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What happens when firms invest?

Investment events and firm performance

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Abstract

The aim of the study is to investigate the firm-level relationship between investment spikes and subsequent productivity developments. We used census data of Polish firms with employment above 9 persons, we measured investment spike and constructed a control sample for comparison. We showed various performance indicators before and after investment spike. We tested for the effects of a spike using generalized difference-in-difference models. The results suggest different effects for SMEs and larger companies. In smaller firms investment spike is associated with subsequent sales and employment expansion and lagged labor productivity rise, consistently with learning-by-doing model. TFP of smaller firms falls directly after a spike and only gradually rises thereafter. In larger firms investment spike also result in expansion of sales, but labor productivity is not improving relative to control group, despite a drop of employment. Moreover, capital deepening of larger firms results in significantly lower TFP, both in absolute and relative terms.

JEL classification: D22, D24, L16, O3

Keywords: investment spike, productivity, TFP, efficiency, firm-level data, difference-in-difference

Introduction and literature overview

At the macroeconomic level the relation between equipment investment and economic growth is well established in the literature – see e.g. (De Long and Summers, 1991). Moreover, on aggregate level investment comoves not only with value added, but also with employment, productivity, profitability of enterprises and other variables exhibiting cyclical variation. But there is much less evidence for the impact of firm-level investment on the ability of firms to grow or to increase efficiency. The link between macro and micro is important, as e.g. (Foster et al., 2001) showed that aggregate labor productivity growth is largely driven by within-firm changes.

Investment lumpiness is a feature of investment, which is important from the perspective of our study. (Doms and Dunne, 1998) showed that years of inactivity or repair and maintenance are followed by one or several years of heavy investment. According to (Gourio and Kashyap, 2007) most of the variation in aggregate investment can be explained by changes in the number of establishments undergoing such large investment episodes (investments spikes). The fact, that investment is lumpy and it is an important feature of investment variation allows us to focus on episodes of investment spikes, as they should be important for the subsequent firm behavior and have potential to change firm behavior. It allows us to check what happens to firms' efficiency directly after investment spikes. Moreover, those episodes are relatively easy to filter out.

The fact that on macroeconomic level investment comoves positively with performance indicators suggests one should expect also a positive relationship between investments and productivity on a micro level. The firm-level theory behind is usually related to the model of embodied technical change (see e.g. (Cooley et al., 1997) or (Jensen et al., 2001) in an empirical context), which treats investments as technological upgrading (as new capital embodies more recent technology). But (Jovanovic and Nyarko, 1996) using a "learning-by-doing" model showed that a technology switch may temporarily reduce firm expertise and induce short-run costs and decline of efficiency. Productivity costs could also arise from destroying a particular organization of production that was used at the firm with a time-consuming creation of the new one. It follows that the direction of firm level relation between investment and efficiency is, to a large extent, an empirical question and may depend on industry and firm characteristics.

The empirical literature on investment spikes and subsequent firm performance is far from consensus, with results pointing at each possible direction. One of the first result (Power, 1998) finds no evidence of investment on productivity or productivity growth. (Grazzi et al., 2016) finds investment spikes are associated with higher productivity, sales and employment, but only in one of two countries analyzed. Also (Nilsen et al., 2009) finds evidence of a positive and significant, but only contemporaneous effect of investment on productivity. The results of (Geylani and Stefanou, 2013) are similar – productivity growth increases after investment spikes but trails off in the longer run. On the contrary, (Huggett and Ospina, 2001) and (Sakellaris, 2004) report (consistently with "learning-by-doing" effect) a fall in productivity just after an investment spike with a subsequent slow recovery thereafter. The results above were established on data from different countries, industries, with different definitions of investment spike and measures of productivity, so they are hard to compare directly, but nevertheless they suggest that relation between investments and performance is complex.

The aim of our study is to investigate the relationship between investment spikes and subsequent productivity development in a developing and catching-up country with stable macroeconomic policies and macroeconomic performance, namely Poland. The choice of this particular country is also important from the perspective of supply-side growth decomposition in (Gradzewicz et al., 2018), which showed that Poland experienced relatively stable contribution of capital to GDP growth with a declining trend growth rate of TFP. Although we admit there could be many potential explanations of this phenomenon, we will try to find whether those two phenomena could be related on microeconomic level.

The contribution of this study to the literature is three-fold. First, we employ a new definition of investment spike, which is better suited to our data. Second, we use a novel methodology to the question at hand. Namely, we use econometric methods designed in natural experiments, as described e.g. in (Angrist and Pischke, 2008) and more precisely – multievent difference-in-difference methodology developed by (Gormley and Matsa, 2011) to verify if firms deciding to make big investment perform significantly different in subsequent periods compared to firms not deciding to invest (the latter found using matching techniques). Third, augmenting the literature, we stress the importance of firm size to the shape of investment-performance relation. Namely, our results suggest that performance improvement after investment spike is rather observed in smaller firms (more in labor productivity than TFP) and does not affect performance of large firms (TFP in that group even deteriorates). Moreover, we utilize the census data from the Polish economy, covering almost whole enterprise sector, whereas prior studies usually focus on manufacturing or narrowly defined industries.

The rest of the paper is organized as follows. Next section presents data sources, measurement and introduces a definition of investment spike. It is followed by the discussion of identification strategy and econometric considerations. Next sections present results and their robustness. The final section offers some concluding comments.

Data sources and investment spikes

Data description

The dataset used in this study comes from a census of Polish enterprises employing more than 9 persons (the census is incomplete for firms employing between 10 and 49 persons due to underreporting). The dataset is annual and covers 14 years (2002-2015) of firms' financial statements: balance sheets, profit and loss accounts and basic firm characteristics, like ownership. The data was gathered by the Central Statistical Office of Poland. The database comprises nonfinancial enterprises from mining, manufacturing construction, market and non-market services (the latter covers only the enterprise sector).

Table 1 Data properties

	2002	*2005*	*2008*	*2011*	*2015*
No. of firms	26136	33611	45056	46320	46980
Employment share	0.641	0.785	0.878	0.847	0.849
Average Employment	120.0	111.5	105.0	100.8	101.0
Capital/ Employment	133.9	139.8	142.2	169.9	198.3
Return on assets	0.015	0.052	0.043	0.054	0.039
Debt to assets	0.157	0.125	0.122	0.138	0.158
Liquidity	0.22	0.34	0.35	0.40	0.41
Productivity (Sales / Employment)	274.8	361.1	434.6	550.8	594.8
Productivity (Value added / Employment)	74.9	89.5	102.2	124.2	139.5
Export share	0.156	0.182	0.181	0.216	0.252
No. of exporters	0.208	0.226	0.214	0.243	0.274

Source: own calculations based on financial statements dataset

The original dataset contains some erroneous or missing observations (firms with no employment or capital or negative calculated value added[1]). Moreover, subsequent econometric analysis relay on some ratios (as liquidity or export share) with non-zero values of denominators. We cleaned the dataset (20% reduction) and constructed an unbalanced panel with 565k properly defined observations with annual number of firms increasing from 26k in 2002 to 47k in 2015, observed over 7.1 years on average.

Table 1 presents some data properties of selected sample in selected periods. Clearly, together with a growing firm number, the total employment coverage of the dataset (the share of employment in firms used in our study in total employment in the whole enterprise sector of the Polish economy) increases to 85%. Simultaneously, as the net increase in the number of firms concerns mainly smaller firms, it translates into falling average employment and increasing average K/L ratio.[2] The liquidity (relation of short-term assets to short-term liabilities) is on average increasing and debt-to-assets is U-shaped. Average productivity (measured here in nominal terms, both as value added or sales per employment) almost doubled during the period of analysis. During the period of the analysis the Polish economy experienced a substantial increase of presence in foreign markets. The share of export proceeds in total revenues increased form 15% in 2002 to 25% in 2015, due to both increasing export intensity, but also due to the growth of the number of exporters – the number and share of firms with export share higher than 2.5% also increased during the period of analysis.

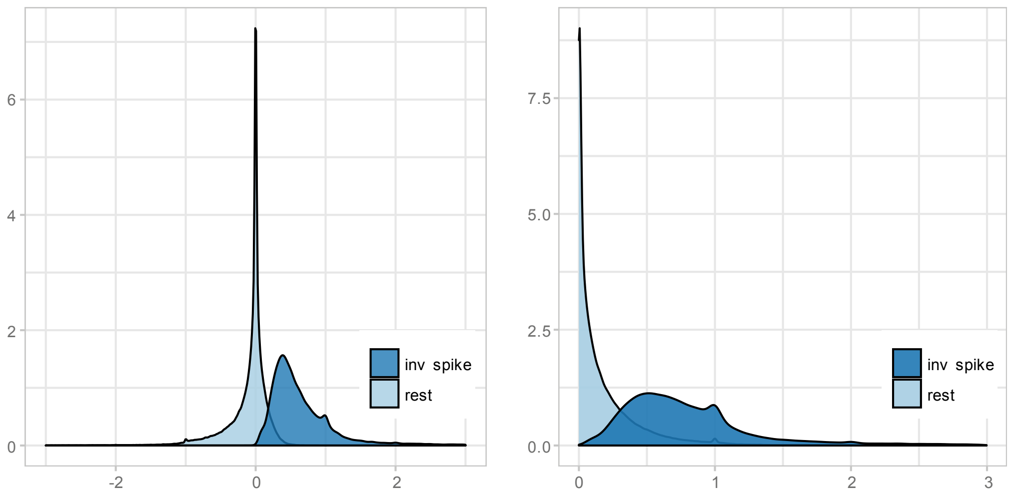
[1] Value added is defined as close as possible to the national accounts counterpart: global output (sales, change of inventories of products and the margin on sales of goods) less intermediate consumption (material, outsourcing and other non-labor costs).

[2] Capital is measured as book value of fixed assets: buildings, machinery and vehicles. The corporate investments in intangibles are very low in the Polish economy, possibly prone to underreporting problem and were excluded from the analysis.

Definition of investment spike events

As was mentioned in the introduction, the lumpiness of investments on a firm level allows us quite easily to define periods when firms engage in huge investments. But lumpiness does not translate into bimodal distribution of changes if I/K and implies rather that this distribution is positively skewed. So, there are different attempts to measure investment spikes, as documented e.g. in (Grazzi et al., 2016).

Figure 1 Distribution of changes (left panel) and levels (right panel) of investment/capital rate in firms engaged in big investments (inv spikes) and the rest of firms

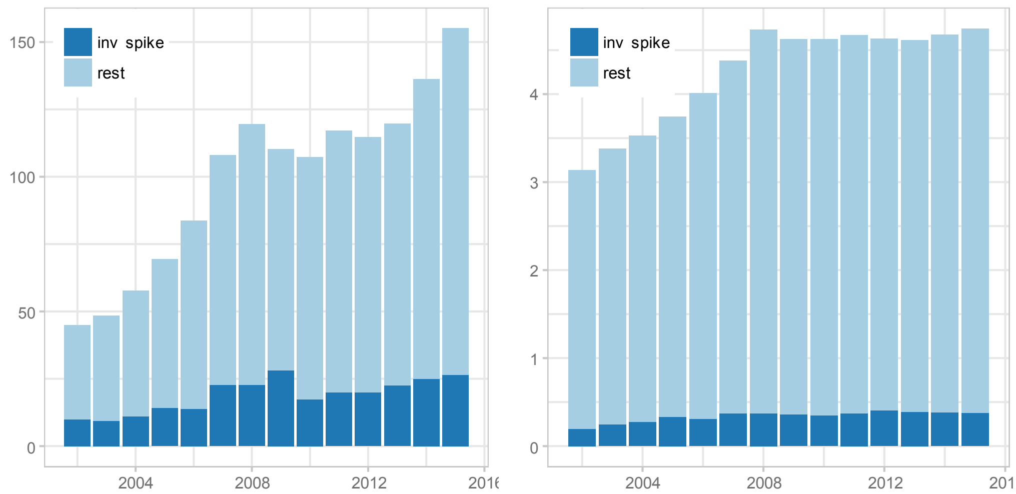


Remarks: The graphs are trimmed for the shape of distribution to be visible.
Source: own calculations based on financial statements dataset

Usual approaches to spike measurement in the literature analyze each firm separately and rely on investment to capital ratio exceeding certain firm-specific threshold (see the discussion in Robustness Appendix). The drawback of this approach is that in case of firms with relatively flat investment path this methodology selects as investment spikes also episodes with mild changes in I/K. This is the case in our dataset and the resulting distributions of both $\frac{I}{K}$ and $\Delta\frac{I}{K}$ are only mildly different from corresponding distribution calculated for the other firms (see Figure 11). Thus, we proposed a conceptually slightly different framework for selecting investment spikes. As our approach is somewhat novel we compared it to a more traditional approach of (Power, 1998) – see the Robustness Appendix for further details.

Our main results are robust, at least qualitatively, to the spike definition but our approach seems to be better suited to the data at hand. Contrary to the literature, we did not define investment spike based on an individual investment path, but based on the whole distribution of investment, taking account of industry and time idiosyncrasy. So, we implicitly assumed that in each industry investment intensity should be homogenous across firms but this intensity can change over time with the business cycle, and a sizable positive departure from this pattern is treated as a spike.

Figure 2 Investment outlays (left panel in bln PLN) and employment (right panel in mln) of big investors (inv spikes) and the rest of firms



Source: own calculations based on financial statements dataset

In this manner investment spike is defined as 12.5% of the highest annual increases of $\frac{I_{it}}{K_{it}}$ calculated separately for each year and sector (defined on a NACE02 level)[3]. The choice of the threshold is, as usual in case empirical research, somehow arbitrary. The lower the threshold, the bigger the differences in distributions of investment intensity measures between big investors and the rest of the sample. But

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[3] Prior to these calculations we excluded investment rate changes of magnitude higher, in absolute terms, than 3 (ca. 1% of observations), as the scale of those changes (investment in a given year exceeding 3 times the value of fixed capital) seems to implausibly large. This additional restriction is irrelevant for the main results of the paper.

simultaneously, the lower the threshold, the lower number of investment events is treated as spikes. Unfortunately, there is no any specific level of the threshold that separates distributions completely or introduces any discontinuities. Our choice of the threshold implies that effectively 10% of observations (ca. 5500 cases) are defined as spikes. This number is close to a number of cases indicated by the method of (Power, 1998) with relatively strict definition of a spike: $\frac{I_{it}}{K_{it}}$ higher than 3.25 times its median calculated for each firm individually. Moreover, this choice seems to offer a relatively good trade-off between the effective number of observations used in the next parts of the study and the separation of investment distributions between investors and non-investors (see Figure 1 and Figure 11 in the appendix).

As stated by (Nilsen et al., 2009), any meaningful spike measure should select episodes of investment that are larger than the unconditional investment rates, which is true in our case (mean investment rate is 0.5 during investment spikes and 0.13 otherwise, see also Figure 1). Another criterion for selection among spike rules is parsimony – ability to capture a large share of total investment with a small number of observations. By construction, the share of big investors in our dataset is close to 10% in each period[4], but their share in employment is less than 8% (ranging from 6,2% to 8,7% in different periods), see Figure 2. And that is more important – investment due to spikes account for almost 19% of total investments, ranging from 16% to 25% in different years.

The selected firms are concentrated in SME sector[5] (94%, although the share of investment spike episodes is similar between SMEs and Non-SMEs) and in domestic private sector (81% vs. 12% in foreign sector and 6% in state owned). A large

[4] One of the robustness checks in the appendix relaxes the assumption of heterogenous investment intensity across time and uses industry grouping only. The resulting share of big investors in the population is less evenly distributed in time (with relatively larger share of big investors at the beginning of the sample) but our main results are unaltered.

[5] SMEs are defined as firms employing less than 250 employees.

share of investment spikes is observed in manufacturing, trade and construction, but accounting for sector size, investment spikes are slightly overrepresented in mining, energy, utilities and real estate sector.

Construction of a control sample

A panel of firms marked with investment spikes allows us to look at the dynamics of various measures, like employment or productivity, before and after investment spike. The comparison of those measures before and after an investment spike allows to check whether the spike affects those measures. But it could be the case that the other firms, not deciding to make big investments, might change their behavior too. The fact that we can pool spikes from different periods makes this case quite unlikely, but still it much more informative to compare post-spike efficiency measures not only to historical path, but also to some control group.

We used matching techniques[6] to find firms resembling big investors in the year of investment spike, with the only difference of not deciding to invest at that time. We matched firms on propensity score, using logit to estimate conditional expectation function of investment spike probability as a measure of distance between firms. Having large sample, we used the nearest neighbor matching and single best match to construct control group, which is the least biased, but simultaneously the least precise estimate of a counterfactual. As e.g. in (Hagemejer and Tyrowicz, 2012) we matched firms on a number of dimensions, referring to size, destination market, technology, performance and financing. As industry (measured on NACE02 level) and ownership status of a firm (ownership coded as state, foreign and domestic private) is an important selection indicator and it is hard to construct measure of closeness of those indicators, we used exact matching on those variables. Moreover, as the coefficients of the underling logit model may vary in business cycle (our sample includes the period of the 2008/2009 recession and, what is more important, we are not

[6] Matching models were estimated using R's MatchIt package, see (Ho et al., 2011).

using any structural model of investment probability to believe any elasticities to be constant), we match firms separately for each year in the sample.

The first set of variables used in matching refers to firm size and we used various aspects of firm size: labor (measured as average employment, in full time equivalent), capital (book value of fixed assets: buildings, machinery and vehicles) and value of sales. There is a large body of empirical literature, see e.g. (Weinberg, 1994) suggesting firm size is an important determinant of various firm decisions. Simultaneously, (Dang et al., 2018) stressed that the measurement of size matters, so we match firms on various dimensions of their size.

We also included in the matching dimensions information of the market on which firm operates. Our dataset does not allow us to determine whether the firm operates on local or national level, but we have the information on the importance of foreign vs. domestic market. We used export share – the share of products sold abroad in total sales. A large body of literature since the work of (Melitz, 2003) showed that the entry and presence on foreign markets is related to firm performance. (Hagemejer and Kolasa, 2011) demonstrated that this is the case also in the Polish economy.

We do not have direct information on firm technology in the database, so we proxied the technology with the share of labor costs in total costs. This simple indicator measures the relative importance of labor in firm's technology choice. An alternative proxy we might use was the capital-to-labor ratio, but in subsequent matching regressions this proxy was often statistically insignificant.

Efficiency dimension in matching was defined both in technological and financial context. We used labor productivity, defined as value added per employee as a measure of firm technological performance and return on assets (ROA) as a measure of its financial efficiency. The choice of labor productivity on the first sight seems to create endogeneity in the further analysis, as we try to determine if decision to invest affects labor productivity. But the matching selects similar firms only in the moment of investment spike and the effects of investments are measured in subsequent periods, relative to the existing difference in the moment of a spike. It implies our subsequent analysis starts with firms with relatively similar productivity in the base period we compare to.

Table 2 Comparison of big investors to the rest of firms and selected control group

	labour	capital	sales	export share	labour share	productivity	roa	liquidity	debt over assets
full sample	105	16767	49221	0.113	0.317	94.5	0.077	1.09	0.087
spikes	86	9447	44580	0.125	0.318	95.2	0.099	0.93	0.090
rest of firms	107	17557	49722	0.112	0.317	94.4	0.074	1.11	0.086
control	86	9897	38790	0.130	0.318	91.8	0.094	0.84	0.086
reduction	0.20	0.44	0.22	-0.16	-0.003	0.0	-0.27	0.25	0.00
(rest-spikes) / spikes	0.25	0.86	0.12	0.10	0.004	0.01	0.25	0.19	0.04
(control-spike) / spikes	0.00	0.05	0.13	0.04	0.002	0.04	0.05	0.11	0.05
t-stat (spikes vs. rest)	**11.94**	**15.34**	**2.36**	**-10.27**	-1.62	-0.83	**-18.6**	**4.85**	**-2.55**
t-stat (spikes vs. control)	-0.23	0.76	**-2.54**	**3.195**	-0.449	**-3.15**	**-3.57**	**-3.26**	**-2.379**

Remarks: Spikes refers to observations of firms in periods selected as investment spikes (pooled across time), rest – to the other firms, control – to firms selected as controls in matching procedure. Reduction is the percent reduction in the difference in means, and last two rows – t-stats from a two sample Welch test for means. Bold numbers marked t-stats significant at 95%.

Source: own calculations based on financial statements dataset

Finally, we match also on two measures of firm financial structure. Liquidity, measured as short-term assets to short-term liabilities rate, measures firms' operational need for financial resources. As firms operate in different environments, with different length of payment schedules with customers and suppliers and access to short-term external financing, but also with different length of production process, the excess of short-term assets over liabilities should be an important matching variable. We also used debt-to-assets ratio, which measures the overall ability for external financing.

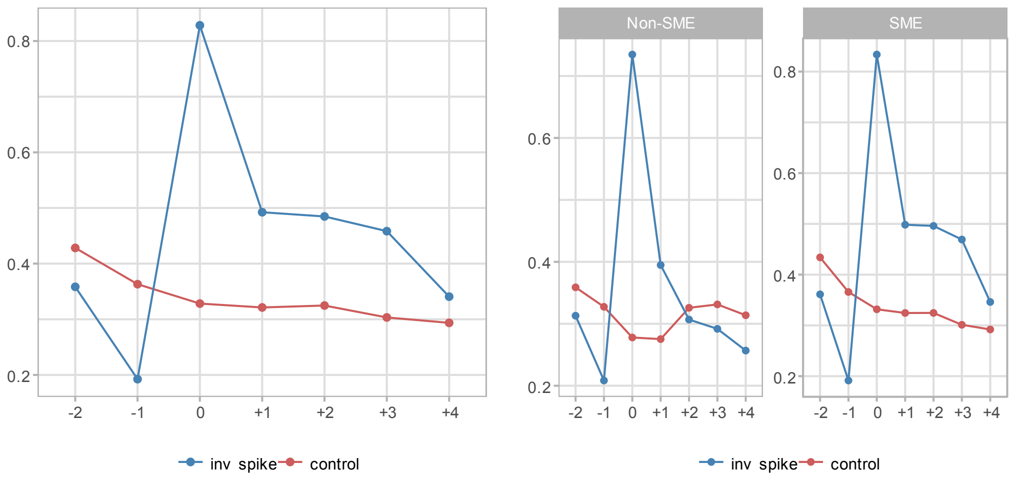
Table 2 shows the comparison of relevant variables of big investors with the rest of observations and with the control group. The last two rows show the t-stats of mean comparison test (big investors versus non-big investors and big-investors versus control group). Big investors are different from the other enterprises: they are on average smaller, in terms of labor, capital and to some lesser extent sales, have lower liquidity, but higher: export share, average ROA and are more indebted. Their labor shares and productivity are statistically indistinguishable from the rest of the sample.

The comparison of big investor to the control group, chosen using described matching procedure shows that control group is much more similar to big investors, although only for labor, capital and labor share the difference between means is statistically insignificant[7]. Only in case of productivity the means difference became significant after matching[8] (average productivity of firms in control group is smaller than both of big investors and non-big investors), but the difference in means is only 4%. The visual inspection of QQ plots of the distribution of big investors versus rest of the firms and firms in the control group (available upon request) indicates that also the distribution of control group is more similar to big investors, although the result of the Kolmogorov-Smirnoff tests indicate that only in case of export share and labor share observations from control and treatment (big investors) group come from the same distribution.

[7] Samples to compare are large – each has above 50000 observations, so within sample variation is considerable, possibly affecting significance tests.

[8] The robustness analysis in the Appendix shows the results after excluding productivity from matching.

Figure 3 Investment-capital ratio close to an investment spike, average for all selected enterprises (left panel) and in size class (right panel).



Remarks: Time, in years relative to investment spike (0), on the horizontal axis; SME – firms with employment less than 250

Source: own calculations based on financial statements dataset

As our final goal is establishing if efficiency of big investors after investment spike differs from efficiency of the control group. One of the desirable feature of properly specified control group is the absence of investment spike at the time of spike in treatment (big investment) group. As we used the threshold in defining investment spike, it could be the case that control group consists of firms just below the threshold (especially if $\Delta\frac{I}{K}$ is a continuous function, which seems to be true in our case). In such scenario we should also observe a spike in the control group. Left panel of Figure 3 shows the average investment-capital ratio both in a sample of big investors[9] and in a control group in the moment of investment spike (measured in relative time and normalized to 0, as actual observations come from different years), prior to

[9] We searched for events of investment spikes and for their controls for all sectors in our dataset, but in case of energy and financial part of enterprise sector (sections: D and K) both the investors selection and matching procedures seem to improperly identify relevant cases. We excluded energy and finance (1.3% of cases) from the subsequent analysis. The omission of those sectors has not changes the aggregate results, but absent those sectors the results for larger firms are visibly less volatile around investment spike.

the investment spike (labelled on x axis with negative number of years relative to investment spike) and in subsequent years (labelled on x axis with positive number of periods)[10].

Investment spike is clearly visible for our sample of big investors – $\frac{I}{K}$ on average more than double on impact, but then quickly fade out, although not completely. It indicates that our procedure of spike selection is valid (the analogous picture for selection method of (Power, 1998) gives similar results). Interestingly, just before the spike, big investors tend to underinvest – the $\frac{I}{K}$ is lower in period -1 than in period -2. It suggests that big investment is not a surprise for firms and they prepare to huge investment by postponing investment outlays prior to investment spike. It also suggests that although our econometric techniques are tailored to causality analysis, in case of investment analysis it is hard to interpret time differences before and after the event as casual due to expectations. In the control group, on the contrary, mean $\frac{I}{K}$ is flat. It indicates that although our matching procedure is far from ideal and is subject to many subjective decisions, at the end of the day it produces valid results.

Left panel of Figure 3 shows $\frac{I}{K}$ around the spike, separately for SMEs (defined as firms with employment less than 250, being 94.5% of investment spike events) and larger firms. The investment pattern is similar across both groups. The preparation period prior to the spike and a spike itself is clearly present in the investor group and is absent in the control group. The spike is somewhat higher in SMEs, although in non-SMEs it fades out more quickly. In SMEs the elevated investment effort seems to last up to 3 years after the spike.

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[10] The number of observations in different years relative to investment spike varies as we have unbalance panel of firms.

Econometric considerations

To find the effects of investment spikes on firm performance we use an estimation approach frequently applied in evaluation studies – difference in differences, see (Angrist and Pischke, 2008). As firm decisions on big investment are hard to treat as a natural experiment (and to treat investment event as a "treatment", e.g. due to expectations, see also the discussion before) we will not aim at causal interpretations of results, but still the econometric method is useful in the context of our study.

If all investment spikes occur in one period (in other words: for a given cohort[11]), a standard generalized diff-in-diff equation measuring the impact of investment spike on a given performance measure y would be:

$$y_{it} = \beta(d_i \times p_t) + \alpha_i + \delta_t + \epsilon_{it}, \quad (1)$$

where d_i is an indicator of firm i being treated (having big investments), p_t is an indicator of treatment occurring after period t. Unit i and period t fixed effects control for independent individual and time effects of d_i and p_t and β measures the impact (change in y after treatment, relative to the control group).

The literature on estimating treatment effect discusses the importance of possible divergence in trends before treatment. Parallel trend assumption facilitates the interpretation of divergence of post treatment developments to the (causal) effect of treatment. Moreover, the effects of treatment may fade in or fade out in time. (Autor, 2003) suggested the simplest solution to account for both these issues – time varying coefficients β_j in equation (1): $\sum_{j \in \{-k,\dots,-1,1,\dots,l\}} \beta_j \times d_i \times \tau_j$, where $\tau_j = 1$ when the difference between current date and treatment date is j and excluding treatment date, $j = 0$, due to collinearity. It follows that β's are measuring treatment effects between treated and control group in different periods around treatment time, relative to the

[11] Cohort c refers to a sample of firms selected as big investors in period c.

difference existing in period 0 (as β_j is dropped from the equation). Thus, the results of the estimation measure changes of performance indicators relative to (and accounting for) possible difference of these indicators in the moment of treatment (the matching procedure does not include all our measures of efficiency as covariates, just the labor productivity). Ideally, $\beta's$ for periods before treatment date should be insignificant (confirming parallel trends assumption), whereas β's for the post treatment dates should be significant (confirming divergence of trends between treatment and control group after treatment).

In our dataset investment spikes occur in different years (cohorts) and we pooled spikes across cohorts. Pooling makes the analysis more robust, as results are not driven by particularities of any period – there is considerable business cycle variation in our sample. Pooling should also imply 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 (in 57% of firms with spikes the spike occur only once per sample, in 27% it occurs twice and in 1,3% more than 4 times). The possible drawback of pooling is that it implies the effects of investment spike are time-invariant.

To account for the cohort effect we use the approach of (Gormley and Matsa, 2011). For each investment spike event in cohort c we create a vector of observations on performance indicator y in a window of -2/+4 years pre- and post-event (we choose asymmetric window as we are relatively more interested in development post treatment whereas pretreatment periods are needed to check for parallel trend assumption). The same window is calculated for control events from cohort c. The resulting set of panels of observations in a window around investment spike for each individual cohort are then stacked together into 3-dimensional (firm, time and cohort) panel. Moreover, if observation that is used as control for a spike in some cohort become a spike itself in subsequent period (in later cohort) within a window, then this observation is dropped and serve as control only till that moment. It assures that development of performance measure in control group post spike event is not affected by observations becoming spikes themselves.

The final model[12] has a form:

$$y_{ict} = \sum_{j \in \left\{ \substack{-2,-1, \\ 1,2,3,4} \right\}} \beta_j d_{ict} \times \tau_j + \alpha_{ic} + \delta_{ct} + \epsilon_{ict}, \tag{2}$$

where d_{ict} is an indicator of firm i being treated in cohort c, τ_j is an indicator of current period t being j periods post (positive j) or before (negative j) treatment year, α_{ic} is a unit-cohort fixed effect controlling for the treatment dummy in each cohort and δ_{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 performance indicator to vary by year.

We account for possible clustering of errors with a set of NACE02 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 FELM package (see (Gaure, 2013)), which utilizes the method of alternating projections to sweep out multiple group effects from the normal equations before estimating the remaining coefficients with OLS.

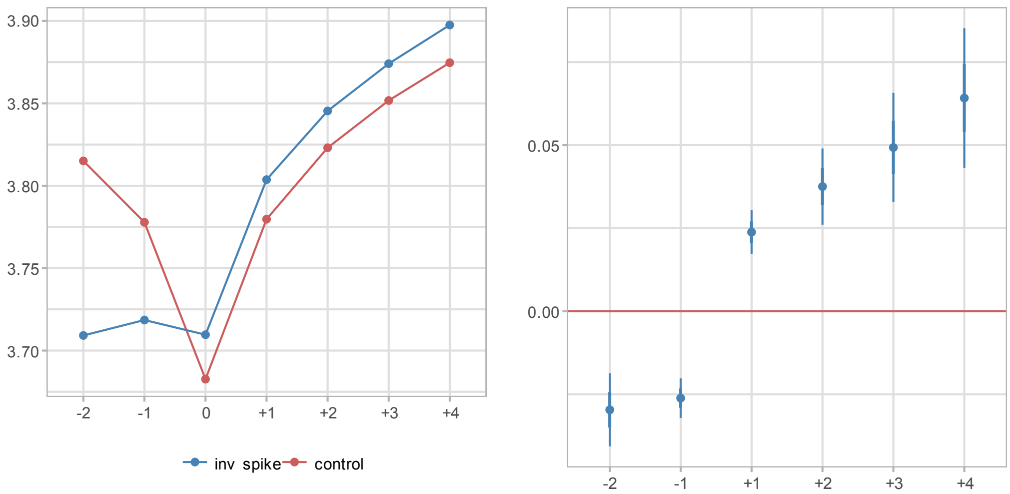
[12] When determining the effects for subsamples (e.g. for SMEs and non-SMEs) we present estimates of β's from equation (2) estimated separately for those subsamples.

Investment spikes and firm performance

In the subsequent analysis we will show how investment spike is associated with subsequent development of performance variables: employment, sales, labor productivity and a measure of TFP. We will present developments of these measures for big investors and firms from control group. We will also show estimates of a relative effect - β_j from regression (2). They measure the effects of investment spike on a given performance measure relative to the control group and relative to the difference in period 0 – the moment of investment spike. We will also present the results for SMEs and non-SMEs.

Employment

Figure 4 Log employment close to an investment spike (left panel) and coefficients from the diff-in-diff estimation (right panel)

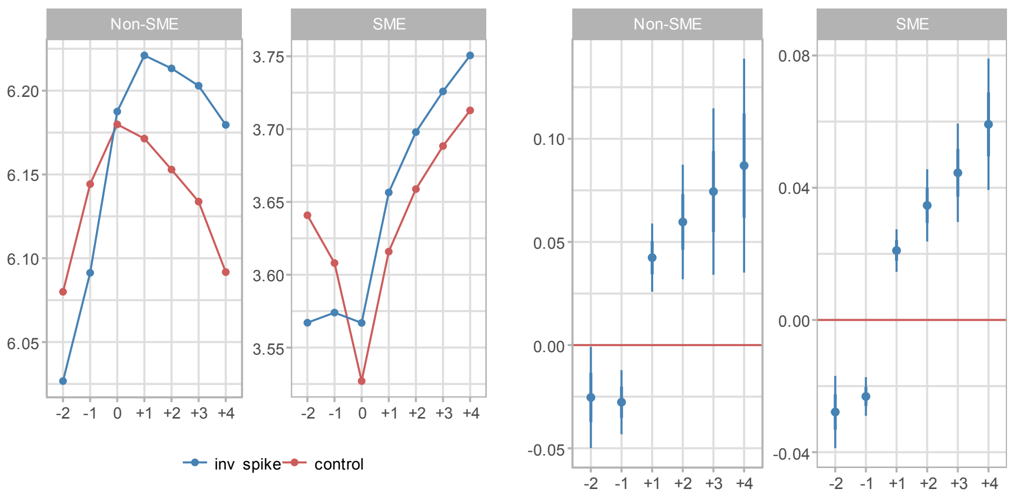


Remarks: Time, in years relative to investment spike (0), on the horizontal axis; thick and thin ranges on left panel refer to 66% and 95% confidence intervals, respectively.
Source: own calculations based on financial statements dataset

On average, the employment of big investors clearly increases after investment spike (see Figure 4), after a period of a flat employment level before a spike. But in a control group employment also rises, after a period of decline. The estimates indicate that of employment effects of investment spike (right panel of Figure 4) are positive (compared to control group), statistically significant and fade in. Unfortunately, the results are undermined by a violation of parallel trends assumption (indicated by a Wald tests of joint significance of estimates prior to spike), being a consequence of a different development of employment before the spike.

The regression analysis of differences between smaller and larger firms (see right panel of Figure 5) shows that employment effects of investment spikes are positive in both groups. The result is stronger in larger firms – due to both obedience with parallel trend assumption (according to Wald tests) and slightly larger measure of effect size. But strikingly, the evolution of employment levels after the spike differ between firm size groups. The level of employment in smaller investors rises after investment spike, but is falls in case of larger investors. The same is observed for the control groups. Thus, the regression results indicate that after investment spike employment in smaller firms rises faster than in the control group, but in larger firms it falls slower than the fall in the control group.

Figure 5 Log employment close to an investment spike (left panel) and coefficients from the diff-in-diff estimation (right panel), both for size class.

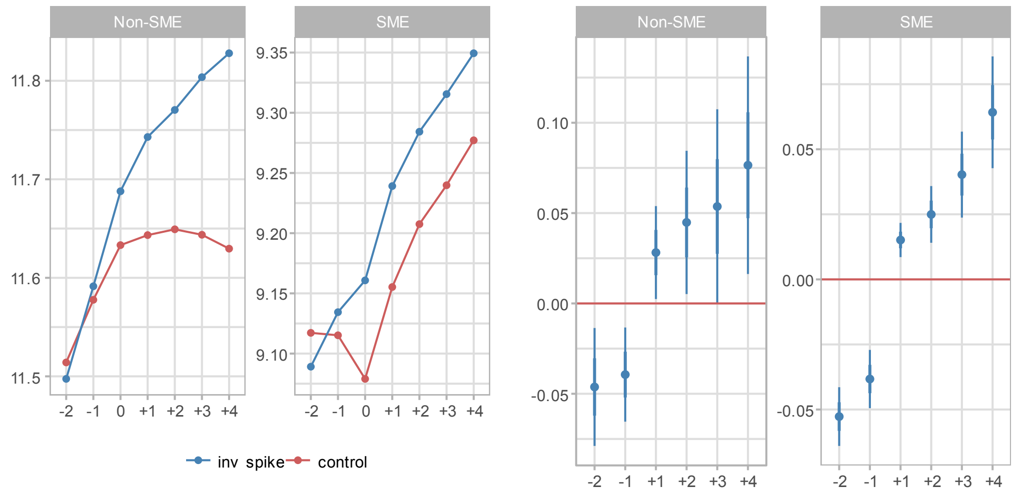


Remarks: Time, in years relative to investment spike (0), on the horizontal axis; thick and thin ranges on left panel refer to 66% and 95% confidence intervals, respectively.
Source: own calculations based on financial statements dataset

Sales

The aggregate effect on sales resembles the employment effect – it sales rise both in levels and in relation to control group (and the parallel trend assumption is violated). We do not report this result here and instead we focus on effect on sales in size classes, see Figure 6. The sales of smaller firms are rising after a spike both for big investors and in control group, but the rise of sales in case of big investors accelerates after the spike. The trends prior to the spike are different in those groups. In larger firms the effect on sales is also positive and statistically significant (according to Wald test of joint insignificance of post-spike regression estimates) and the right panel of Figure 6 shows that indeed sales of larger investors increase substantially whereas they are stagnant in the control group. The results indicate that smaller firms tend to be more dynamic and they tend to grow regardless of investments, but investment outlays translate into higher growth. On the contrary, the growth dynamics of larger firms is lower and sales growth seems to be conditioned on investment outlays, with sales of similar firms that not decide to invest staying flat.

Figure 6 Log sales of products and commodities close to an investment spike (left panel) and coefficients from the diff-in-diff estimation (right panel), both for size class.



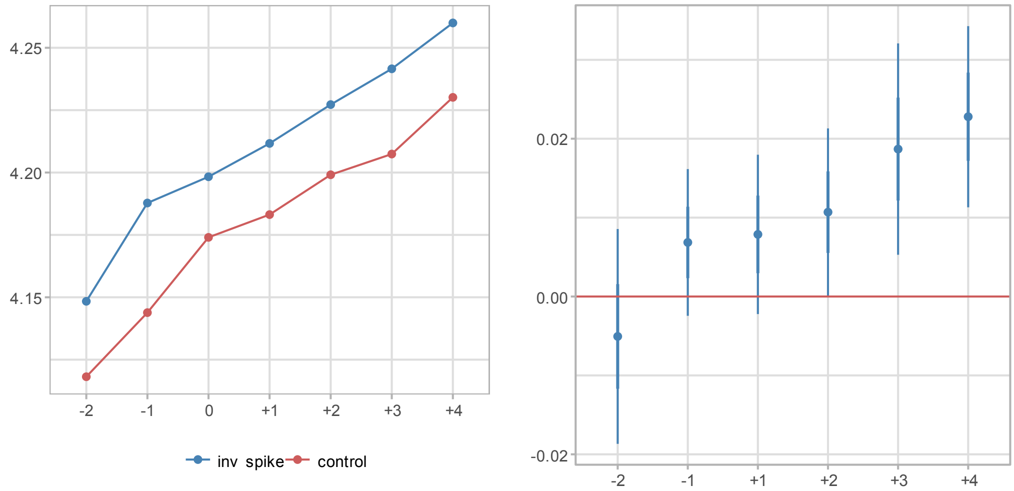
Remarks: Time, in years relative to investment spike (0), on the horizontal axis; thick and thin ranges on left panel refer to 66% and 95% confidence intervals, respectively.

Source: own calculations based on financial statements dataset

Labor productivity

We measure labor productivity with value added per employee and the effect of investment spikes on this variable is driven by the relative strength of employment and sales effects (as demand for materials is almost proportional to sales, the reaction of value added to investment spike resembles the sales effect).

Figure 7 Log labor productivity close to an investment spike (left panel) and coefficients from the diff-in-diff estimation (right panel)



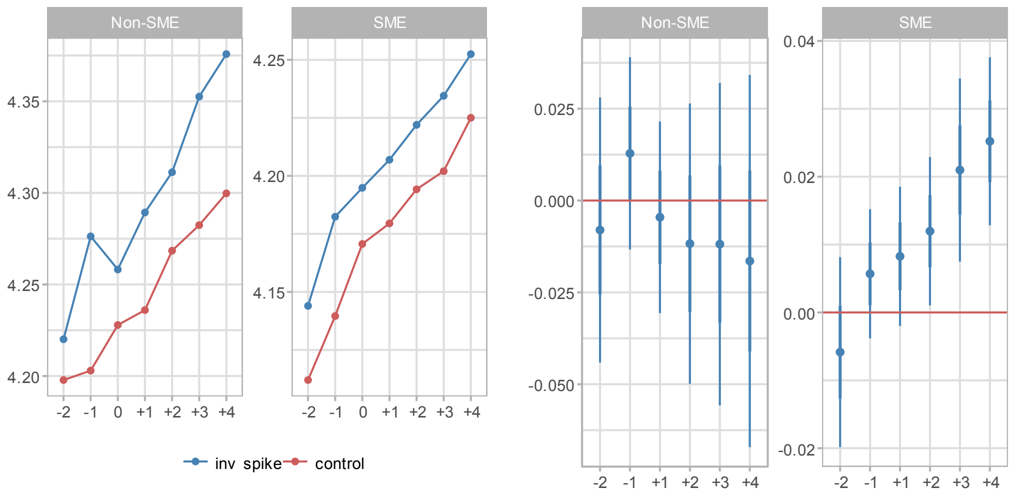
Remarks: Time, in years relative to investment spike (0), on the horizontal axis; thick and thin ranges on left panel refer to 66% and 95% confidence intervals, respectively.
Source: own calculations based on financial statements dataset

The estimation results (see right panel of Figure 7) indicate that labor productivity tends to be higher in investing firms after the spike, so the increase of sales and value added dominates the rise of employment. Although the Wald tests of joint insignificance of all post spike coefficients is not rejecting the null hypothesis with a p-value of 0.13, this is only due to insignificant coefficients in the first 2 years after the spike. In longer term, productivity effect of investment spike tends to be positive and significant, with an average labor productivity gain of 2%. This fade-in of productivity gain is consistent with a learning-by-doing model of (Jovanovic and Nyarko, 1996). The left panel of Figure 7 show the evolution of productivity levels, indicating that productivity rises in both groups, but the rise is faster in case of investing firms.

Moreover, the results of Wald tests confirm the common trend assumption before the spike.

The results for effects on labor productivity differ in size classes (see Figure 8). In smaller firms the results are roughly the same as in the aggregate case – productivity rises after a spike, but some delay, indicating a short period of learning-by-doing effect. The productivity gain 3-4 years after the spike is ca. 2-3% and is significant. The parallel trend assumption is obeyed. The similarity of results of smaller firms to the whole sample results is due to the fact, the economy is dominated by SMEs and we do not weight the results of regression (and thus we do not weight the averages in pictures of levels).

Figure 8 Log labor productivity close to an investment spike (left panel) and coefficients from the diff-in-diff estimation (right panel), both for size class.



Remarks: Time, in years relative to investment spike (0), on the horizontal axis; thick and thin ranges on left panel refer to 66% and 95% confidence intervals, respectively.
Source: own calculations based on financial statements dataset

In case of larger firms, the level of productivity also increases after a spike, but this increase is statistically indistinguishable from the simultaneous productivity increase of control group. In other words, investment spike has no effect on subsequent productivity development, which is indicated by both Wald test of joint insignificance of all β_j with positive j and t-stats for separate coefficients. It also implies that there is no learning-by-doing effect in case of larger firms. Given the fact, that labor productivity is a function of K/L and TFP, it implies that TFP should fall after investment spike. We will explore this thread in next section.

Total factor productivity

Labor productivity, although simple, is not a perfect measure of firm performance and efficiency. 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 $\frac{\partial f}{\partial K/L} > 0, \frac{\partial f}{\partial TFP} > 0$. As we are interested in productivity response to big investment, so out shock directly shifts K/L outward. Any definition of investment spike implies a significant jump in K and our preceding analysis shows that labor on average increases only gradually (and falls in larger firms), implying an increase of K/L and increasing tendency of labor productivity. So, the effect of investment spike on labor productivity is an important result, but more informative is an effect on Total Factor Productivity.

Measurement of TFP is unfortunately more complicated and is a subject to many problems, recognized for many years, see e.g. (Marschak and Andrews, 1944). One of the most important is the problem of simultaneity between unobservable productivity (being part of error term) and observable input choices. As profit-maximizing firm' response to positive productivity shock is to expand output, in turn, using more inputs, it follows that productivity shock would be positively correlated with variable inputs, inducing upward bias in the estimated coefficients on variable inputs.

To address the simultaneity problem (Olley and Pakes, 1996) proposed to use investment as a proxy to control for the part of the error term, which is correlated with inputs. This approach utilizes the fact that profit maximization implies that investment demand function is strictly increasing in productivity and thus can be inverted to express unobservable productivity as a function of observables and hence to control for productivity in estimation. The problem with OP approach discussed in the literature is that firms often have periods with zero investment. In our case, additional complication arises as we are concentrating on periods with unusually high investment compared with neighboring periods, which implies the OP method results in an abrupt drop of TFP in the moment of big investment (particularly large in SMEs).

An alternative approach to measure TFP, which we apply here was introduced by (Levinsohn and Petrin, 2003), which suggested using materials instead of investment as a proxy variable. Demand for intermediate inputs also rises with productivity shock as there is limited substitution possibilities between materials and other production factors. Moreover, intermediate inputs respond more smoothly to productivity shocks and are more useful proxy in the estimation procedure. Thus, we use LP method in the subsequent analysis.

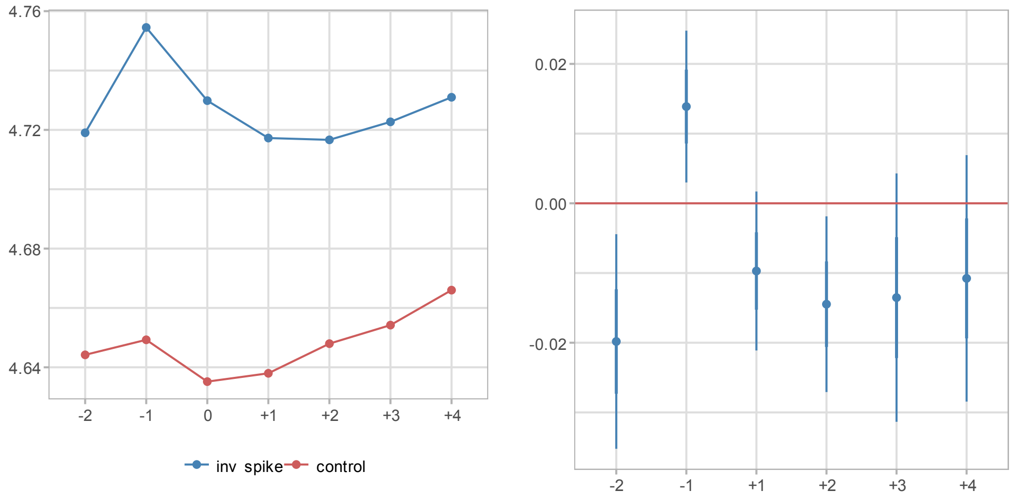
Our panel is unbalanced and there is considerable firm entry and exit in our sample. Various studies, e.g. (Olley and Pakes, 1996) discuss that firm exit substantially affects TFP estimates and we control for firm exit in the estimation[13]. Unbalanced nature of the sample also implies that perpetual inventory method for capital calculation is troublesome, so we use book value of fixed assets instead. Fortunately, (Baily et al., 1992) find that properties of productivity are unaltered by definition of capital. Moreover, in the subsequent analysis we will be comparing TFP of firms from different sectors and periods. So, we estimated the parameters of the production function jointly for the whole sample, not allowing for the elasticities or other features of production function to vary across industries. It is a serious limitation of our approach, but it is a consequence of a limitation of the TFP concept.

In TFP measurement we use deflated variables of interest. Capital measure was deflated by capital price index (constructed from Eurostat data with sectoral and

[13] We used esprod package in R, (R Remédio, 2017).

type of asset heterogeneity). Measures of value added and intermediate inputs (for definitions of both see footnote 1) were expressed in real terms using sectoral value added deflator (also taken from Eurostat national accounts annual database). Production function estimation is more data-demanding and it was not possible to construct TFP measures for all data points we use in our analysis. Due to inability to calculate TFP we dropped almost 14% of big investment events and almost 25% of controls.

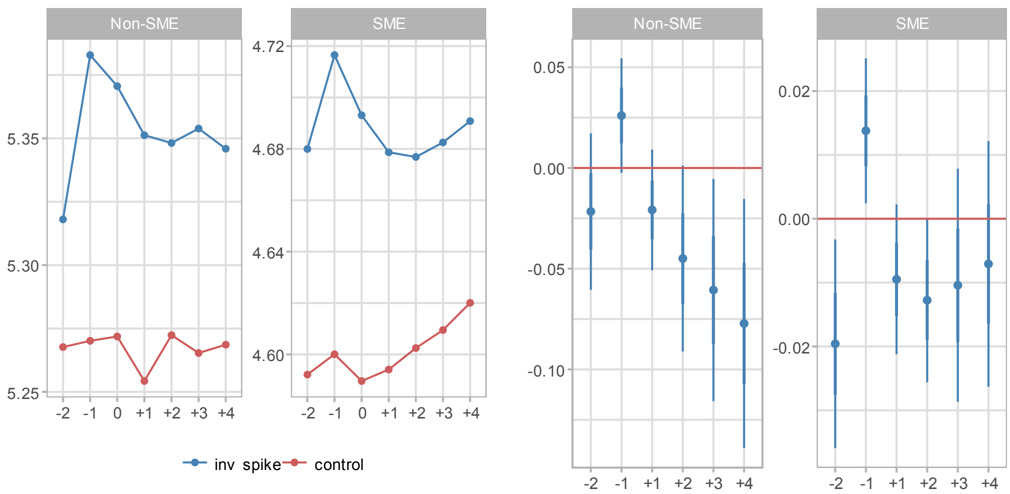
Figure 9 Log TFP (Levinsohn-Petrin) close to an investment spike (left panel) and coefficients from the diff-in-diff estimation (right panel)



Remarks: Time, in years relative to investment spike (0), on the horizontal axis; thick and thin ranges on left panel refer to 66% and 95% confidence intervals, respectively.
Source: own calculations based on financial statements dataset

As mentioned by (Geylani and Stefanou, 2013) identifying the relationship between investments and productivity is challenging and proved to be complicated in our study. Figure 9 reveals some important observations. First, big investors are on average more productive than firms in the control group – the log-difference between TFP average measures in the moment of spike is almost 9.5%. Second, productivity gain of big investors persist within the window of observation around investment spike. Third, investment spike is not associated with subsequent TFP improvement. On the contrary – TFP seems to deteriorate in absolute terms just after an investment spike and rise only gradually more than 2 years after the spike (on average after 4 years restoring TFP level from the base period). But Wald tests of joint significance of all post spike effects with p-value of 0.18 indicate that overall effect of a spike on TFP within 4-years horizon is negligible. It follows that the positive labor productivity effect discusses earlier sourced mainly from higher capital deepening with no effect on TFP. Any possible subsequent TFP expansion may come with a substantial lag of more than 4 years after a spike.

Figure 10 Log TFP (Levinsohn-Petrin) close to an investment spike (left panel) and coefficients from the diff-in-diff estimation (right panel), both for size class.



Remarks: Time, in years relative to investment spike (0), on the horizontal axis; thick and thin ranges on left panel refer to 66% and 95% confidence intervals, respectively.
Source: own calculations based on financial statements dataset

As previously mentioned the aggregate results are governed to a large extend by the adjustment of SME companies and the average effect in the group of SMEs resembles that of the whole sample – we do not observe any significant effect of investment spike on subsequent TFP, see Figure 10. There is some indication of learning-by-doing effect at the end of the observation window but it is small and statistically insignificant within this window.

The story is somewhat different in case of larger companies. Here also the big investors' TFP level deteriorates after a spike, but there is no indication of TFP increase even at the end of the observation window (even 4 years after the spike level of productivity is well below level at a spike). Regression results show that when compared with control group TFP of big investors drops after a spike and the deference widens as time passes. So, in case of larger companies, no change of labor productivity after a spike is accompanied by a fall of TFP, with no indication of a learning-by-doing effect.

Summing up the results, important differences between smaller and larger companies emerge. In smaller firms investment spike is associated with subsequent sales expansion and employment increase. Labor productivity also rises, but this effect becomes significant 2-3 years after the spike, indicating short learning-by-doing period. But the whole rise of labor productivity seems to be driven by capital deepening, as TFP drops directly after a spike and only gradually rises thereafter. These results suggest that in smaller firms big investments aim at higher market share at the cost of temporarily lower productivity.

In larger firms sales expansion is also observed after a spike, but it is associated with a drop of employment (although it falls less than in the control group). The resulting labor productivity increase in absolute terms, but this rise is the same as in the control group, so the relative productivity is not improving. If follows also that in the case of larger companies capital deepening results in significantly lower TFP, both in absolute and relative terms. So, in larger firms big investments also seem to aim at higher market share but at the cost of lower productivity for an extended period of time, in spite of employment reduction.

Conclusions

Our study aimed at investigating the relationship between investment spikes and subsequent productivity at firm level. We use the census data of Polish firms with employment above 9 persons and proposed a measure of an investment spike, fulfilling the criteria of a meaningful definition of a spike. We constructed a control sample – a set of firms similar to big investors in size, market, technology, performance and financing, industry and ownership status, with the only difference of not investing during the period of interest. For each event of big investment and a corresponding control observation we created a panel of observations within a window -2/+4 years around the spike. We showed the evolution of employment, sales labor productivity and TFP within the observation window of both big investors and firms in the control group. Moreover, we estimated a difference-in-difference models in the spirit of (Gormley and Matsa, 2011) to test whether differences between both groups after a spike are significant.

We showed that the results are strikingly different for SMEs and larger companies. Investment spike in smaller firms is associated with subsequent sales and employment expansion, suggesting that in those investments aim at higher market share. Labor productivity also rises, but only 2-3 years after the spike. It indicates a short learning-by-doing period, consistently with a model of e.g. (Jovanovic and Nyarko, 1996). The labor productivity surge seems to be driven by capital deepening only, as TFP falls directly after a spike and only gradually rises thereafter. It follows, the cost of larger market share is temporarily lower productivity.

In larger firms investment spike also result in expansion of sales, but it is simultaneously associated with a drop of employment. Labor productivity is not improving after a spike in relation to the control group. Moreover, capital deepening of larger firms results in significantly lower TFP, both in absolute and relative terms. So, in larger firms big investments also seem to aim at larger market share but at the cost of lower productivity for an extended period of time, despite employment reduction. The results for efficiency in larger firms may also suggest the existence of agency problems and managerial ability, like e.g. in (Bromiley, 1991), but our dataset does not allow to test for that hypothesis.

Our results also suggest that the strength of macroeconomic relation between investment activity and productivity may change in time and may be heavily affected by the composition of investment growth. They also suggest that the relation between investments and labor productivity may substantially differ than the relation of investment and TFP. Although our results give rather mixed picture of firm-level relationship between investment and efficiency, but both labor productivity and TFP of investing firms tends to be higher than non-investing. It suggests that the positive relation between investments and various measures of efficiency observed at the macroeconomic level could be to a large extend driven by improvement of allocative efficiency as resources, capital and labor in case of smaller firms are attracted to more effective firms after an investment spike. This results adds a new thread to a growing literature on misallocation - see the literature review in (Restuccia and Rogerson, 2013).

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Appendix - robustness

As there were many decisions we made in the study, we also tried to present and assess robustness of our results. We concentrate on productivity and TFP differences, measured by coefficients of diff-in-diff equations (2). Tables 3-6 show results for those two measures and for SMEs and larger companies separately.

Table 3 Robustness analysis – labor productivity in Non-SMEs

	baseline	*definition*	*no date*	*no productivity*
	(1)	*(2)*	*(3)*	*(4)*
-2	*-0.008 (0.018)*	*-0.000 (0.016)*	*-0.022 (0.021)*	*-0.031* (0.018)*
-1	*0.013 (0.013)*	*0.009 (0.011)*	*0.002 (0.015)*	*0.002 (0.010)*
+1	*-0.005 (0.013)*	*-0.021 (0.013)*	*-0.014 (0.011)*	*-0.004 (0.012)*
+2	*-0.012 (0.019)*	*-0.041** (0.020)*	*-0.013 (0.015)*	*-0.013 (0.017)*
+3	*-0.012 (0.022)*	*-0.050** (0.020)*	*-0.011 (0.019)*	*-0.015 (0.018)*
+4	*-0.016 (0.026)*	*-0.036 (0.025)*	*-0.017 (0.021)*	*-0.031 (0.023)*
Observations	*25032*	*23534*	*23824*	*25074*
R^2	*0.922*	*0.926*	*0.928*	*0.924*
Adjusted R^2	*0.895*	*0.901*	*0.903*	*0.897*
Residual Std. Error	*0.259 (df = 18617)*	*0.249 (df = 17550)*	*0.247 (df = 17700)*	*0.257 (df = 18634)*

Apart from baseline results (showed in graphs in the main text of the study and in 1st column of tables in the appendix) we repeated the whole analysis with 3 important changes:

- Definition of investment spike. We followed more conventional approach of (Power, 1998) and defined investment spike as all events where:

$$\frac{I_{it}}{K_{it}} > \alpha \times median_i(\frac{I_{it}}{K_{it}}),$$

calculated for each firm. α was set at 3.25, which is a conservative choice, coherent with number of firms in baseline parametrization. We have not decided to use this definition as baseline, as it allows much more relatively small cases of both $\frac{I}{K}$ and $\Delta\frac{I}{K}$ (compare Figure 1 and Figure 11). Moreover, with this parametrization, a visible, but relatively smaller spike of $\frac{I}{K}$ in control group (in smaller enterprises) was observed a year after a spike of big investors, which makes the interpretation of results more troublesome. Results are presented in column 2: definition.

- No date grouping in the definition of investment spike. In the baseline, we have chosen firms with highest increases of investment rate for each industry and year. It follows that the share of big investors in the population is evenly distributed across time. Here, we relaxed this assumption and used industry grouping only, which resulted in more even distribution of number of firms across time. It follows that relatively more investment spikes are observed in the first years of the sample, especially in the period of high investment growth before the crisis of 2008/2009. Results are presented in column 3: no date.

Table 4 Robustness analysis - TFP in Non-SMEs

	baseline	*definition*	*no date*	*no productivity*
	(1)	*(2)*	*(3)*	*(4)*
-2	-0.022 (0.020)	-0.025 (0.018)	-0.022 (0.021)	-0.044*** (0.017)
-1	0.026* (0.015)	0.020 (0.012)	0.013 (0.016)	0.007 (0.009)
+1	-0.021 (0.015)	-0.034** (0.015)	-0.035*** (0.012)	-0.020 (0.015)
+2	-0.045* (0.024)	-0.075*** (0.023)	-0.032** (0.016)	-0.043** (0.019)
+3	-0.061** (0.028)	-0.100*** (0.026)	-0.038** (0.019)	-0.062*** (0.022)
+4	-0.077** (0.032)	-0.110*** (0.033)	-0.054** (0.022)	-0.083*** (0.030)
Observations	22,551	21,625	21,463	22,534
R^2	0.904	0.906	0.911	0.903
Adjusted R^2	0.868	0.872	0.877	0.866
Residual Std. Error	0.271 (df = 16385)	0.261 (df = 15818)	0.259 (df = 15547)	0.272 (df = 16342)

- Omission of the most problematic variable in the matching procedure. Baseline parametrization used productivity as a measure of technical efficiency to match on, but empirical results suggested that difference in means of productivity increased and became significant after matching (while it was insignificant before matching). When we excluded productivity from variables to match on, the difference on productivity became insignificant and it have not affected significantly other tests. The rest of most important results are presented in column 4: no productivity.

The results for larger companies, presented in Table 3 and Table 4 showed that in all cases of robustness check the general shape of labor productivity and TFP adjustment to investment spike remained roughly unchanged. Productivity response, although rather negative, remains insignificant in all periods post investment spike. Only in case of change in the definition of investment spike, which imposed significant change in the distribution of investment spikes in the sample, productivity of big investors is lower than in the control group, but only in the short term. The differences in labor productivity before spike were insignificant, which is also the case in TFP analysis of Table 4. But in case of TFP lower (than in control group) labor productivity in big investors post investment spike is significant, both in the short- and long-term. The scale of difference is increasing over time and is more pronounced in regressions with change definition of investment spike (column 2).

Table 5 Robustness analysis – labor productivity in SMEs

	baseline	*definition*	*no date*	*no productivity*
	(1)	(2)	(3)	(4)
-2	-0.006 (0.007)	-0.025*** (0.008)	-0.018*** (0.006)	-0.008 (0.008)
-1	0.006 (0.005)	-0.006 (0.006)	-0.009 (0.005)	0.002 (0.007)
+1	0.008 (0.005)	-0.017*** (0.006)	0.007* (0.004)	0.000 (0.006)
+2	0.012** (0.006)	-0.023*** (0.008)	0.007 (0.006)	0.008 (0.006)
+3	0.021*** (0.007)	-0.020** (0.010)	0.014** (0.006)	0.021*** (0.006)
+4	0.025*** (0.006)	-0.031** (0.013)	0.023*** (0.007)	0.019*** (0.007)
Observations	356,659	418,440	356,945	355,960
R^2	0.856	0.849	0.854	0.858
Adjusted R^2	0.814	0.808	0.813	0.817
Residual Std. Error	*0.315 (df = 277184)*	*0.311 (df = 328231)*	*0.315 (df = 278033)*	*0.313 (df = 276686)*

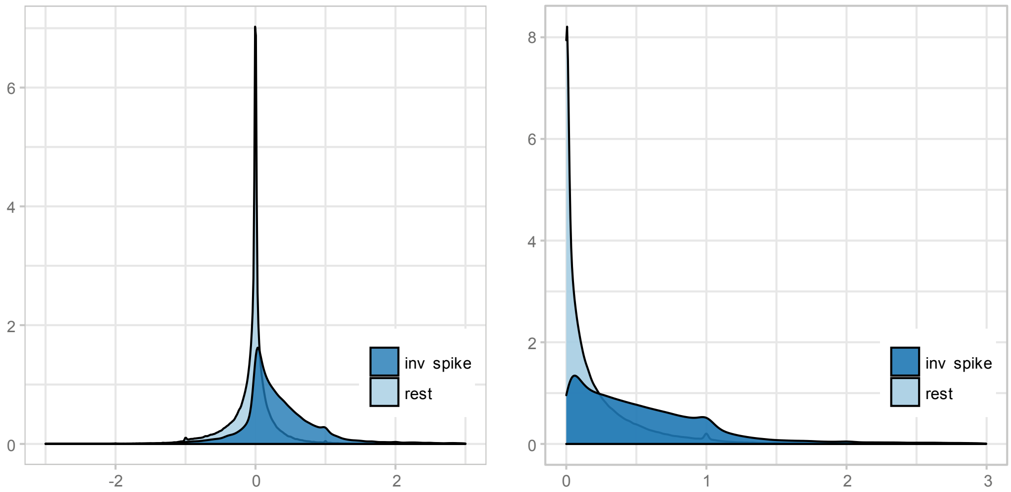
Also in case of SMEs the general picture in comparing coefficients in Table 5 and Table 6 indicated that there are no substantial differences among analyzed cases.

In almost all cases in Table 5 labor productivity of big investors among SMEs is higher than average of control group of SMEs, only in case of change of definition (column 2), the opposite is true. It is a consequence of faster increase of productivity in control group than increase of productivity of big investors, hence the negative signs of coefficients. The results for TFP (Table 6) are more coherent – in all cases TFP of investors is lower compared to control group and only in baseline parametrization the negative effect is statistically insignificant.

Table 6 Robustness analysis - TFP in SMEs

	baseline	*definition*	*no date*	*no productivity*
	(1)	(2)	(3)	(4)
-2	-0.020** (0.008)	-0.028*** (0.009)	-0.029*** (0.007)	-0.021** (0.009)
-1	0.014** (0.006)	0.006 (0.006)	0.002 (0.006)	0.014* (0.007)
+1	-0.009 (0.006)	-0.033*** (0.007)	-0.015*** (0.005)	-0.018*** (0.006)
+2	-0.013* (0.007)	-0.050*** (0.010)	-0.023*** (0.006)	-0.017*** (0.007)
+3	-0.010 (0.009)	-0.056*** (0.013)	-0.020*** (0.007)	-0.010 (0.009)
+4	-0.007 (0.010)	-0.074*** (0.016)	-0.015* (0.009)	-0.016* (0.010)
Observations	304,126	366,103	305,138	303,342
R^2	0.856	0.848	0.855	0.857
Adjusted R^2	0.808	0.801	0.807	0.809
Residual Std. Error	0.308 (df = 228296)	0.305 (df = 279027)	0.308 (df = 229745)	0.307 (df = 227761)

Figure 11 Robustness - distribution of changes (left panel) and levels (right panel) of investment/capital rate in firms engaged in big investments (inv spikes) and the rest of firms (changed definition of investment spike)



Remarks: The graphs are trimmed for the shape of distribution to be visible.
Source: own calculations based on financial statements dataset

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