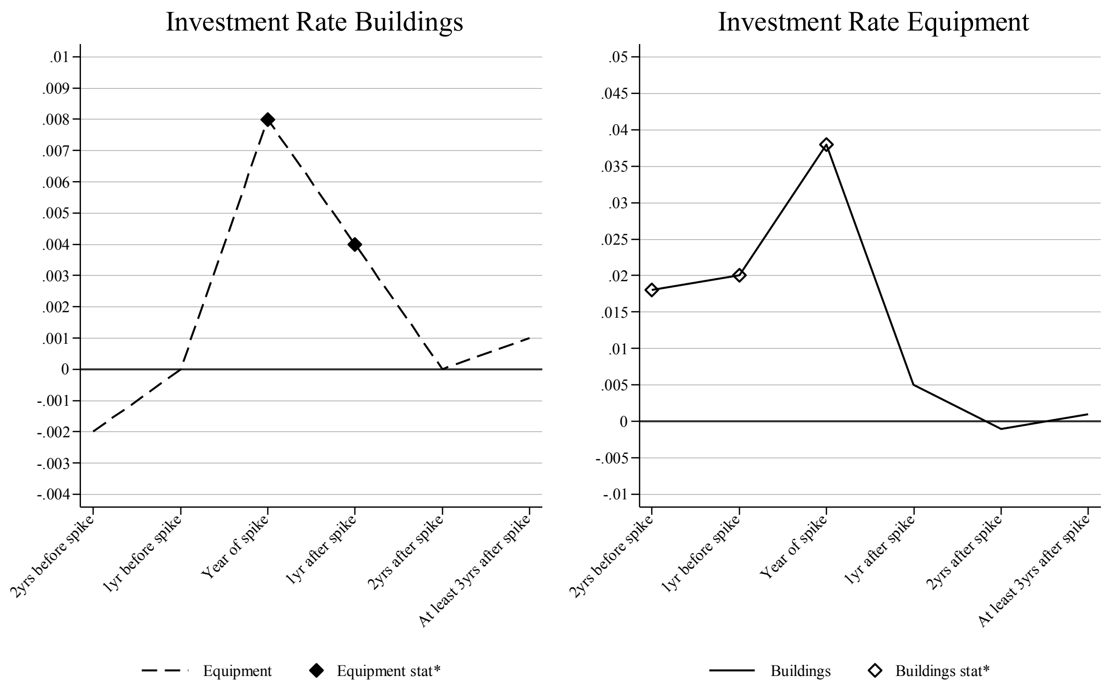
Productivity Buildings (8) Productivity Equipment (9) Total Costs / Sales. Parameter estimates, conditioned upon observing an investment spike, are documented by investment spike time and investment type. Statistical significance is reflected by: * $p \leq .10$, ** $p \leq .05$, *** $p \leq .01$.

Table 5: Sample Breakdown by Sector, Innovation Intensity and Labour Intensity

1993 SBI Code	Sector	N	%	Innovation Intensity	Labour Intensity
15-16	Food and drinks; Tobacco	918	16%	Low-tech	Low
17-19	Textile; Clothes; Leather goods	180	3%	Low-tech	High
20	Wood	162	3%	Wood	High
21	Paper and pulp	461	8%	Wood	Medium
22	Publishers, printing companies etc.	351	6%	Wood	Low
23-24	Oil and coal; Chemicals	638	11%	High-tech	Low
25	Rubber and plastics	241	4%	High-tech	Medium
26	Non-metallic minerals	441	8%	Low-tech	Medium
27	Metals	237	4%	Low-tech	Low
28	Metal products	662	11%	Low-tech	High
29	Machines and apparatuses	700	12%	High-tech	Low
30-32	Office machinery and computers; Electronic Machines and equipment; Audio, video and telecom devices	294	5%	High-tech	Medium
33	Medical and optical apparatuses and instruments	139	2%	High-tech	Medium
34	Cars and trailers	178	3%	High-tech	High
35	Other transportation means and products	95	2%	High-tech	High
36	Furniture and other products	171	3%	Low-tech	Medium
	Total	5868	100%		

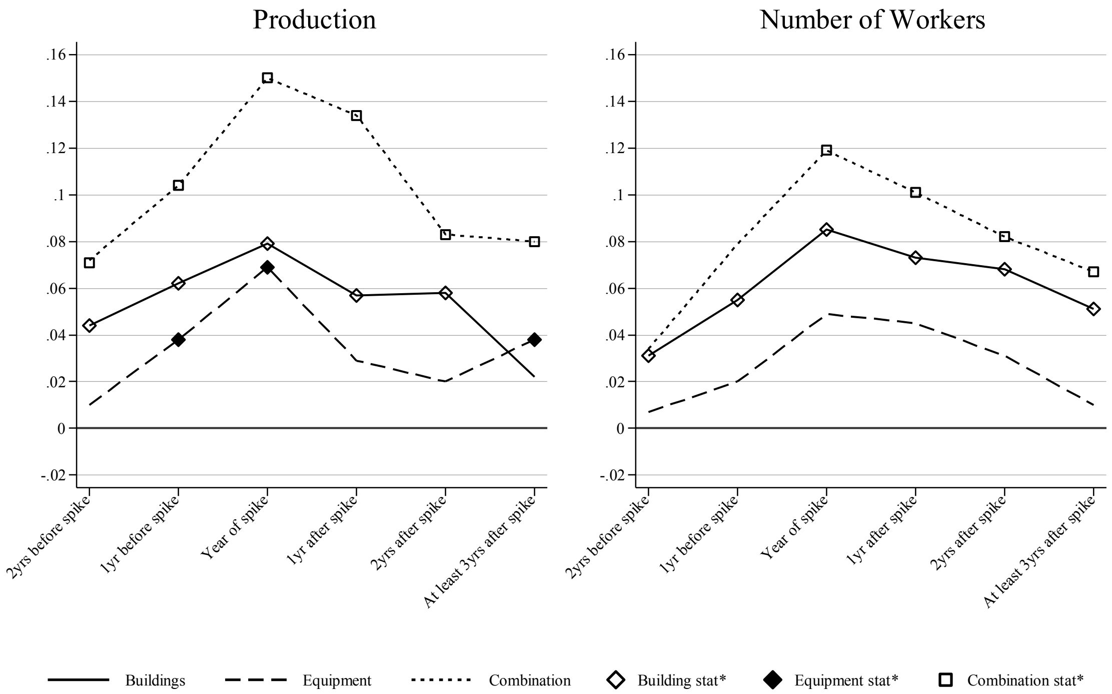
Notes: Table 5 documents the frequency of our sample by industry classification, technology intensity and labour intensity. Sectors have been aggregated into bigger groups, as Statistics Netherlands (CBS) requires reported statistics to be based on some minimum number of firms to ascertain anonimity of findings. The SBI classification system is the Dutch equivalent of the United States SIC system. Innovation intensity classification based on Raymond *et al*. (2006) and labour intensity classification based on Ramirez *et al*. (2005).

Figure 1: Interrelation between Investment Types



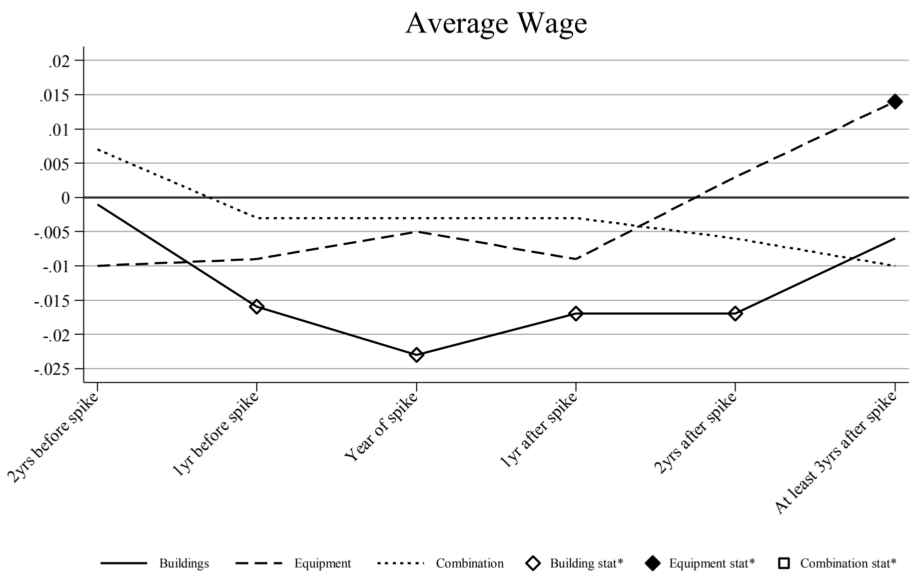
Notes: Figure 1 depicts investment rate of either equipment or buildings before, during and after the investment spike in the other investment type. The vertical axis represents the difference relative to firms that experienced no spike event. Markers represent estimates significant at $p < .10$ level (two-tailed).

Figure 2: Production Scale and Number of Workers



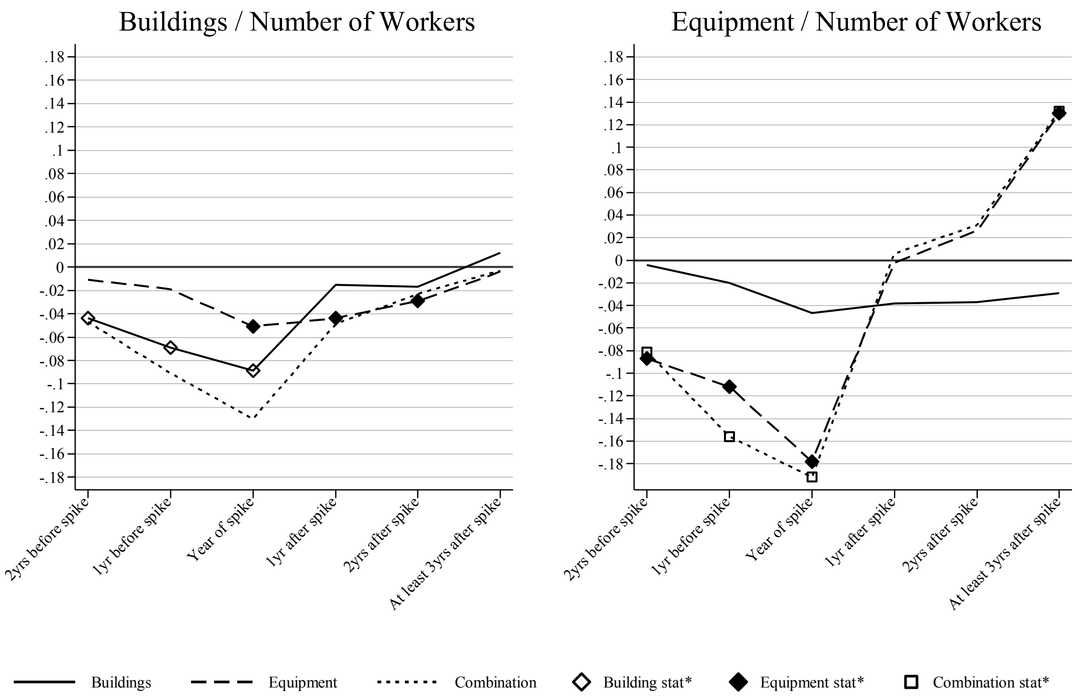
Notes: Figure 2 depicts the production scale and number of workers before, during and after the investment spike. The vertical axis represents the percentage difference relative to firms that experienced no spike event. Markers represent estimates significant at $p < .10$ level (two-tailed).

Figure 3: Development Wage



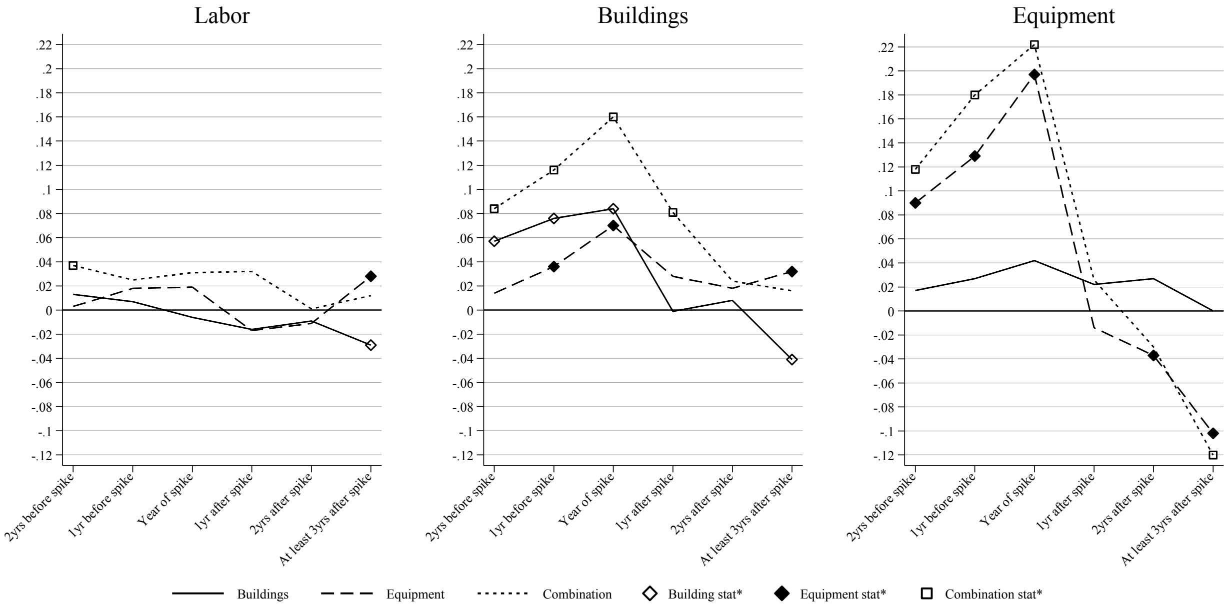
Notes: Figure 3 depicts the average wage per worker before, during and after the investment spike, relative to firms that experienced no spike event. Markers represent estimates significant at $p < .10$ level (two-tailed).

Figure 4: Capital Intensity



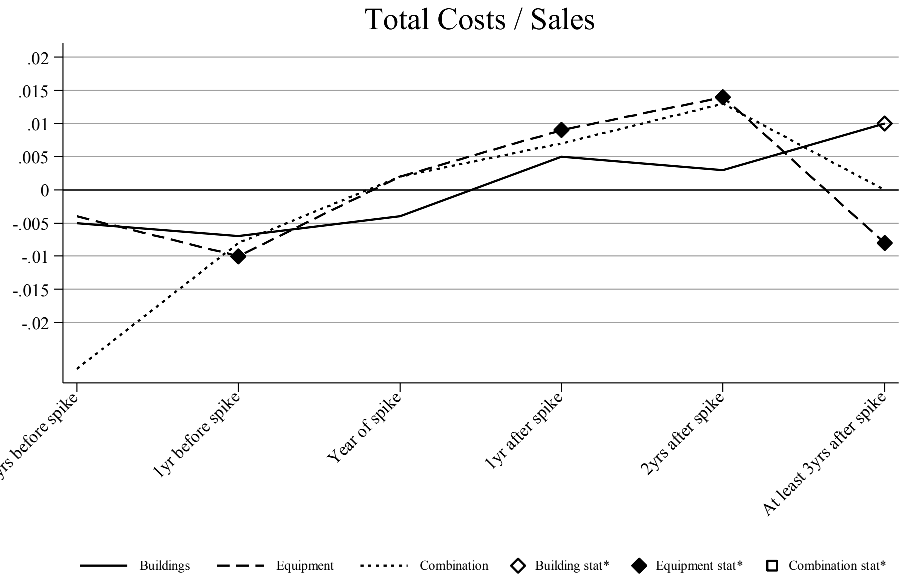
Notes: Figure 4 depicts the capital stock of buildings or equipment as a percentage of the number of workers. The vertical axis represents the percentage difference relative to firms that experienced no spike event. Markers represent estimates significant at $p < .10$ level (two-tailed).

Figure 5: Labour, Buildings and Equipment Productivity



Notes: Figure 5 depicts productivity for labour, buildings and equipment. The vertical axis represents the percentage difference relative to firms that experienced no spike event. Markers represent estimates significant at $p < .10$ level (two-tailed).

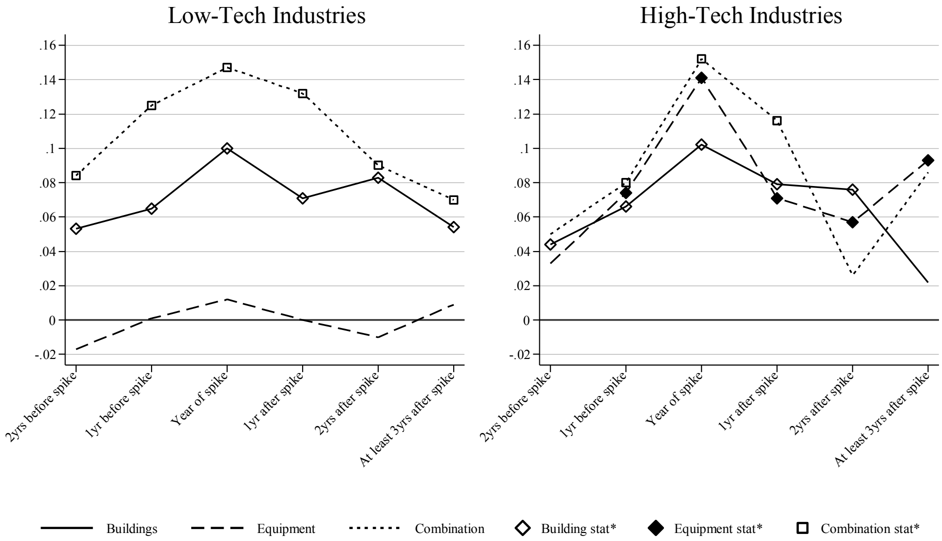
Figure 6: Operational Efficiency



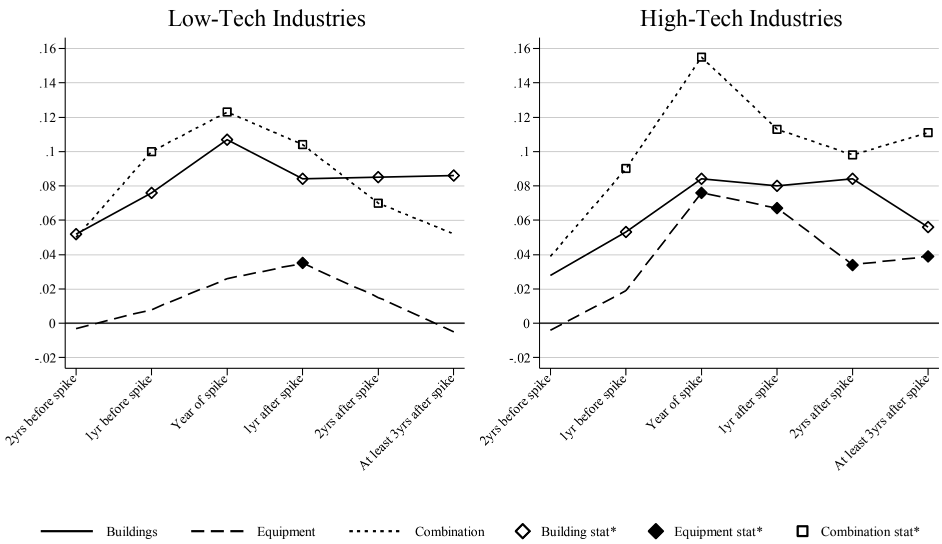
Notes: Figure 6 depicts total costs relative to total sales of the firm, reflecting a basic measure of firm operating efficiency. The vertical axis represents the percentage difference relative to firms that experienced no spike event. Markers represent estimates significant at $p < .10$ level (two-tailed).

Figure 7: Production (a) and Number of Workers (b) by Sector Innovation Intensity

a. Production



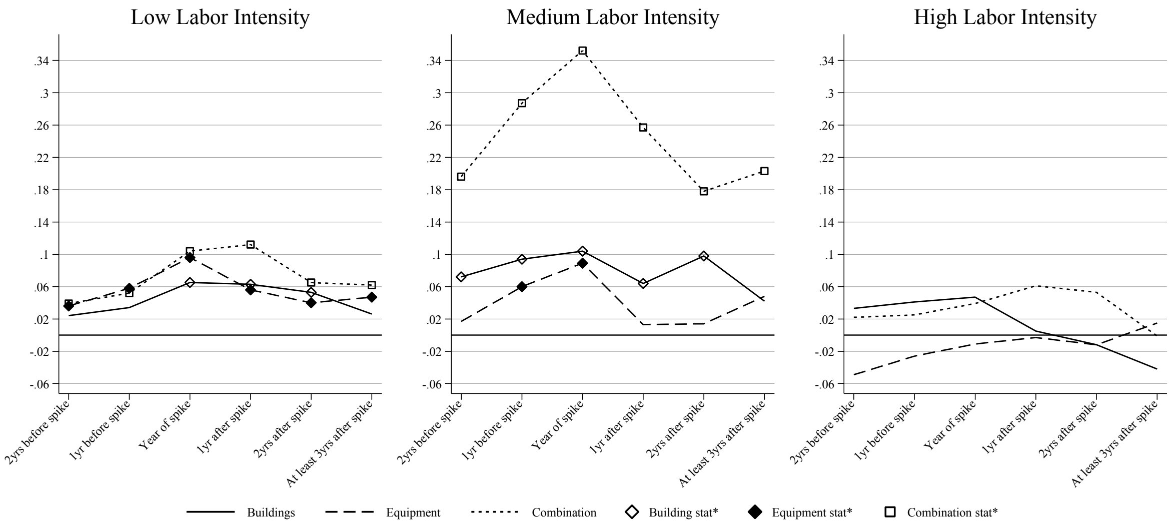
b. Number of Workers



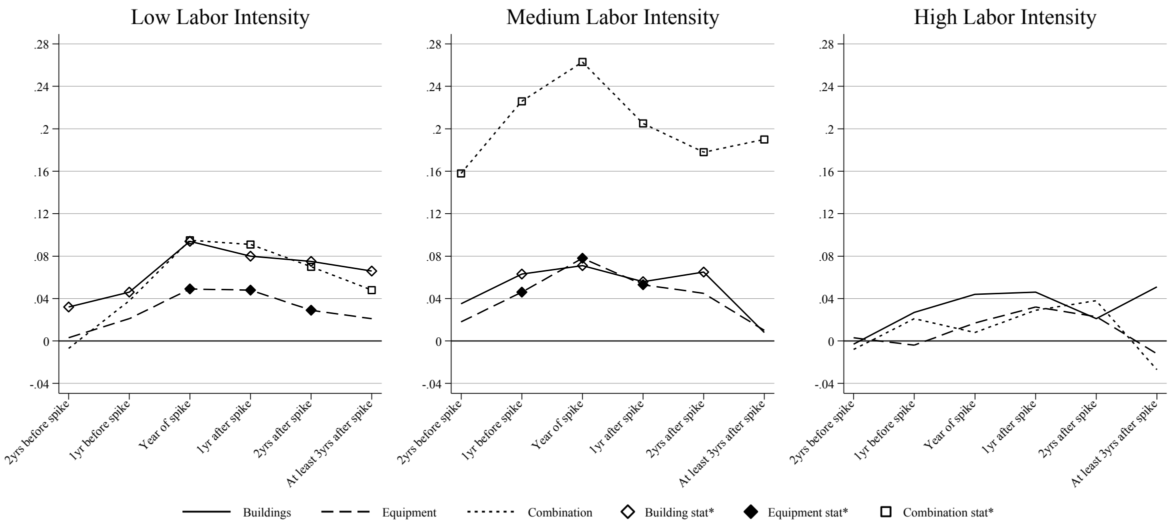
Notes: Figure 7 depicts production and the number of workers, broken down by different levels of innovation intensity. The vertical axis represents the percentage difference relative to firms that experienced no spike event. Markers represent estimates significant at $p < .10$ level (two-tailed).

Figure 8: Production (a) and Number of Workers (b) by Sector Labour Intensity

a. Production



b. Number of Workers



Notes: Figure 8 breaks down the sample by labour intensity, and shows the effect of investment spikes on production and the number of workers for low, medium and high labour-intensive sectors. The vertical axis represents the percentage difference relative to firms that experienced no spike event. Markers represent estimates significant at $p < .10$ level (two-tailed).