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What happens after an investment spike -  
investment events and firm performance

Michał Gradzewicz

# What happens after an investment spike - investment events and firm performance

Michał Gradzewicz\*  
National Bank of Poland and  
Warsaw School of Economics

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## Abstract

Our study aims at investigating the relationship between investment spikes and subsequent productivity development at the firm level. We propose a novel identification scheme for the effects of an investment spike, using matching techniques and adequate econometric modelling. It allows us to find efficiency differentials against matched firms. We showed that TFP falls after an investment spike and slowly recovers thereafter, which is consistent with learning-by-doing effects. For smaller firms the fall is more pronounced and the subsequent recovery is longer. On the contrary, labor productivity rises after an investment spike, driven mainly by capital deepening. The increase of sales after a spike suggests that expansion is the main purpose of an investment spike and rising employment confirms that this type of investment is complementary to labor. As firms with spikes are on average more efficient and investment spikes attract resources and production factors, it suggests that improved allocative efficiency is an important factor driving positive macroeconomic correlation between investment and TFP.

*Keywords:* difference-in-difference, investment spike, matching, productivity, TFP

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# 1 Introduction and motivation

In this paper we investigate the link between firms' investments in tangible assets and their subsequent performance. Since the seminal paper by Doms & Dunne (1998), it is widely known that investments on a firm level are lumpy - years of repair and maintenance are followed by one or several years of heavy investment. We will focus on these episodes of 'investment spikes' – they are naturally important from the firms' perspective and have the potential to affect firm performance. Moreover, Gourio & Kashyap (2007) or Nilsen & Schiantarelli (2003) among others showed that large investments episodes account for a large fraction of total investment, so these episodes are also important from a macroeconomic point of view.

The macroeconomic relation between equipment investment and economic growth is well established in the literature – see e.g. De Long & Summers (1991). Moreover, investment co-moves with productivity, both in long and short-term. But the firm-level relation between investment and efficiency can be more complicated. On theoretical grounds the vintage capital model of Cooley et al. (1997) treats investments as technological upgrading (as new capital embodies more recent technology), resulting in a positive investment-performance relationship both in short and long-term. But, in learning models of Klenow (1998) or Jovanovic & Nyarko (1996), productivity increases as firms learn about the given technology. The switch of technologies connected with investment temporarily reduces expertise because technical knowledge is highly specific to particular production processes. It follows that productivity may initially fall when firms adopt new technologies, but gradually rise as firms get experience with the new technologies. We will discuss empirical literature below.

Empirical literature presents several definitions of a firm-level investment spike, as discussed in Grazi et al. (2016). All are based on investment normalized by the size of the stock of capital from the previous period (or beginning of the period):  $I_t/K_{t-1}$ . The simplest rule follows theoretical work of Cooper et al. (1999) and defines an investment rate exceeding 0.2 as spike episodes. Power (1998) considers spikes as large investment events relative to each firm's investment and sets the threshold as a multiple (usually between 1.75-3.25) of the firm's median investment rate over the period of interest. However, Nilsen

et al. (2009) noticed that investment ratios of small firms exhibit more volatility than for large firms and the probability that a small firm has an investment ratio above some threshold is larger than for a large firm. They model the threshold as a falling linear function of a firm's capital stock to correct for size. Grazzi et al. (2016) additionally accounted for convexity of the relationship and modelled the investment rate - capital relationship using a non-parametric kernel fit. In our data nonlinearities are also present so we use a spike definition similar to the kernel rule in Grazzi et al. (2016). In the robustness appendix we also present results with different spike definitions.

The empirical literature on the firm level link between investment spikes and firm performance uses reduced form regressions and the results vary – indicating either a short term rise or fall of efficiency measures after an investment spike. Papers reporting a positive relationship usually find it small (or quickly disappearing), given the size of a spike. The first result, Power (1998), using data from the U.S. manufacturing sector finds (defining a spike relative to median investment rate) a slightly positive, but very small link of investment and labor productivity or productivity growth (she concludes there is virtually no observable relationship). Geylani & Stefanou (2013) presents evidence from the U.S food industry using a similar spike definition as Power (1998) and finds that efficiency, measured with TFP (based on the production function estimation in Levinsohn & Petrin (2003)) rises, but again the rise is small and short lived – in longer term the positive effect trails off. Small, short-lived positive efficiency effects are also found by Grazzi et al. (2016) and Nilsen et al. (2009), the former using data on Italian (where there is no effect) and French manufacturing firms, the latter for two Norwegian manufacturing and one service sector. Both papers use labor productivity as an efficiency measure and adjust the spike definition by the size of the firm's capital. A negative investment-performance relation in U.S. manufacturing firms is found by Sakellaris (2004). He uses a simple definition of a spike (following Cooper et al. (1999)) and concludes that productivity remains relatively flat after the spike whereas TFP drops and then recovers slowly after 2 years. Huggett & Ospina (2001) use data from the Colombian manufacturing sector and also find a fall of TFP growth after an investment spike (measured with a simple threshold), with no indication of a long-term positive level effect. Shima (2010), using Japanese manufacturing

data, finds also a negative relationship. These results indicate that on a firm level the investment-performance link may be complex and learning effects associated with the introduction of new technologies may be an important driver of the link. We will elaborate on that issue later on.

The contribution of our study to the literature is two-fold. The first is the identification scheme. All of the cited papers establish the investment-performance link by estimating change in performance measure after the spike using standard panel methods. Implicitly, they measure the strength of the link relative to all other firms. Instead, we use matching techniques, pioneered by Rosenbaum & Rubin (1985) to find “statistical twins” to investing companies and measure the link not only using time, but also a group of matched firms to compare efficiency. As spike events occur in different time periods, we use the sample construction method proposed by Gormley & Matsa (2011) and estimate the size of after-spike performance change (comparing to matched firms) using a diff-in-diff estimator. The methods we implement are used in social sciences to mimic an experimental research design. A firm’s decisions to invest is not an exogenous factor, so it is impossible to interpret the results in causal terms. Still, the methods are intended to mitigate the effects of extraneous factors and selection bias and are useful in the context of the study.

The second contribution to the literature is empirical. Existing literature presents aggregate results whereas we stress interesting differences between smaller and larger enterprises – smaller firms tend to perform relatively worse after an investment spike. We are not aware of any theoretical model giving rise to such a difference, but it suggests that learning new technologies can be non-trivial for firms. Smaller firms tend to have less qualified staff (see e.g. Bertrand & Schoar (2003) for the importance of staff quality for firm performance), which may negatively affect their learning curves. Moreover, we stress the reasons why results for labor productivity and TFP may differ. We also stress that investment spikes seem to be aimed at market expansion, being simultaneously complementary to labor. We also find that a positive macroeconomic investment-performance relation is driven by an improving allocation efficiency after an investment spike. All these considerations potentially help to understand the differences in the investment-performance link observed in the literature.

The rest of the paper is organized as follows. Next section presents data sources. Then, we define the concept of investment spike and discuss its properties. It is followed by the discussion of an identification strategy and econometric issues. The next section presents results, both for aggregates and for larger and smaller firms. The final section offers some concluding remarks and comments.

## 2 Data

Our annual data cover the 15-years period (2002-2016) and come from financial reports and balance sheets of all Polish enterprises employing more than 49 (full time equivalent) employees and with the majority<sup>1</sup> of firms employing between 10 and 49 persons. The data are collected by the Central Statistical Office and comprise non-financial enterprises from mining, manufacturing construction, market and non-market services (the latter covers only the enterprise sector).<sup>2</sup>

The original data is an unbalanced panel of almost 0.77 million observations – almost 120.000 firms were observed for on average 6.4 years, while also containing missing observations. We trimmed the original data to be usable for further analysis – 7.4% of observations on labor, tangible capital or sales (for definition of variables see Appendix) were missing or zero (mainly due to missing values of capital). Further analysis requires positive observations on the value added, which additionally removes 16% of observations. The final data consists of 0.58 million observations on 88 thousand firms observed for 6.75 years on average.

Table 1 presents the most important properties of our data. The first three columns present selected properties at the beginning, in the middle and at the end of our final data, 4<sup>th</sup> column - the parallel numbers for the last year of the original (before trimming) data. The last two columns present discussed properties for smaller (SME, with employment less than 250, 93% of observations) and larger (Non-SME) enterprises for the last year of final data. Our original data cover 90% and 85% of employment and value added in the whole enterprise sector of the Polish economy respectively. The final dataset covers ca. 77%

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<sup>1</sup>Some firms decide not to fill the compulsory form to the statistical office, which is subject to a fine.

<sup>2</sup>The data was used e.g. for an internalization analysis in Hagemeyer & Kolasa (2011).

of both employment and value added. Removing unusable observations increased average employment and  $K/L$  ratio but did not change significantly data properties.

Table 1: Data properties

	final	final	final	original	SME	Non-SME
year	2002	2008	2016	2016	2016	2016
Number of firms	33903	38443	43612	56629	40724	2888
Emp. coverage	0.72	0.80	0.77	0.90	-	-
VA coverage	0.81	0.84	0.77	0.85	-	-
Av. employment	104	112	101	91	48	841
Av. $K/L$	113	132	195	175	153	229
Av. ROA	0.00	0.05	0.13	0.12	0.13	0.13
Av. debt/asset	0.14	0.11	0.39	0.41	0.31	0.45
Av. liquidity	0.19	0.34	0.38	0.42	0.40	0.37
Av. $VA/L$	73.3	107.8	150.5	149.5	121.9	173.9
Av. export share	0.15	0.18	0.27	0.26	0.19	0.32
Av. no. exporters	0.21	0.23	0.29	0.26	0.27	0.59

Our final data show first increasing and after 2008 falling average employment, but  $K/L$  rises monotonically indicating capital deepening of Polish firms. In most years ROA fluctuates between 4% and 8% and the debt-to-assets ratio between 11-15%, but in 2016 those indicators increased to 13% and 39% respectively. Liquidity is on a rising trend, as well as productivity, which doubled on average during the 15 years period of our analysis. The average export share almost doubled as well, partly due to an increased share of exporting firms.

## 3 Identification strategy

### 3.1 Investment spikes

Grazzi et al. (2016) discusses various approaches to identify investment spikes in the data, showing that the failure to account for the scaling relation between investment rate and firm size noticed by Nilsen et al. (2009) can result in identification biases. Negative, non-linear relation between investment rates and firm size is also present in our data, so our spike identification follows Grazzi et al. (2016).<sup>3</sup> Specifically, we define an investment spike as:

$$S_{it} = \begin{cases} 1 & \text{if } \frac{I_{i,t}}{K_{i,t-1}} > \max[\alpha E_j[\frac{I_{i,t}}{K_{i,t-1}}|K_{i,t-1}], 0.2] \\ 0 & \text{otherwise} \end{cases}, \quad (1)$$

where  $\alpha = 2.75^4$  and  $E_j[I_{i,t}/K_{i,t-1}|K_{i,t-1}]$  is obtained through non-parametric estimation of a class of generalized additive models (see e.g. Hastie & Tibshirani (1990)) accounting for a negative and non-linear relation between investment rate and capital. Models were estimated for each 2-digit NACE sector ( $j$ ) with the number of observations exceeding 9. We excluded from the selection rule cases with  $I_{i,t}/K_{i,t-1} > 12$ , which we treat as implausibly high (0.8% of observations, unimportant for final results).

As stated by Nilsen et al. (2009), any meaningful spike measure should identify episodes with investment rates larger than the unconditional means. Average investment rates during identified spike periods are 2.5 and 0.8 otherwise. Capital-weighted mean investment rates are smaller – 0.79 for investment spikes and 0.12 for other observations. Another criterion for selection among spike rules stressed by Nilsen et al. (2009) is parsimony – the ability to capture a large share of total investment with a small number of observations. Our selection rule yields 48227 spike events, on average 8.1% of all observations, with a maximum of 11% in 2007 - see Figure 2. The share of employment of firms having in a given year an investment spike in total employment is only slightly higher and amounts on average to 9.7%. But the analogous ‘investment share’ is much higher – investment spikes on average account for 27.6% of total investment. Figure 2 shows that this share is highly

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<sup>3</sup>In the Appendix we also show our main results for spike identification methods proposed by Power (1998) and Nilsen et al. (2009).

<sup>4</sup>Which is in the range analysed e.g. by Power (1998).

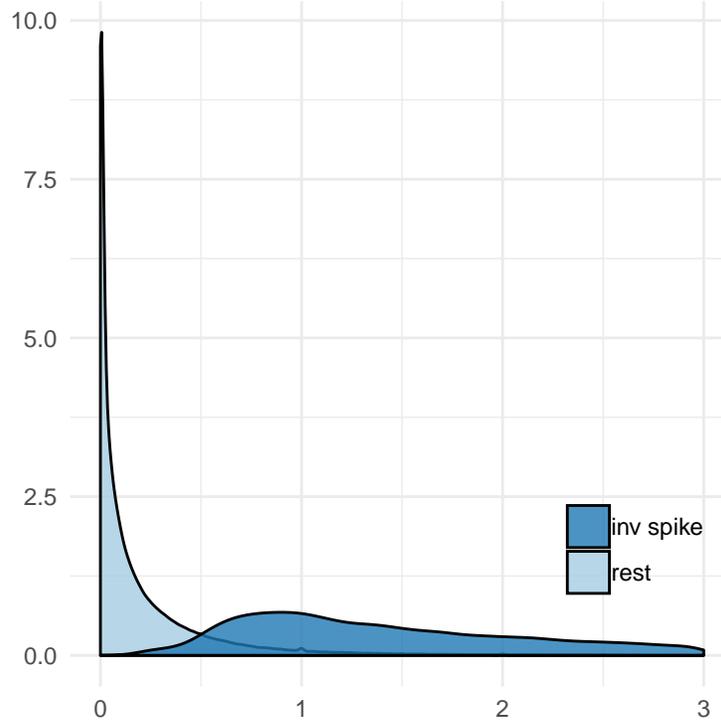


Figure 1: Density of  $I/K$  for the events of investment spikes and the rest of observations

volatile and pro-cyclical - with peaks in periods 2007-2009 and 2015. Our selection rule for spikes results in a share of spikes in SMEs<sup>5</sup> and larger firms – respectively 7.8% and 11.5% of the total number of observations in a relevant size class – that roughly matches the proportions in the data.

### 3.2 Matched firms

The identification of investment spikes allows us to look at the dynamics of various performance measures, like productivity or TFP, directly before and after an investment spike. Widely used panel data methods used to identify what happens to performance measures in adjacent periods measure the strength of the link relative to all other firms, which could be subject to endogeneity bias. To minimize this bias we decided to compare the evolution of post-spike efficiency measures not to all other firms, but to a carefully chosen group of relatively similar firms, but conducting a normal investment schedule during that time.

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<sup>5</sup>SMEs are defined as firms employing less than 250 employees.

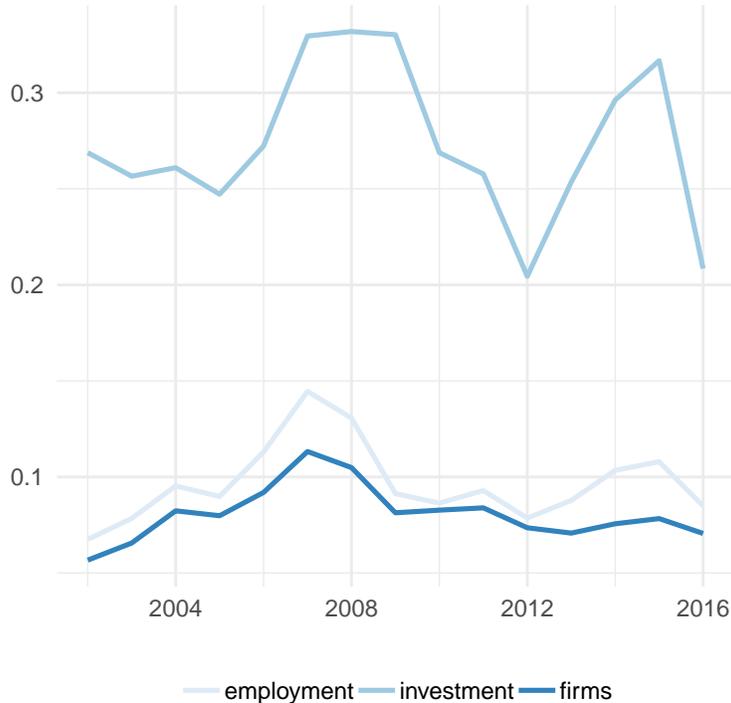


Figure 2: Importance of investment spikes events

We used matching techniques to identify the comparison group of firms, which we will call matched firms. We matched firms on a propensity score, using logit to estimate the conditional expectation function of investment spike probability as a measure of distance between firms. Having a large sample, we used the nearest neighbor matching and single best match without replacement to identify matched firms, which is the least biased, but simultaneously the least precise estimate of a counterfactual. As we are not using any structural model of investment decision (moreover, our sample includes the period of the 2008/2009 recession), we estimated the underlying logit model separately for each year. We matched firms on a number of dimensions commonly used in the literature, referring to size, destination market, technology, performance and financing. Within each estimated matching model we used exact matching on a 2-digit NACE sector and ownership status (public, private-domestic, private-foreign).<sup>6</sup>

Weinberg (1994) suggested that firm size is an important determinant of firm decisions.

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<sup>6</sup>In the Appendix we also present the main results of the paper in case of treating all non-spike firms as a comparison group — resigning from matching, and in the case of estimating one model for all years.

Moreover, Dang et al. (2018) stressed that firm size can be measured on various dimensions and that it is important for the firm performance. We used both employment and sales as various measures of firm size in matching models. We also matched on export share as a proxy indicating the market, on which firms operate. Moreover, Bernard & Jensen (2004), among others, showed evidence that more productive firms self-select into exporting, so controlling for the export share seems to be reasonable in matching logit. We proxied the technology that the firm uses with the share of overall labor costs in total operating costs. The efficiency dimension in matching was defined both in a technological and financial context. We used labor productivity<sup>7</sup> as a measure of firm technological performance and return on assets (ROA) as a measure of its financial efficiency. Finally, we match also on two measures of the firm financial structure – liquidity and debt share. Liquidity measures the firms’ operational need for financial resources, as firms have a different length of production processes and have varying payment schedules and access to short-term external financing. Debt share measures the extent of external financing used by a firm. All level variables (employment, sales, productivity) were expressed in logs.

Table 2: Matching properties

	L	S	Ex/S	wL/C	Y/L	ROA	liquid	debt
all	3.730	9.313	0.117	0.331	4.134	0.100	0.851	0.110
spikes	3.969	9.801	0.137	0.296	4.343	0.165	0.827	0.098
no-spikes	3.709	9.270	0.115	0.334	4.116	0.094	0.853	0.111
matched	4.017	9.800	0.135	0.294	4.350	0.155	0.882	0.103
reduction	0.814	0.998	0.912	0.935	0.970	0.857	-1.083	0.644
t-test (spike vs non-spike)	0.000	0.000	0.000	0.000	0.000	0.000	0.105	0.000
t-test (spike vs matched)	0.000	0.895	0.309	0.044	0.182	0.001	0.239	0.188
KS-test (spike vs. non-spike)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

<sup>7</sup>The choice of labor productivity on the first sight seems to create endogeneity in the further analysis, as we try to determine if the decision to invest affects labor productivity. But the matching identifies similar firms only in the moment of an investment spike and the potential effects of investments are measured in subsequent periods, relative to the existing difference in the moment of a spike. This implies that our subsequent analysis starts with firms with a relatively similar productivity in the base period.

	L	S	Ex/S	wL/C	Y/L	ROA	liquid	debt
KS-test (spike vs matched)	0.000	0.000	0.741	0.000	0.303	0.000	0.000	0.000

Remarks: First four rows present means of variables of interest in different populations, 5<sup>th</sup> row presents reduction of bias in means after matching, 6<sup>th</sup> and 7<sup>th</sup> rows – p-values of t-tests of difference in means, next two rows – p-values of Kolmogorov-Smirnoff tests of distribution similarity and the last two rows – relative standard deviations. L - log employment, S - log sales; Ex/S - export share; wL/S - wage share in total operational costs; Y/L - labor productivity; liquid - liquidity; debt - debt-to-assets ratio.

Table 2 shows the comparison of investment spikes observations with both the rest of observations (non-spikes) and matched observations. It shows that spikes compared to other firms are on average larger in terms of both employment and sales, more productive, and more capital-intense (lower labor share). They are also more export-oriented and profitable, but simultaneously less liquid and less indebted. The results of t-tests of difference in means between spikes and non-spikes show that the above-mentioned differences are highly significant (with the exception of liquidity). The matched observations are much more similar to spikes than non-spikes – bias reduction achieved is in most cases in the range of 80%-90%. Only in case of debt share the reduction statistic is smaller, with 64%. Liquidity seems to be more problematic, as the reduction is negative and matched firms are on average less similar to spikes than the non-spike firms, but relevant t-tests show that in both cases differences in means are insignificant. Formal tests show that means of only log employment and ROA remain significantly different after matching.

The reduction of mean differences is important in assessing matching quality, but distribution resemblance also matters. Figure 3 shows that distributions of all relevant variables after matching are much closer to the distribution of spikes than in the case of a spike-nonspike comparison. However, Kolmogorov-Smirnoff tests (see Table 2) show that only in case of export share and log productivity spikes and matched observations are drawn from the same distribution. In the other cases KS-statistics were much smaller, but above critical value.

A critical feature of the properly specified comparison group of matched firms is the absence of significant change of  $I/K$  in the period of interest. As we used the threshold in

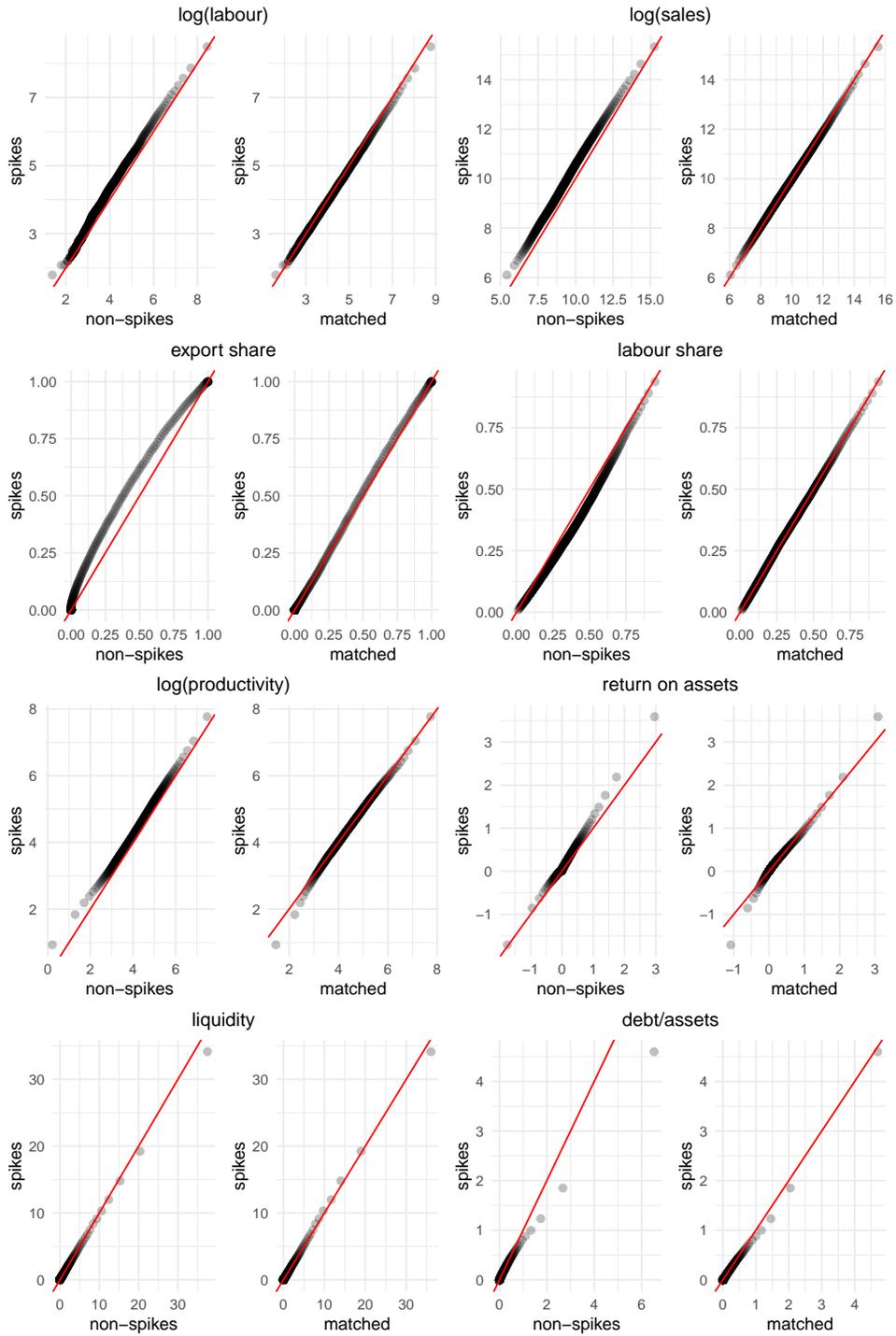


Figure 3: QQ plots of spike-nonspike and spike-matched distributions

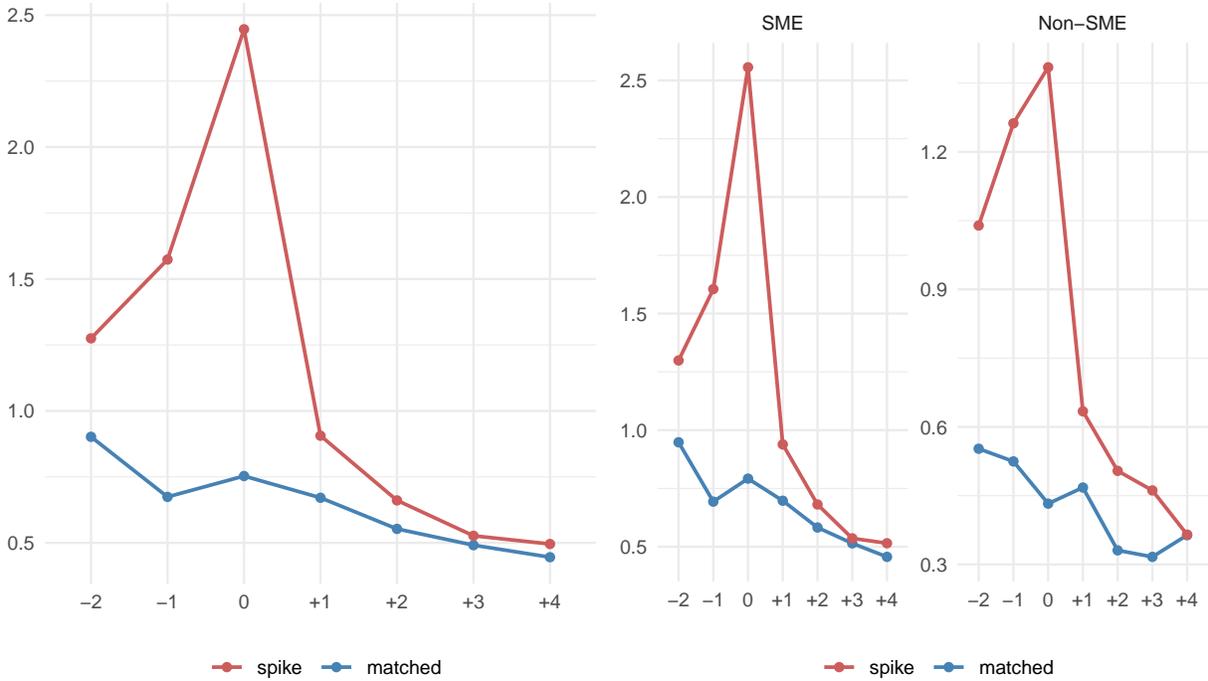


Figure 4: Average  $I/K$  of spike and matched firms in periods adjacent to a spike

defining the investment spike, it could be the case that matched firms are just below the threshold, also experiencing a spike, but with smaller magnitude. Figure 4 shows that it is not the case – the red line of Figure 4 shows the evolution of mean  $I/K$  in spike firms in the year of a spike (0 on the horizontal axis) and in the adjacent periods - up to two years before a spike and up to four years after a spike. The blue line shows the corresponding averages for matched firms. The evolution of median  $I/K$  is very similar for both groups.<sup>8</sup> Figure 4 presents also investment rates for smaller and larger firms. The spikes are identified properly and show some notable differences across size classes: investment process in larger firms seems to be on average longer – the investment rates are heightened even two years before a spike. Moreover, the magnitude of a mean spike in larger firms is half of a spike

<sup>8</sup>A detailed examination of the evolution of the investment rate of both groups of firms in NACE sectors showed that in the case of Mining, Energy and Information (sectors: B, D and J), spikes were also present in matched firms and in Science (sector M), a bigger on average spike was observed four years after the identified spike period. We decided to remove observations from those sectors (7% of identified spikes, mainly in Science, leaving 44839 spike observations) from further analysis. Figure 4 presents means for a trimmed sample, which on aggregate does not differ from the whole sample results.

in SMEs.

### 3.3 Estimation

To estimate the effects of investment spikes on firm performance we compare the behavior of performance measure changes of the firms with an investment spike and matched firms around the time of an investment spike. For each year in the sample we construct a cohort  $c$  of firms with spikes in this year and matched firms from this year using firm-year observations for the two years before and four years after the spike. Firms are not required to be in the sample for the full analysed time span around the event. Then we pool the data across cohorts. If an observation that is used as matched firm in some cohort becomes a spike itself in any subsequent period within a four-year window, this observation is dropped. So we exclude the possibility that performance measures in matched firms after a spike are affected by observations becoming spikes themselves. The data construction follows Gormley & Matsa (2011) in which events under consideration are also distributed over time.

Pooling makes the analysis more robust, as results are not driven by any particular year and there is considerable business cycle variation in our sample. Pooling also implies that the identified effects of spikes shouldn't be driven by any specific set of firms, as it is highly implausible that these firms are always selected as spikes.<sup>9</sup> On the other hand, pooling makes the estimated effects time-invariant.

We estimate the following panel regression:<sup>10</sup>

$$y_{ict} = \sum_{j \in \{-2, -1, 1, 2, 3, 4\}} \beta_j d_{ict} \times \tau_j + \alpha_{ic} + \delta_{ct} + \epsilon_{ict} \quad (2)$$

where  $d_{ict}$  is an indicator of firm  $i$  having a spike in cohort  $c$ ,  $\tau_j$  is an indicator of the current period  $t$  being  $j$  periods post (positive  $j$ ) or before (negative  $j$ ) the spike year,  $\alpha_{ic}$  is a unit-cohort fixed effect controlling for the independent individual effect in each

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<sup>9</sup>In 59% of firms with spikes in any time period the spike occurs only once, in 24% it occurs twice and in 2.5% more than four times

<sup>10</sup>When determining the effects for sub-samples (e.g. for SMEs and non-SMEs) we present estimates of  $\beta$ s from the equation (2) estimated separately for those sub-samples

cohort and  $\delta_{ct}$  is a time-cohort fixed effect, controlling for post dummy in each cohort. The inclusion of both fixed effects accounts for possibly different individual mean performance across firms and it allows for common change in the performance indicator to vary by year.

The  $\beta_j$  estimates measure the difference of performance indicator  $y$  around the spike period between firms with spikes and matched firms from a proper cohort, pooled across different cohorts. Due to collinearity  $\beta_0$  is dropped from the equation (2), so measurement is relative to any difference existing in the moment of a spike. For example,  $\beta_2$  measures the average difference of  $y$  between firms with spikes and matched firms 2 years after a spike, relative to a difference occurring during a spike period. Time-varying  $\beta$ s allow us to both check for possible divergence in trends of spike and matched firms before the spike (parallel trend assumption) and to allow for a spike effect to fade in or fade out, as in Autor (2003). Ideally,  $\beta_j$  for periods before a spike (negative  $j$ ) should be insignificant, confirming the parallel trends assumption.

We account for possible clustering of errors with a set of 2-digit NACE dummies. Industry-level clustering controls for two phenomena. First, as firms within industries have more in common than firms from different industries, industry-level clustering allows for within industry correlation. Moreover, as shocks are usually persistent, clustering at industry level accounts for errors being correlated over time within industries. Models were estimated using the method of alternating projections to sweep out multiple group effects from the normal equations before estimating the remaining coefficients with OLS (see Gaure (2013)).

### 3.4 Identification of TFP

Measurement of TFP is not straightforward and is subject to many problems. One of them, first recognized by Marschak & Andrews (1944), is simultaneity between unobservable productivity (being part of the error term in the production function equation) and observable input choices. As a profit-maximizing firm's response to a positive productivity shock is to expand output, which requires more inputs, it follows that productivity shock would be positively correlated with variable inputs, inducing upward bias in the estimated coefficients on variable inputs.

Olley & Pakes (1996) address this issue, using investment as a proxy to control for the part of the error term, which is correlated with inputs. They utilize the monotonicity of the investment demand function in productivity, which can be inverted to express unobservable productivity as a function of observables and hence to control for productivity in estimation. Two problems arise with the approach of Olley & Pakes (1996). First, the literature stresses that firms often have periods with zero investment. Second, we concentrate on periods with unusually high investment compared to adjacent periods, which introduces high variability in TFP estimates.

We use instead the identification of TFP proposed by Levinsohn & Petrin (2003), which uses materials instead of investment as a proxy variable, using similar assumptions applied to demand for intermediates. Limited substitution between materials and other factors of production translate into smoother response of materials to productivity shocks.<sup>11</sup> As the panel we use is unbalanced, we control for firm exit in the TFP estimation, as it can substantially affect results (see the discussion in Olley & Pakes (1996)). We estimated TFP jointly for the whole sample, not allowing for the elasticities or other features of production function to vary across industries, as in the subsequent analysis we will use averages of TFP of firms from different sectors and periods.

We use the book value of fixed assets as a measure of capital (Baily et al. (1992) argues that capital definition has little effect on properties of resulting productivity estimates). We used 1-digit NACE price deflators of output and capital (the latter measured separately for different tangibles) to express all variables in real terms. The production function estimation is more data-demanding and it was not possible to construct TFP measures for 14% of observations in the sample.

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<sup>11</sup>In the Appendix we also present the results for TFP identification correction proposed by Akerberg et al. (2015).

## 4 Investment spikes and firm performance

### 4.1 Total factor productivity

We start the discussion of our results with the answer to the main question – does TFP rise following an investment spike. Then we will discuss the reasons for observed behavior of TFP after a spike. Top panels of Figure 5 show the evolution of mean TFP in firms with spikes and of matched firms in the periods adjacent to a spike and the difference between them measured using  $\beta_j$ s from the equation (2).<sup>12</sup>

First, TFP of firms with spikes rises before a spike, falls by two log points just after a spike and then slowly builds up. Four years after a spike the TFP level is on average slightly higher than just before a spike. The estimated differences against matched firms show that the TFP fall of firms with a spike is statistically significant, but then the difference evaporates. As the level of TFP of spike firms is ca. five log-points higher than matched firms, it means that this difference persists. The evolution of TFP is similar to the one predicted by Jovanovic & Nyarko (1996) and indicates the existence of learning-by-doing effects. But the results show that on average even after four years after a spike, the TFP level of investing firms is not higher than that of matched firms (non-investing during that time) firms. The results are similar to Sakellaris (2004) and Huggett & Ospina (2001).

Bottom panels of Figure 5 show that the story is relatively similar for smaller and larger firms, but in case of the former, the TFP fall is more pronounced and the subsequent TFP recovery is muted, both in absolute and relative (measured with  $\beta$ s from equation 2) terms, leading to a still trimmed TFP level even four years after a spike. For larger firms the TFP difference is insignificant for almost all periods after a spike and the rise of the TFP level, which starts two years after a spike, leads to a level of TFP higher than before a spike, although the difference against matched firms is insignificant.

### 4.2 Labor productivity

Measuring productivity is a non-trivial task and although it is a very good measure of efficiency, it is subject to additional assumptions and measurement errors. Labor productivity

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<sup>12</sup>Whiskers in left panels of Figure 5 show the 66% and 95% confidence intervals.

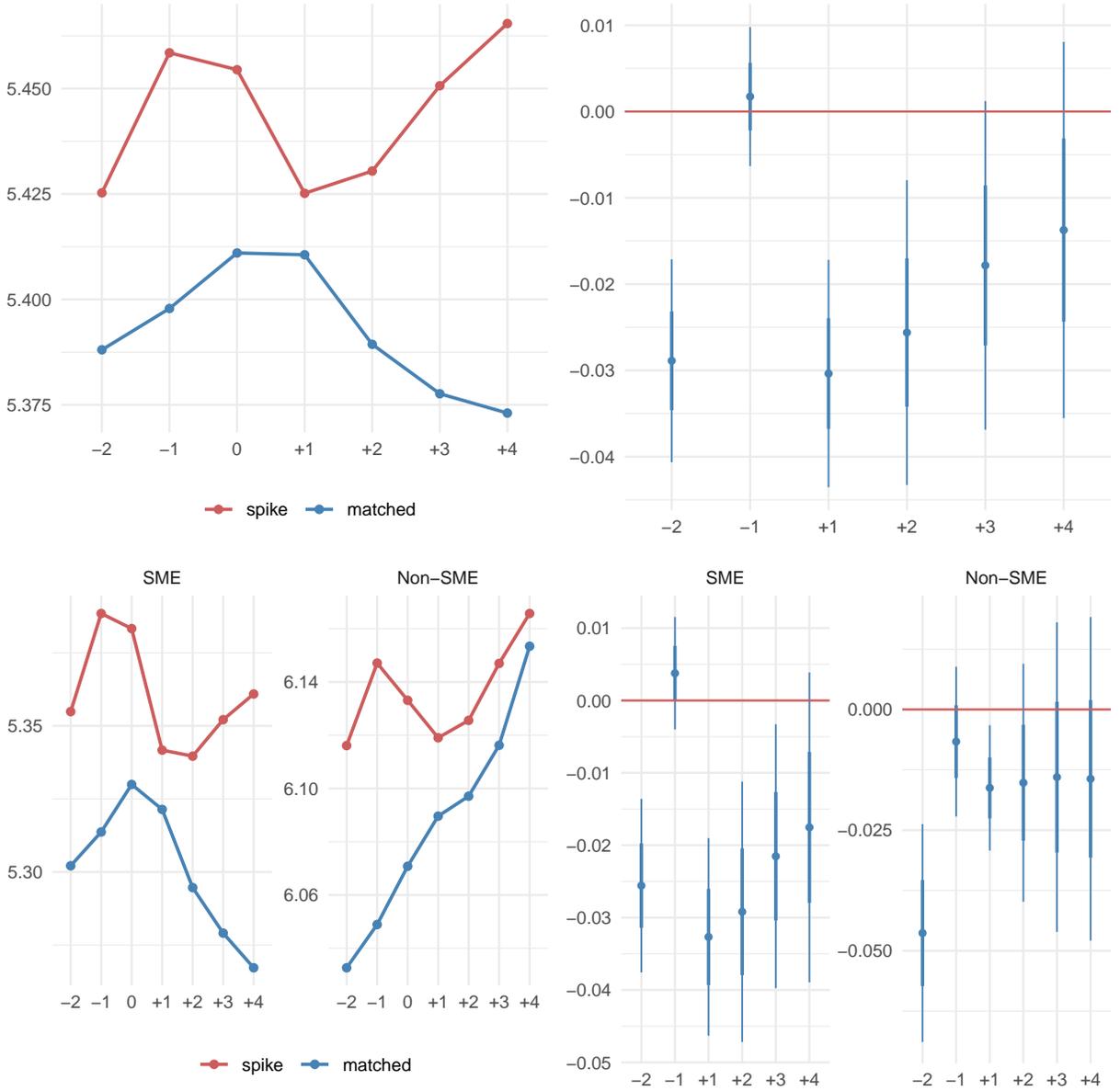


Figure 5: Log TFP - mean levels (left panels) and coefficients from the diff-in-diff estimation (right panels); full sample (top panels) and size classes (bottom panels)

(value added per employee) is a simpler, but widely used, measure of performance, but it has some drawbacks. First, it measures the efficiency of labor only. Second, it is affected by capital deepening. Namely, for a broad category of production functions with classical properties one can show that  $\frac{Y}{L} = f(\frac{K}{L}, TFP)$  with  $\frac{\partial f}{\partial K/L} > 0$ ,  $\frac{\partial f}{\partial TFP} > 0$ .<sup>13</sup> Any definition of an investment spike, including ours, implies a significant jump in  $K$  a year after a spike. We will discuss it later in detail, but Figure 7 shows that labor on average increases only gradually, so  $K/L$  increases. Increasing capital deepening implies an increasing tendency of labor productivity. Figure 6 shows that this is indeed the case. Labor productivity is slightly lower only at the moment of an investment spike, stays on average flat for two years and then rises to the levels above the maximum attained a year before a spike. Compared to matched firms, labor productivity increase is significantly higher in all periods after a spike.

The lower panel of Figure 6 shows also that positive labor productivity difference is mostly driven by smaller firms. The labor productivity gain for smaller firms is ca. three log points. In larger firms, the labor productivity increase is admittedly steeper, but is no greater than the increase in matched firms, so the difference stays insignificant for the whole four years period after a spike. So, combining the results for performance indicators: in case of SMEs labor productivity is relatively higher after a spike, but the increase is completely driven by the direct effect of capital deepening as TFP actually falls in the short run relative to matched firms and rises only gradually to the end of the observation window. In larger firms, capital deepening is relatively smaller and both relative labor productivity and TFP are virtually unaffected by a spike.

### 4.3 Employment, sales and $K/L$

Apart from performance indicators, we also analysed the results for auxiliary variables, like log employment, log real sales and  $K/L$ . The results are presented in Figure 7, for brevity only for the whole sample. The upper panel of Figure 7 shows that employment rises after an investment spike, so spikes do not induce a substitution effect between capital and labor.

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<sup>13</sup>The measurement of TFP used here assumes a Cobb-Douglas production function, so the relation between TFP and labor productivity is particularly simple.

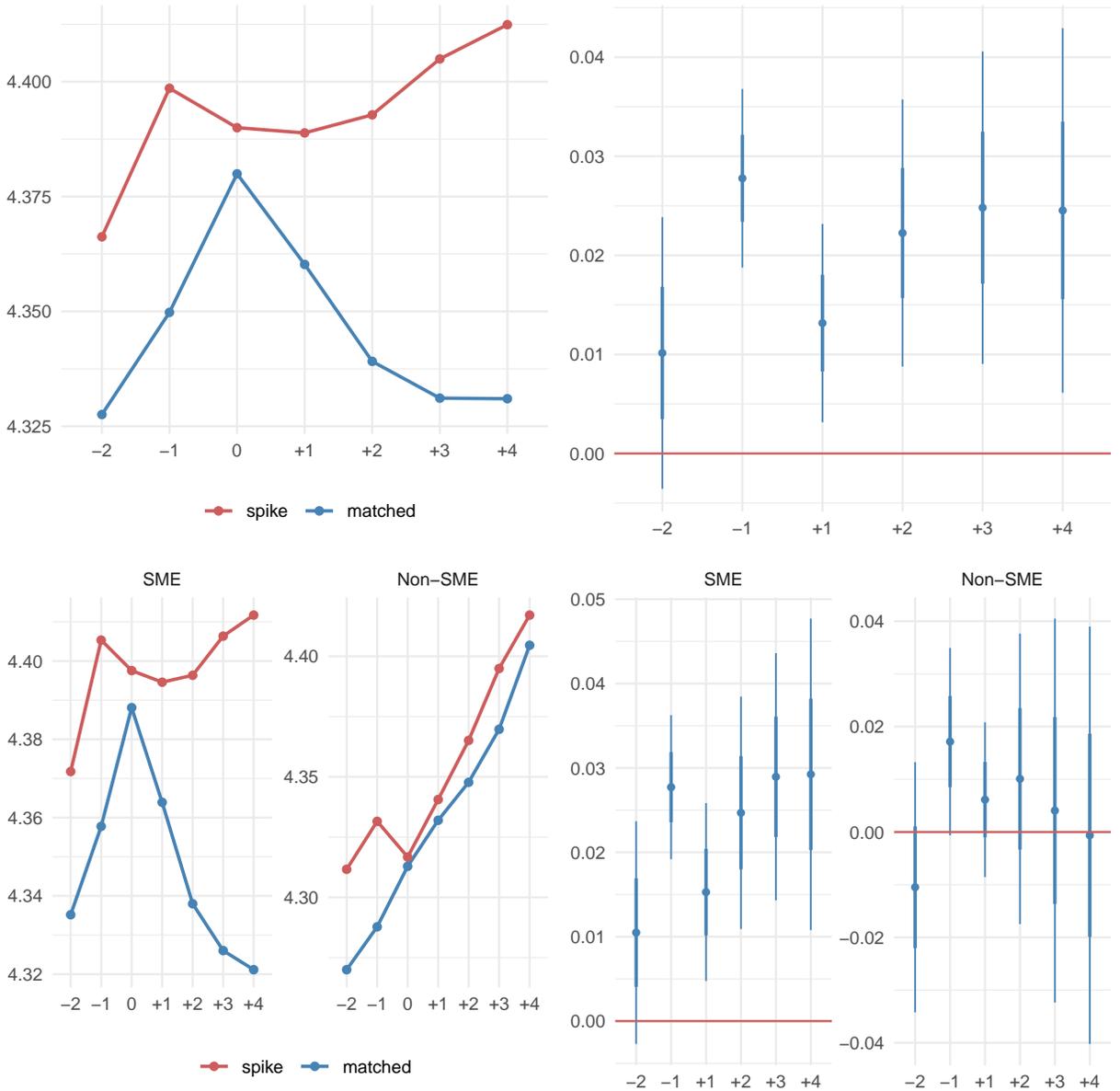


Figure 6: Log labor productivity - mean levels (left panels) and coefficients from the diff-in-diff estimation (right panels); full sample (top panels) and size classes (bottom panels)

The difference against matched firms is substantial – five log points within a year after a spike and additional ten log points within next three years. The middle panel of Figure 7 suggests why investment spikes do not substitute for labor – spikes are associated with the subsequent rise of real sales in a scale comparable with employment. The results for smaller and larger firms (not reported here) confirm that these patterns are very similar among size classes of firms.

#### 4.4 Interpretation

This observation allows us to infer the reasons for investment spikes. It looks like firms decide to increase substantially and relatively quickly their capital stock in order to expand sales. Sales expansion needs to be complemented with additional employment, but significant employment expansion takes time due to rigidities, stressed e.g. in search&matching models of the labor market. It follows that despite investment spikes being usually short-lived, subsequent employment adjustment is sustained, together with sales adjustment.

The relative decline of TFP after a spike is consistent with this interpretation. The observed rise of labor productivity is mainly driven by capital deepening, depicted in lower panels of Figure 7. Joint efficiency of factors of production is not improving after a spike, suggesting that technology or cost improvement was not its primary goal (and even if it was – firms fail to meet it). Moreover, sales expansion driven by an investment spike induces a relatively long period of reduced efficiency of the way production factors are being used at a firm level.

This observation is important. There are various possible goals of investment in tangibles, but output expansion and efficiency improvement seem to be the most important ones. The information on kinds of tangibles firms invest or capacity utilization are only a crude proxy of investment goals. The information on the importance of investment spikes, like the one depicted in Figure 2, gives additional evidence on investment purposes.

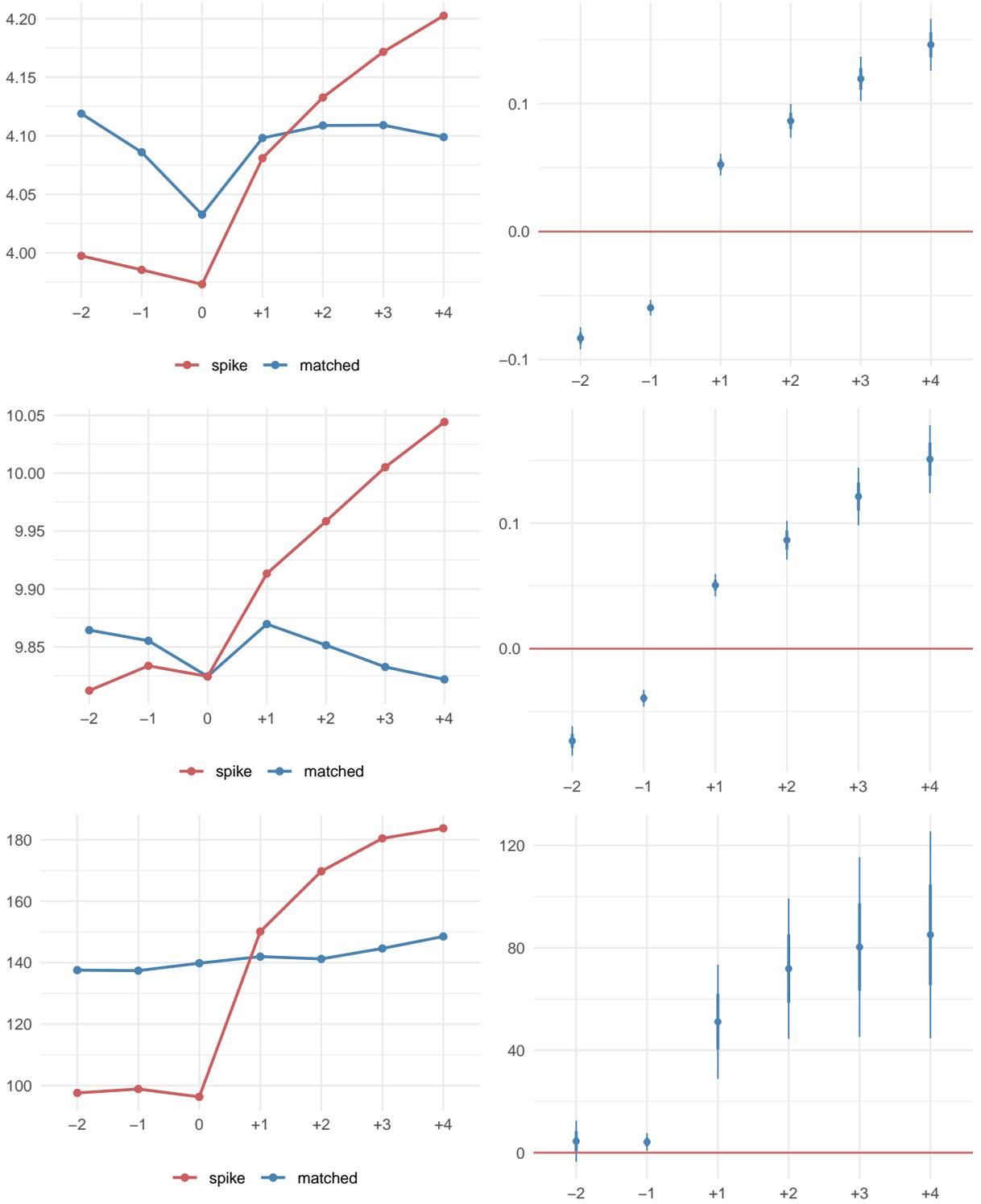


Figure 7: Log labor (top panels), log real sales (middle panels) and  $K/L$  (bottom panels) - mean levels (left panels) and coefficients from the diff-in-diff estimation (right panels)

## Conclusions

Our study aims at investigating the relationship between investment spikes and subsequent productivity development at the firm level. We use the firm-level data on enterprises from Poland with employment above nine persons. We showed that the definition of an investment spike we applied is meaningful and identifies events that contribute substantially to total investments. We propose a novel identification scheme for effects of an investment spike. First, we utilize matching techniques to find “statistical twins” to investing firms – firms similar on many important dimensions, but not investing much during that time. As the events of investment spikes are distributed in time, we follow the data construction procedure proposed by Gormley & Matsa (2011). For each cohort we created observations for firms with spikes and matched firms both in the cohort period and in adjacent periods. Then we stacked together data on all cohorts and estimated a model identifying a measure of a difference in performance of firms with spikes against matched firms after a spike.

We showed that TFP falls after an investment spike and slowly recovers thereafter. For smaller firms the fall is more pronounced and the subsequent recovery is longer. The evolution of TFP is similar to the theoretical predictions of Jovanovic & Nyarko (1996) and indicates that significant build-up of capital stock changes the way a firm operates. Firms need time to adjust their processes, train and recruit staff, so significant learning-by-doing effects are present. These results are similar to Sakellaris (2004) and Huggett & Ospina (2001). On the contrary, labor productivity is relatively higher after an investment spike (but no significant effects are identified for larger firms), but this effect is mainly driven directly by capital deepening.

Investment spikes are also associated with subsequent significant sales increase, which allows us to conclude that expansion is the main purpose of an investment spike. The subsequent rise of employment (required for sales expansion) observed for an extended period of time suggests the existence of labor market rigidities and implies that this type of investment is complementary to labor. Depressed performance suggests that this process is costly (in terms of efficiency) for investing firms.

We should also stress that the relation between investments and labor productivity may substantially differ from the relation between investment and TFP. Somewhat puzzling is

the disparity between positive investment-TFP relation at the macroeconomic level and negative micro-relation. Our analysis shows that both labor productivity and TFP in investing firms (firms with spikes) is higher than in matched firms (and also than in the non-spike firms). Investing firms attract resources and despite the TFP fall, they are still more efficient, which suggests that improved allocative efficiency is an important factor driving a positive macroeconomic investment-TFP correlation. This result adds a new thread to a growing literature on misallocation (see the literature review in Restuccia & Rogerson (2013)).

# Appendix

## Robustness analysis

Although we discuss how various variables change after an investment spike, we check the robustness of our main result - falling TFP after a spike. Table 3 presents estimates of coefficients<sup>14</sup> from equation 2 estimated for log TFP with changed identification schemes, which will be discussed below. As we made a lot of modelling decisions we tried to check if our results are robust to changing particularly important aspects of our identification scheme (keeping the other elements of our identification scheme unchanged).

**TFP identification.** Our baseline estimation identifies the TFP using method proposed by Levinsohn & Petrin (2003). Akerberg et al. (2015) recently proposed an alteration to the TFP identification scheme using a more informative restriction to identify elasticity of output to labour in the production function estimation. Column (2) of Table 3 shows that ACF TFP is less affected by an investment spike. The fall of log TFP just after a spike is half as deep as in the case of baseline and lasts only one year. Four years after a spike TFP starts to be significantly (at 10% level) higher than in the spike period. The estimation for firm size classes (not presented here) shows very similar results for both classes.

**Spike definition – Power (1998) and Nilsen et al. (2009).** As discussed by Grazzi et al. (2016) there are many possible ways for the identification of a spike. Our baseline case takes into account the negative relation between investment rate and firm size and, as suggested by Grazzi et al. (2016), estimates this relation as nonlinear, using a flexible, non-parametric relation. Columns (3) and (4) of Table 3 present the results for spikes defined as in Power (1998) and Nilsen et al. (2009) respectively. The former uses the definition:

$$S_{it} = \begin{cases} 1 & \text{if } \frac{I_{i,t}}{K_{i,t-1}} > \max[3.25 \times \text{median}(\frac{I_{i,t}}{K_{i,t-1}}), 0.2] \\ 0 & \text{otherwise} \end{cases},$$

which yields 13.1% of observations identified as spikes, accounting for 21.8% of investments on average. It follows that this identification scheme is less efficient than the one used in

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<sup>14</sup>The baseline case, corresponding to column (1) of Table 3, was presented in graphical form in Figure 5.

the baseline – it identifies more spike observations accounting for lower investment share, identifying mostly smaller firms. The approach of Nilsen et al. (2009) is similar to the baseline – the definition of  $S_{it}$  is identical to equation (1), but with a linear expectation function. It identifies 9% of observations as spikes, accounting for 51% of investments on average. Not accounting for non-linearity in investment rate - firm size relation results in the identification of much larger firms – 25% of identified spikes are Non-SMEs, compared to 6.6% in our data and 11.4% in the baseline identification scheme.

Various ways of investment spike identification do not change the main result that TFP falls directly after a spike and slowly recovers thereafter. In case of identification of Power (1998) the depth of the TFP fall is twice as large as in the baseline. Moreover, the fall is fading in, not fading-out, suggesting that the adjustment is much longer. In case of identification of Nilsen et al. (2009) the fall is shallower and recovery quicker than in the baseline. In our baseline case we stressed that the TFP difference in case of smaller enterprises is larger than in case of large firms, which is consistent with the results in columns (3) and (4), taking into account the relative importance of smaller and larger firms in these cases.

**No matching.** Applying a matching procedure involves a lot of subjective decisions on its parametrisation. It is hard to check the robustness to its aspects, but using no matching at all is very informative in this context. Column (5) of Table 3 shows how not using matching affects the final results. As in other robustness checks we leave all other aspects of the identification scheme unaltered, so for each period we treat all firms with no spikes as matched firms and follow our estimation strategy (including dropping matched firms that encounter a spike within four year window of post-event observations). It vastly increases the number of observations used in the estimation, but preserves our main result. The fall of TFP observed in this the case is even larger than in the baseline case. Furthermore, the fall is estimated to be longer.

**One matching.** In the baseline case we estimated matching logit separately for each year, to account for possible parameter changes. Column (6) of Table 3 shows the results if we estimated one matching model for all periods. In this case we used exact matching on date, as we wanted to identify firms that are matched to firms with spikes exactly in

the moment of a spike. The resulting matched sample is less balanced, with means of employment, sales, labor share and ROA statistically different from their counterparts in the spike sample. Despite that the estimated depth and length of TFP fall after a spike are very similar.

Table 3: Robustness checks – coefficients from the diff-in-diff equation for log TFP

	log(TFP)					
	baseline	ACF (2015)	Power (1998)	Nilsen (2009)	No matching	One matching
	(1)	(2)	(3)	(4)	(5)	(6)
-2	-0.029*** (0.006)	-0.040*** (0.006)	-0.043*** (0.008)	-0.019*** (0.006)	-0.079*** (0.008)	-0.032*** (0.006)
-1	0.002 (0.004)	-0.006 (0.004)	-0.009* (0.005)	0.009* (0.005)	-0.035*** (0.006)	0.0001 (0.004)
+1	-0.030*** (0.007)	-0.013** (0.007)	-0.045*** (0.005)	-0.024*** (0.008)	-0.054*** (0.008)	-0.031*** (0.009)
+2	-0.026*** (0.009)	-0.001 (0.009)	-0.056*** (0.007)	-0.025** (0.010)	-0.059*** (0.011)	-0.032*** (0.009)
+3	-0.018* (0.010)	0.013 (0.010)	-0.062*** (0.008)	-0.009 (0.011)	-0.055*** (0.012)	-0.025*** (0.010)
+4	-0.014 (0.011)	0.021* (0.011)	-0.079*** (0.009)	-0.002 (0.014)	-0.054*** (0.012)	-0.022* (0.011)
<i>N</i>	425,388	425,388	697,571	418,592	2,360,395	390,687
R <sup>2</sup>	0.864	0.888	0.855	0.884	0.875	0.863
Adjusted R <sup>2</sup>	0.831	0.861	0.819	0.856	0.843	0.830
Residual Std. Error	0.309	0.314	0.308	0.311	0.301	0.309

*Notes:*

\*\*\*Significant at the 1 percent level.

\*\*Significant at the 5 percent level.

\*Significant at the 10 percent level.

## Measurement of variables

Below we show measurement details of variables used in the study:

- Employment is measured in full time equivalent.
- Value added is defined as sales of products (plus change in inventories and value of production for internal purposes), profits realized on reselling goods and other operating revenues less material, outsourcing and other operational costs.
- Labor productivity - value added per employee.
- Capital – is measured as the beginning of period book value of fixed assets: buildings, machinery and vehicles.
- ROA – net operational and financial and extraordinary profits over value of assets (book value of the total assets), both measured at the beginning of period
- Debt/assets – long-term debt over total assets (liabilities), both measured at the beginning of period
- Liquidity – short-term assets to short-term liabilities, both measured at the beginning of period

Real values of value added and sales (and value of materials used for the estimation of TFP) were calculated using a sectoral value added deflator, taken from Eurostat. Real value of capital (used for the estimation of TFP) was calculated using capital price indices, taken from Eurostat, available for NACE sectors and asset types. Autor (2003), Akerberg et al. (2015)

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