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Analyzing the impact of investment spikes on dynamic productivity growth ☆

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ABSTRACT

Firm-level data usually show that a large portion of firm-level investment takes place in a few investment episodes. This paper assesses productivity growth and its components in production framework that accounts for the dynamics of capital adjustment and relates this to investment spikes using firm-level data of the Spanish meat processing industry over the period 2000–2010. Using the method of impulse responses by local projections, it is shown that investment spikes produce a significant productivity change loss of 0.7% in the first year after the spike. The worsening of technology is the main cause of the reduction of productivity growth in the first year. Technology then improves in the fifth year as a result of investment spike, resulting in the U-shape pattern of relationship. Scale inefficiency significantly improves by 0.4% and 0.5% in the first and second year after the spike has occurred, respectively. All these effects, however, largely depend on the firms' size. In particular, it is shown that the loss of technology in the first year mainly pertains to smallest firms, while larger firms experience a negative impact on the contribution of technical inefficiency change to productivity growth.

1. Introduction

Firms invest to address their productive capabilities by increasing their stock of capital, replacing existing capital or implementing technological innovations. These different types of investments are referred to as expansionary, replacement and retooling investments, respectively. Firm level data show that these investments can often take place in a few large, discrete investment episodes, referred to as spikes [11,9,36,18].

The impact of investment spikes on the firm's productivity growth remains an open question. Investment spikes that are expansionary or replacement investments are not expected to impact productivity in the long run. While retooling investments are expected to improve productivity ultimately. Also, the short-term impacts of investment spikes are expected to differ from their long-term impacts. Models on the adoption of innovations hypothesize that a period of adjustment exists after a new technology is adopted, where production units engage in technology-specific learning [40,28,53]. Jovanovic and Nyarko [23]'s learning-by-doing model hypothesizes that productivity under the new technology can be lower than under the old technology immediately after the technology implementation, but then increases as the firm learns how to use the new technology.

The existing empirical literature is inconclusive about the impact of investment spikes on productivity. Power [41] investigates the link between investment and productivity empirically at the plant level in the U.S. manufacturing industries and finds that the timing of investment spikes is not linked to improved labor productivity. The findings of Letterie et al. [31] for German firms indicate that most investment spikes reflect an expansionary type of investment that have no direct relationship with improved productivity, while episodes of large investments in new technology that enhance productivity are very rare. Nilsen et al. [37] find only very small changes in labor productivity associated with investment spikes, suggesting that productivity improvements are not related to technological change through investment spikes. Sakellaris [43] and Huggett and Ospina [20] find that investment spike episodes lead to productivity falling after the investment spike, which starts to recover slowly in the US and Columbian manufacturing plants, respectively. Licandro et al. [32] for Spanish manufacturing firms find that expansionary and innovative type of investment spike increase the firms' productivity after the spike, however long learning curves are associated with innovative investment. Bessen [4] also reports the new plant productivity improvement as a result of learning-by-doing, indicating also that

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new plant adjustment is different than mature plant adjustment after an investment spike; in particular, the large new plant lowers its workforce as it grows older. Geylani and Stefanou [17] investigate the relationship between productivity growth and investment spikes using plant-level data of U.S. food manufacturing firms finding empirical support for the learning-by-doing hypothesis and shows that the most pronounced impact of investment age on productivity growth occurs during the fifth year post-investment spike. This implies that productivity gains tend to be fully realized in the U.S. food manufacturing industry after a 5-year technology learning period.

Previous research into the link between investment spikes and productivity growth has a number of limitations which motivate the present investigation. First, previous studies relating productivity growth with investment spikes measure the time since the firms' most recent investment spike and its impact on productivity growth in a single OLS regression model. This study is the first to use impulse response functions (IRF) to identify the impact of investment spikes on productivity growth in the post-investment spike period by calculating multi-step predictions using a series of OLS regressions. Second, few studies address the capital adjustment dynamics' impact on the relationship between investment spikes and productivity. Cooper and Haltiwanger [10] allow for productivity shocks in addressing capital adjustment in the presence of investment spikes. However, previous studies analyze static productivity measures which do not account for the full presence of the costs of adjustment in the year of the investment. Hence, the analyses of static productivity measures (e.g. [17]) confound adjustment costs in the year of investment with learning by doing in the period post-investment spike. This study analyzes the impact of investment spikes on a dynamic productivity growth measure, thereby controlling for adjustment costs in the year of investment. Thirdly, the literature linking investment spikes and productivity growth has not addressed fully the separate contributions of productivity growth components such as technical inefficiency change, technical change and scale inefficiency change in the post-investment spike period. With our study, we identify more clearly the sources of productivity changes that are associated with investment spikes.

Modeling performance under a structure that leads to dynamic decision processes using nonparametric frameworks can take several forms. In the adjustment-cost perspective, Silva and Stefanou [46] use a nonparametric dynamic Data Envelopment Analysis (DEA) to describe the input requirement set in the context of dynamic cost minimization to measure efficiency hyperbolically for Pennsylvanian farms over a six year period, while Kapelko et al. [25] measure dynamic efficiency for the Spanish construction industry in the directional distance function context. The adjustment cost perspective is also assumed in the study of Fallah-Fini et al. [14] who model intertemporal dependencies between consumption of inputs and realization of outputs in highway maintenance operations. Epure et al. [12] model efficiency and dynamic productivity growth using a radial input distance function which can be used for benchmarking a firm's performance against local competitors. Their investigation of Spanish banks finds that the evolution of productivity is influenced by banking deregulation and technical change. Tone and Tsutsui [50] present a non-radial distance function to address long-term performance within a dynamic DEA framework accounting for slacks and find considerable gains in overall efficiency ranking over the non-dynamic case, while Tone and Tsutsui [51] extend a dynamic DEA slacks-based framework to the network setting. Kao [24] further extends Tone and Tsutsui [50,51] models by proposing a general slacks-based model for network systems and decomposing the system efficiency into a weighted average of the process efficiencies. More applications of dynamic network DEA are found in Avkiran [1] and Hung et al. [21].

This study takes on a dynamic adjustment perspective and facilitates a more complete decomposition of the sources of productivity changes that are associated with investment spikes with the dynamic Luenberger productivity growth indicator being used to control for adjustment costs in the year of investment [38,26]. The Luenberger indicator and its components are computed using DEA. The impact of investment spikes in the post-investment spike period is addressed by specifying an impulse response function (IRF) estimated by the local projections method [22,49].

The empirical application focuses on panel data of Spanish meat processing firms over the period 2000–2010. The meat processing industry is a significant sector within Spanish food manufacturing accounting for approximately 20% of total sales and employment within the food industry and 2% of Spanish GDP in 2009 [35]. During the period analyzed, the Spanish meat processing industry was facing increasing production costs associated with the implementation of European Union (EU) regulations regarding food safety, consumer information and the mandatory adoption of environmentally-sustainable practices which can reduce the productivity of the food industry. Coping with this more stringent regulatory climate, European firms had to undertake additional investments [13,52]. From 2008 onwards, the Spanish meat processing industry is also affected by the economic crisis as reflected by the decrease in meat processing firm turnover. Hence, the Spanish meat processing industry is operating in a rapidly changing environment, requiring investments in new technology, which makes it an interesting case for the analysis of dynamic productivity growth and its relation with investment spikes.

The remainder of this paper is organized as follows. Section 2 discusses the methods for computing the dynamic Luenberger productivity growth indicator and the impulse responses. This is followed by a presentation of the data in Section 3 and the results in Section 4. The last section offers concluding comments.

2. Methods

2.1. Dynamic Luenberger indicator of productivity growth

The Luenberger indicator of dynamic productivity growth is defined by a dynamic directional distance function. The input requirement set using the vectors of variable inputs $(\mathbf{x}_t)$ and quasi-fixed inputs $(\mathbf{k}_t)$ to produce the vector of outputs $(\mathbf{y}_t)$ can be represented as $V_t(\mathbf{y}_t : \mathbf{k}_t) = \{(\mathbf{x}_t, \mathbf{I}_t)$ can produce $\mathbf{y}_t$, given $\mathbf{k}_t\}$, where $\mathbf{I}_t$ is the vector of gross investments in quasi-fixed inputs. The input requirement set is defined by Silva and Stefanou [45] and assumed to have the following properties: $V_t(\mathbf{y}_t : \mathbf{k}_t)$is a closed and nonempty set, has a lower bound, is positive monotonic in variable inputs $\mathbf{x}_t$, negative monotonic in gross investments $\mathbf{I}_t$[1], is a strictly convex set, output levels increase with the stock of capital and quasi-fixed inputs and are freely disposable.

The input-oriented dynamic directional distance function measuring dynamic technical inefficiency with directional vectors for inputs $(\mathbf{g}_x)$ and investments $(\mathbf{g}_I)$, $\overrightarrow{D}^i_t(\mathbf{y}_t, \mathbf{k}_t, \mathbf{x}_t, \mathbf{I}_t; \mathbf{g}_x, \mathbf{g}_I)$ is defined as follows:

$$\overrightarrow{D}^i_t(\mathbf{y}_t, \mathbf{k}_t, \mathbf{x}_t, \mathbf{I}_t; \mathbf{g}_x, \mathbf{g}_I) = \max\{\beta \in \Re : (\mathbf{x}_t - \beta \mathbf{g}_x, \mathbf{I}_t + \beta \mathbf{g}_I) \in V_t(\mathbf{y}_t : \mathbf{k}_t)\},$$

$$\mathbf{g}_x \in \Re^N_{++}, \quad \mathbf{g}_I \in \Re^F_{++}, (\mathbf{g}_x, \mathbf{g}_I) \neq (\mathbf{0}^N, \mathbf{0}^F) \qquad (1)$$

if $(\mathbf{x}_t - \beta \mathbf{g}_x, \mathbf{I} + \beta \mathbf{g}_I) \in V_t(\mathbf{y}_t : \mathbf{k}_t)$ for some β, $\overrightarrow{D}^i_t(\mathbf{y}_t, \mathbf{k}_t, \mathbf{x}_t, \mathbf{I}_t; \mathbf{g}_x, \mathbf{g}_I) = -\infty$, otherwise. This distance function is a measure of the maximal translation of $(\mathbf{x}_t, \mathbf{I}_t)$ in the direction defined by the vector $(\mathbf{g}_x, \mathbf{g}_I)$,

[1] The assumption of negative monotonicity of the dynamic directional distance function in gross investments implies that the producer cannot overinvest to such an extent that it decreases output.