What happens when firms invest?  
Investment events and firm performance

Michał Gradzewicz

Abstract

The aim of the study is to investigate the firm-level relationship between investment spikes and subsequent productivity development. To that end, we used census data of Polish firms with employment above 9 persons, defined and measured investment spike and constructed a control sample. We showed the evolution of various performance indicators within the observation window around the event of investment spike and test the difference in behavior between groups of enterprises using a difference-in-difference models. The results are strikingly different for SMEs and larger companies. In the former investment spikes are associated with higher sales, employment and relatively higher survival probability, but at the cost of depressed productivity, consistently with learning hypothesis. In larger companies, investment spike results in a fall of employment, sales and productivity and the results suggest big investments are a way to avoid possible bankruptcy. The results for larger companies may suggest the existence of agency problems at play. Moreover, the results also suggest that the composition of investment growth could change the strength of macroeconomic relation between investment and productivity and may be rather due to improvement of allocation efficiency rather than improvement of productivity within investing firms.

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

JEL classification: D22, D24, L16, O3

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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). 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) shows that aggregate labor productivity growth is largely driven by within-firm changes.

An important from the perspective of our study aspect of investments is their lumpiness. (Doms and Dunne, 1998) show that years of inactivity or repair and maintenance are followed by one or several years of heavy investment. (Gourio and Kashyap, 2007) show that most of the variation in aggregate investment can be explained by changes in the number of establishments undergoing such large investment episodes (investments spikes). Moreover, investment lumpiness allows us to focus the analysis on such episodes, as they naturally seem to be important for the subsequent firm behavior.

The theory behind a positive relationship between investments and productivity relates to the model of embodied technical change (see e.g. (Cooley et al., 1997) or in an empirical context (Jensen et al., 2001)), which describes investments as technological upgrading (as new capital embodies more recent technology). But (Jovanovic and Nyarko, 1996) made an argument using a “learning-by-doing” model that a switch of technologies may temporarily reduce expertise and thus induce short-run costs. Moreover, productivity costs seem also to arise from building and destroying a particular organization of production.

The empirical literature on investment spikes and subsequent firm performance is far from consensus, with results pointing each possible direction. One of the first result, (Power, 1998) finds no evidence of investment effect on productivity or productivity growth. (Grazzi et al., 2016) finds investment spikes associated with higher productivity, sales and employment, but only in one of the countries analyzed. Also (Nilsen et al., 2009) finds evidence of a positive and significant, but only contemporaneous effect, similar to (Geylani and Stefanou, 2013) where productivity growth increases after investment spikes but trails off in the longer run. On the contrary, (Huggett and Ospina, 2001) and (Sakellaris, 2004) report a fall in productivity after an investment spike, which start to recover slowly thereafter, consistently with “learning-by-doing” effect. The results reported above are hard to compare directly, as they come from to different countries, industries, definitions of investment spike and measures of productivity, but suggest that relation between investments and performance is complex.
The aim of our study is to investigate the details of relationship between investment spikes and subsequent productivity development in a developing and catching-up country with stable macroeconomic policies and performance, namely Poland. What is more important, the supply-side growth decomposition in (Gradzewicz et al., 2018) showed that Poland experienced a quite stable contribution of capital to GDP growth with a declining growth and role of TFP. Although we admit there could be many potential explanations of this phenomenon, we try to find microeconomic evidence whether TFP slowdown is connected to investment process.

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, given the lumpy nature of investment on a firm level, it is quite easy to detect events of big investments. Having distilled these events in the data, is straightforward to use the econometric methods designed in natural experiments to check for causality, as described e.g. in (Angrist and Pischke, 2008). We use multievent difference-in-difference methodology, as in (Gormley and Matsa, 2011), to verify if firms deciding to make big investment perform significantly different than similar firms, not deciding to invest (determined using matching techniques). Third, augmenting the prior literature, we stress the importance of the firm size to the shape of investment-performance relation. Namely, our results suggest that only for smaller firms investments are conductive to performance improvement, whereas larger firms performance deteriorates after investment spike. Moreover, we utilize the firm census from the Polish economy, covering almost whole enterprise sector, whereas prior studies usually concern manufacturing or specific industries.

The rest of the paper is organized as follows. Next section present data sources, measurement and introduces a definition of investment spike. This is followed by the discussion of econometric considerations for identification strategy for the effects of investment spikes on performance. Next sections discuss the 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 10-49 due to underreporting of firms). The dataset is annual and covers 14 years (2002-2015) of firms’ financial statements: balance sheets and profit and loss accounts. 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).
The original dataset contains some erroneous or missing observations (firms with no employment or capital or negative value added). Moreover, subsequent econometric analysis rely 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 observations with annual number of firms increasing from 26k in 2002 to 47k in 2015, observed over 7.1 years on average.

Table 1 Data properties

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

Source: own calculations based on financial statements dataset

Table 1 presents some data properties of selected sample in 3-year periods. Clearly, along with growing firm number, the employment share of the dataset (the share of employment in firms used in our study in total employment in enterprise sector of the Polish economy) increases to 85%. Simultaneously, the net increase of number of firms translate into a falling average employment, but an increase of $K/L$ ratio. The firms liquidity (short-term assets to short-term liabilities) is on average increasing and debt-to-assets is U-shaped. Productivity (measured both as value added of sales per employment) is also increasing. The share of export proceeds in total revenues is increasing form 15% in 2002 to 25% in 2015, due to both increasing export intensity, but also due to the number of exporters – share of firms with export share higher than 2.5% also increases.

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1 Value added is defined as close as possible to national accounts counterpart, as global output (sales and change of inventories of products plus 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.
**Definition of investment spike events**

As was mentioned in the introduction, lumpiness of investments on a firm level allows us quite easily to define periods when firms engage in huge investment outlays. There are different attempts to measure investment spikes, as documented e.g. in (Grazzi et al., 2016). Most of them rely on ratio of investment to capital exceeding certain threshold. We also tried those methods (see the robustness appendix for details), but finally decided for a different way of defining investment spike, based on \( \Delta I/K \), which is, as we believe, better suited to the data at hand.

*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*

![Distribution of changes and levels](image)

**Remarks:** The graphs are trimmed for the shape of distribution to be visible.

*Source: own calculations based on financial statements dataset*

Namely, investment spike is defined as 12.5% of the highest annual increases of \( \frac{I_{it}}{K_{it}} \) calculated separately for each year and NACE02 sector, to account for heterogeneity of investment characteristics across different industries and in business cycle\(^3\). The threshold is chosen to give about 5500 incidents of big investments, almost 10% of effective observations and close to the number of incidents selected by the method of (Power, 1998), with relatively strict definition of a spike: \( \frac{I_{it}}{K_{it}} \) higher than 3.25 times the median calculated for a given firm across time. We observed that definition based on individually high level of investment (although quite natural) is not well suited to cases with relatively flat investment episodes. Our method performs relatively better, as it selects episodes with significant increases of investment rates

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\(^3\) Prior to calculations we excluded investment rate changes of magnitude higher, in absolute terms, than 3 (1% of observations), which was irrelevant for the main results.
within an industry (assuming homogeneity of technologies within industry) and controlling for time variation in overall investment activity.

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

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 parsimoniousness – ability to capture a large share of total investment with a small number of observations. By definition, the share of big investors in our dataset is close to 10% in each period, 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 – the share of investment spikes in total investments is twice as large – those firms account for almost 19% of total investments (ranging from 16% to 25% in different years).

The selected firms are concentrated in SME sector4 (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 share of investment spikes is observed in manufacturing, trade and construction, but within an industry investment spikes are slightly overrepresented in mining, energy, utilities and real estate.

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4 SMEs are defined as employing less than 250 employees.
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 such an event. But it might be the case that other firms, not engaging in big investment during that time for some reason made similar decisions. The fact that we have spikes defined in various period makes that case less likely, but still it could be a good idea to check if firms deciding to engage in big investment act differently not only compared to themselves in neighboring periods, but also to other firms, not having investment episodes then – control group. Treating all other firms as control group is not very wise, especially in the multiperiod setting of spike events.

To find firms similar to big investors, but which did not decide to invest, we use matching techniques\textsuperscript{5}. We decided to match on propensity score, using logit to estimate conditional expectation function of probability of investment spike 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 counterfactual. As e.g. in (Hagemejer and Tyrowicz, 2012) we used a suite of indicators as dimensions to match firms on (referring to size, market, technology, performance and financing). As industry (measured on NACE02 level) and ownership status of a firm (coded as state, foreign and domestic privately owned) is an important selection indicator, we used exact matching on these variables. Moreover, as different phases of business cycle may affect the estimates, we separately match “twin firms” for each year in the sample.

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

Market, on which firm operates, is another dimension of firm type, related also to its competitive environment. Our dataset does not allow us to determine whether the firm operates on local or national level, but we can measure share of products sold abroad in total product sale revenues. (Hagemejer and Kolasa, 2011) showed that the export share is an important determinant of firm performance.

We do not have direct information on firm technology in the database, so we used proxy. The share of labor costs in total costs measures the relative importance of labor in firm’s

\textsuperscript{5} Matching models were estimated using MatchIt package of R.
technology choice. We did not use capital-to-labor ratio, as both are already used and this variable was usually insignificant. We measure efficiency both in technological and financial context. Productivity, defined as value added per employee measures firm technological efficiency and return on assets (ROA) its financial efficiency. The further analysis checks if decision to invest affects firm performance, so on first sight the choice of performance measures to matching procedure seems to create endogeneity. But matching determines similar firms only in the moment of investment spike and its effects are measured in subsequent periods. Moreover, our analysis implies comparing effects of investments between firms of comparable efficiency.

Finally, we use two financial aspects of firm type. Liquidity, measured as short-term assets to short-term liabilities ratio, measures firm operational need for financial resources, and indirectly – the length of production process. Debt-to-assets ratio measures the extent of overall external financing and the ability to finance investment needs.

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

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

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

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 are usually different from the rest of the sample: 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 debt. Their labor share and productivity are indifferent from the rest of the sample. The simple comparison of means shows that control group is much
closer to big investors, although only for labor, capital and labor share the difference is insignificant\(^6\). Only in case of productivity the difference became significant after matching, but the bias in means is only 4\%. The visual inspection of QQ plots of the whole distribution (available upon request) indicates that control group is more similar to big investors group, although Kolmogorov-Smirnoff tests indicate that only distributions of export share and labor share became statistically indistinguishable after matching.

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

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

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 to check if productivity of firms selected as big investors differs from the control group, we need to check how the investment spike looks like on average in both these groups of firms. Left panel of Figure 3 shows the average investment-capital ratio in a sample of firms selected as big investors\(^7\) in the moment of investment spike (normalized to 0), prior to the investment spike (labelled -1 and -2) and in subsequent years\(^8\). Investment

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\(^6\) Samples to compare are large – each has above 50000 observations, so within sample variation is considerable, possibly affecting significance tests.

\(^7\) We defined investment spikes and their controls for all sectors in the data and in all sectors, except energy and financial part of enterprise sector, the procedures applied seem to properly identify relevant cases. We excluded energy and finance from subsequent analysis (1.3\% of cases), this choice was irrelevant for main results, but absent those sectors results for larger firms have less volatility around investment spike.

\(^8\) The number of observations in different years relative to investment spike varies as we have unbalance panel of firms.
spike is indeed visible – on average $\frac{I}{K}$ more than double on impact, but then quickly fade out, although not completely. Interestingly, just before the spike, firms tend to underinvest and the $\frac{I}{K}$ drops substantially. The results suggest that big investment is anticipated and firms prepare to huge investment postponing investment outlays prior to investment spike. In the control group $\frac{I}{K}$ is relatively flat, as it should be.

Left panel of Figure 3 shows the same results, calculated separately for SMEs (with employment less than 250, it is 94.5% of investment spikes) and larger firms. The investment pattern is similar across both groups, with prior preparation period and visible spike (higher in SMEs), although in non-SMEs investment fades out quicker and then, after 4 years a second spike is present. We will not deal with this interesting issue in the subsequent analysis, as it is behind the scope of the study.

**Econometric considerations**

To find the effects of investment spikes for firm performance we use an estimation approach frequently applied in evaluation studies - difference in differences, see (Angrist and Pischke, 2008). Although firm decisions on big investment is hard to treat as a natural experiment (and investment event as a “treatment”), so it is not straightforward to interpret the results in terms of causality, but still the methods are useful in the context of our study.

If all investment spikes occur in one period (or, for a given cohort\(^9\)), standard generalized diff-in-diff equation measuring the impact of investment spike on subsequent performance measure \(y\) is:

\[
y_{it} = \beta (d_i \times p_t) + \alpha_i + \delta_t + \epsilon_{it},
\]

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

The literature on estimating treatment effect discusses the possibility of divergence in trends before treatment. Parallel trend is an important assumption allowing for 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. (Autor, 2003) suggested the simplest solution –time varying coefficients \(\beta_j\) in \(\sum_{j \in [-k,...,-1,1,...,l]} \beta_j \times d_i \times \tau_j\), where \(\tau_j = 1\) when the difference between current date and treatment date is \(j\), excluding treatment date, \(j = 0\), due to collinearity. It follows that \(\beta_j\)’s are measuring treatment effects between treated and control

\(^9\)Cohort \(c\) refers to a sample of firms marked as big investors in period \(c\).
group relative to the difference in period 0, so accounting for the possibility that firms in treated and control group may differ in the moment of treatment (which may be the case given that matching was not perfect). Ideally, \( \beta' \)'s for periods before treatment date should be insignificant (parallel trends), whereas \( \beta' \)'s for post treatment dates should be significant (divergence after treatment).

In our case investment spikes occur in different years (cohorts). This setting makes the results more robust, as they should not be related to a particular period and the effect of treatment should be similar across different time periods. Moreover, as there is considerable business cycle variation in our sample, the identified effect of treatment shouldn’t be driven by a particular set of treated firms.

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. 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 become a spike itself in some subsequent period (in later cohort) within a window, then it is dropped and serve as control only till the moment of itself being a spike.

The final model has a form:

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

where \( d_{ict} \) is an indicator of firm \( i \) in period \( t \) being treated in cohort \( c \) (\( c \leq t \)), \( \tau_j \) is an indicator of current period \( t \) being \( j \) periods post (positive \( j \)) or before (negative \( j \)) treatment, \( \alpha_{ic} \) is a unit-cohort fixed effect, equivalent to treatment dummy in each cohort and \( \delta_{ct} \) is a time-cohort fixed effect, equivalent to post event dummy\(^{10}\).

We account for possible clustering of errors with a set of NACE02 dummies, important in enterprise data, see (Gormley and Matsa, 2011). Industry-level clustering controls for two phenomena. First, as firms within industries are relatively more similar than firms from different industries, industry-level clustering allows for within industries correlation. Moreover,

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\(^{10}\) When determining the effects for subsamples (e.g. for SMEs and non-SMEs) we present estimates of \( \beta' \)'s from equation (2) estimated separately for those subsamples.
as shocks are usually persistent, clustering at industry level accounts for errors being correlated over time within industries. Models were estimated using FELM package of R, which utilizes the method of alternating projections to sweep out multiple group effects from the normal equations before estimating the remaining coefficients with OLS.

**Investment spikes and firm performance**

In the subsequent analysis we show how investment spike is associated with subsequent development of performance variables: employment, labor productivity, two measures of TFP and survival probability. We will present both developments of measures in group experiencing investment spike and control group, as well as the estimate of a relative effect - $\beta_j$ from regression (2), measuring the effects of investment spike on a given variable relative to the control group and relative to the difference in period 0 – the moment of investment spike. We will also present both average results for all selected firms and distinguishing between SMEs and non-SMEs.

**Employment**

The employment of big investors clearly increases after investment spike (see Figure 4), but expansion of employment starts prior to spike. Employment in control group is more stable, but also rises (after a 2-period decline). The estimates of employment effects of investment spike (right panel of Figure 4) indicate that it is positive (compared to control group), significant and persistent. Wald tests of joint significance of prior difference indicate that the assumption of parallel trends is violated.

*Figure 4 Employment close to an investment spike (left panel) and coefficients from the diff-in-diff estimation (left 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.*
Strikingly, employment effects are drastically different for SMEs and non-SMEs (see Figure 5). The employment in smaller firms rises after investment spike and the effect is statistically significant, persistent and increasing over time (even accounting for rising employment in control group). In larger firms the positive impact of investment spike on employment (relative to control group) is also present and is significant but in absolute terms it translates not into rise, but into smaller employment decrease. In other words, results of diff-in-diff estimation suggest that absent investment spike, employment in non-SME firms would fall even more than it is observed.

Figure 5 Employment close to an investment spike (left panel) and coefficients from the diff-in-diff estimation (left 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.

Labor productivity

The results of estimation (see right panel of Figure 6) indicate that labor productivity (value added per employee) adjustment after an investment spike is consistent with learning-by-doing model. First, productivity of investing firms is higher than in the control group, not only in the moment of investment spike, but also in a +/- years window around. Second, after 2-years since the investment spike the higher relative productivity of big investors became significant and is increasing thereafter. But simultaneously, it doesn’t mean that productivity of investors becomes higher in absolute terms post investment spike. Left panel of Figure 6 suggest that investing firms gain on productivity before investment spike and then that gains
slightly evaporates, although remain significantly above that of non-investing firms. Productivity of non-investing firms remains relatively flat and is higher only in the period of investment spike.

Figure 6 Log labor productivity close to an investment spike (left panel) and coefficients from the diff-in-diff estimation (left 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

Like in case of employment, smaller and larger enterprises differ in some important aspects of productivity development close to investment spike (see Figure 6). The whole sample is dominated by SMEs and the story for the whole sample (with learning-by-doing effects) coincides with the picture for SMEs. But the adjustment of larger companies is different. Their productivity also increases prior to the spike, but the increase is much smaller and insignificant. Moreover, productivity stays flat thereafter (whereas is smaller companies it deteriorates). In contrast, productivity in the control group has an increasing tendency within the whole window of analysis. Regression analysis indicates that productivity gain of larger enterprises after investment spike is insignificant comparing to non-investing firms (in fact, productivity is smaller, although insignificantly).

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

**Total factor productivity**

Labor productivity, although simple, is not a perfect measure of firm performance, as it concerns only efficiency of labor. To capture the efficiency with which inputs of capital as well as labor are used, we need to measure TFP. But estimation of production function needed to calculate TFP is subject to the problem of simultaneity between unobservable productivity and observable input choices. As profit-maximizing firms’ 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 (see the discussion in (Marschak and Andrews, 1944)).

To address the simultaneity problem (Olley and Pakes, 1996) proposed investment as a proxy to control for the part of the error correlated with inputs. He 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 this approach in case of firm level production function estimation is that firms often have zero investment periods, suggesting non-convex adjustment costs (leading to non-responses of investment to some productivity shocks).

(Levinsohn and Petrin, 2003) suggested to use materials instead of investment. Demand for intermediate inputs also rises with productivity shock, especially with no substitution possibilities between materials and other production factors, which is the case in most industries. They argue that intermediate inputs respond more smoothly to productivity shocks and are more useful proxies in the estimation procedure. We decided to use materials as a
proxy used to address the simultaneity bias and used (Levinsohn and Petrin, 2003) methodology to calculate TFP\textsuperscript{11}. Although the choice of proxy is rather empirical and should be related to industry in question, in our case (Olley and Pakes, 1996) methodology has one important drawback. We calculate the productivity around investment spike, in a highly nonlinear environment. It follows that the Olley-Pakes TFP estimates exhibit a sudden one period drop in big investors TFP in the period of big investments, apparent especially in SMEs. The Levinsohn-Petrin TFP estimates were much smoother around investment spike.

The panel used in the study is unbalanced, and there is important variation in productivity due to demography. Thus, we control for firm exit in the estimation. 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. Capital measure was deflated by capital price index (constructed from Eurostat data for different kinds of assets and sectors). Measures of value added and intermediate inputs (for definitions of both see footnote 1) were expressed in real terms with sectoral value added deflator (from Eurostat). As in subsequent analysis we will be comparing TFP across different enterprises and different period, we estimated the parameters of the production function for the whole sample, not allowing for the parameters to vary across industries, which is a serious limitation of the TFP concept.

Figure 8 Log TFP (Levinsohn-Petrin) close to an investment spike (left panel) and coefficients from the diff-in-diff estimation (left 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

\textsuperscript{11} To calculate TFP we used estprod package of R.
As mentioned by (Geylani and Stefanou, 2013) identifying the relationship between productivity and investment is challenging and proved to be complicated in our study. Figure 8 reveals some important observations. First, big investors are on average more productive than firms in the control group and that productivity gain persist within the window of observation around investment spike. Second, investment is not associated with subsequent TFP improvement. On the contrary – TFP seems to deteriorate in absolute terms after investment spike and the increase in productivity is observed before the spike. Third, TFP development in control group has roughly constant, slightly increasing tendency. It follows then that the productivity surge associated with the investment spike occurs prior to the spike and is transitory. Estimation results (right panel of Figure 8) show that relative to the huge TFP difference in period 0 subsequent productivity differentials between big investors and control group are indistinguishable (and only in 2 years after the spike TFP of investors falls short relative to control enterprises). The highest productivity differential is observed during a year before investment spike and then productivity differential is even higher than in period 0.

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

Like in the case of employment and labor productivity the aggregate results for TFP are governed mainly by the adjustment of SME companies and the description from the previous paragraph applies also to them. In case of larger companies, the story is different in some important dimensions, see Figure 9. Similar is the fact that big investors among non-SMEs are more productive, productivity gain is observed before the spike and TFP falls thereafter. But the fall is very steep and after 4 years the level of productivity is well below levels prior to spike. Moreover, similar pattern is observed in control group and the productivity difference
in the moment of spikes quickly evaporates and after 2 years the productivity difference is negative and significant.

Summing up, the results some observations emerge. First, the average results for the whole sample are to a large extent driven by adjustment of SMEs to investment spike. And those coincide with a coherent story. Investing firms are on average more productive than non-investing firms and investment spike induce employment expansion. Increase of the firm size is not neutral for efficiency and possible learning-by-doing effects associated with both new employees and new equipment makes labor productivity and total factor productivity decrease (although still being above pre-investment levels and above the average of the control group). This story is complemented by behavior of sales, see Figure 10, which indicate the reason why firm decided to engage in big investment in the first place. Namely, prior to the investment firms experience substantial surge of sales and investment is probably a mean to sustain an expansion in market share – sales after investment spike continue to rise. Probably the main purpose of those investment is capacity expansion, not oriented at cost optimization, and additionally induce prolonged learning period, thus no productivity gains are observed.

Figure 10 Log sales of products and commodities close to an investment spike (left panel) and coefficients from the diff-in-diff estimation (left 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

The story is much more different for larger firms. Employment (Figure 5) and sales (Figure 10) reactions to investment spike indicate that expansion is not the main reason for significant investment outlays. Or, even if expansion was a strategy backing engagement in
investment, it fails. Cost optimization does not seem to be the main reason behind big investment of big firms, or even if was, it failed, as labor productivity flatten after an investment spike (and rises in case of non-investing firms) and total factor productivity drops more than the average of non-investing firms. Next section puts more light on the question why large firms decide to invest.

**Survival probability**

To check the effects of investment spike for survival probability we first calculated the binary variable $I_{ict}$ indicating if the firm $i$ from a cohort $c$ was observed both in period $t$ and period $t+1$, corrected for “dropping” effect due to the end of sample in cohorts close to the sample end. The definition of $I_{ict}$ variable assumes that dropping out of the sample is due to firm bankruptcy. In our case this measure is only a rough proxy of bankruptcy, as firm may cease to report to statistical agency or its employment may drop below the threshold level of 10. Although not reporting to statistical agency is subject to a fine, but there is some underreporting in the sample, especially in smaller firms, with employment less than 50. We don’t have any additional information that indicates what is the reason for firm quitting the sample. To check for the possibility of quitting due to passing the threshold of 10 employment, we check the results in the sample restricted to firms with employment above 15, and those remained unchanged.

*Figure 11: Survival probability close to an investment spike (left panel) and coefficients from the diff-in-diff estimation (left 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*
Left panel of Figure 11 shows the means of $I_{ict}$ variable in the samples of big investors and control group, calculated separately for SME and larger companies. These figures represent estimates of survival probability in subsamples. Right panel presents additionally the results of diff-in-diff regression, given by equation (2), with $I_{ict}$ being dependent variable. In case of SMEs the survival probability of big investors has a natural declining tendency, similar before and after the investment spike. On the contrary, the survival probability of smaller firms, which did not decide to invest declines substantially in that moment and one year after and then survival probability goes back to its slightly declining tendency. It follows, that investment spikes in smaller enterprises result not only in greater market share and employment, but also affects positively (and significantly) the survival probability, as much more non-investing firms drops out of sample during that time. The cost of that expansion is depressed productivity.

The story is relatively similar for larger companies, but in that case the survival probability of big investors remains approximately constant close to the investment spike and declines only 3 years after the event. On the contrary, survival probability in the control group drops substantially one year after the event and then level off. Given the previous results on drop of employment, sales and productivity after investment spike, it looks like a decision to invest in larger firms is a way to avoid future bankruptcy. And it looks like it works only for about 2 years, as then the survival probability declines again, possibly due to unsatisfactory effects of big investment. Our results may be driven by agency problems and diffusion of responsibility, usually more pronounced in larger firms (for the discussion on firm size and different forces at work see e.g. (Ziv, 1993)). The results of (Bromiley, 1991) and (Yung and Chen, 2017) are only examples of research indicating that managerial ability, risk taking and firm performance are closely related. Unfortunately, our data preclude as from testing this hypothesis.

Conclusions

The 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 also 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 that time. 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, TFP and survival probability within the observation window of 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 post spike event are significant.
We showed that the results are strikingly different for SMEs and larger companies. Investment spikes in smaller firms result in an increase of sales and employment. Moreover, big investments of smaller firms affect positively (and significantly) their survival probability compared to non-investing firms, as much more firms from the latter group drops out of sample during that time. The only cost of such an expansion of smaller firms seems to be depressed productivity, consistently with learning models of e.g. (Jovanovic and Nyarko, 1996).

The results are completely different for larger companies, for which a drop of employment, sales and productivity was observed after an investment spike. Moreover, the survival profanity of big investors remains unchanged for 2 years after the spike, whereas in case of non-investing larger firms, it drops substantially. These results suggest a decision to invest in larger firms is a way to avoid possible bankruptcy, working only for 2 years, possibly due to unsatisfactory effects of big investment. The results for larger companies may 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. There are also many forces at play. If the investment surge is mainly driven by smaller firms, the increase of productivity on aggregate level is not due to the productivity increase within investing firms. It seems rather be due to increase of allocation efficiency, as those firms are on average more productive, with higher survival probability, and they are engaging resources. On the contrary, if larger firms are driving investment surge, there is much less space for subsequent productivity increase (and productivity may even decrease). Although big investor among larger companies are more productive than other firms, their productivity declines after investment spike and their employment falls. The only positive effect for aggregate productivity seems to come from relatively higher survival probability.

Bibliography


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

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

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:

$$\frac{I_{it}}{K_{it}} > \alpha \times \text{median}_t \left( \frac{I_{it}}{K_{it}} \right),$$
calculated for each firm. \( \alpha \) 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 12). 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. By definition, the share of big investors in the population is then 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.

- 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.

### Table 4 Robustness analysis - TFP in Non-SMEs

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

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

<table>
<thead>
<tr>
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<th>baseline</th>
<th>definition</th>
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<th>no productivity</th>
</tr>
</thead>
<tbody>
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<td>-0.018*** (0.006)</td>
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</tr>
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<td>+1</td>
<td>0.008 (0.005)</td>
<td>-0.017*** (0.006)</td>
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<td>0.000 (0.006)</td>
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<td>0.008 (0.006)</td>
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<td>0.021*** (0.007)</td>
<td>-0.020** (0.010)</td>
<td>0.014** (0.006)</td>
<td>0.021*** (0.006)</td>
</tr>
<tr>
<td>+4</td>
<td>0.025*** (0.006)</td>
<td>-0.031** (0.013)</td>
<td>0.023*** (0.007)</td>
<td>0.019*** (0.007)</td>
</tr>
</tbody>
</table>

| Observations | 356,659 | 418,440 | 356,945 | 355,960 |
| R²           | 0.856   | 0.849   | 0.854   | 0.858   |
| Adjusted R² | 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

<table>
<thead>
<tr>
<th></th>
<th>baseline</th>
<th>definition</th>
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<th>no productivity</th>
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<tr>
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<td>-0.029*** (0.007)</td>
<td>-0.021** (0.009)</td>
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<tr>
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<td>0.002 (0.006)</td>
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</tr>
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<td>+1</td>
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<td>-0.033*** (0.007)</td>
<td>-0.015*** (0.005)</td>
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<td>+2</td>
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<td>-0.074*** (0.016)</td>
<td>-0.015* (0.009)</td>
<td>-0.016* (0.010)</td>
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</table>

<p>| Observations | 304,126 | 366,103 | 305,138 | 303,342 |
| R²           | 0.856   | 0.848   | 0.855   | 0.857   |</p>
<table>
<thead>
<tr>
<th>Adjusted $R^2$</th>
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<th>0.801</th>
<th>0.807</th>
<th>0.809</th>
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<tr>
<td>Residual Std. Error</td>
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<td>0.305 (df = 279027)</td>
<td>0.308 (df = 229745)</td>
<td>0.307 (df = 227761)</td>
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</table>

**Figure 12** 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