Innovation and the growth of service companies

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Innovation and the growth of service companies:

The variety of firm activities and industry effects

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Abstract

This paper examines the relationship between innovation performance and employment growth in firms by taking a closer look at specific innovation activities and industry effects in the context of the services sector. Firm-level CIS data on Polish services firms in 2004-2009 are analyzed using robust M-estimation. The results indicate that the effects of product, process and organizational innovations depend strongly on the level of technological opportunities in the industry in question. Given the widely acknowledged role of marketing innovations in services, possible synergies between innovations in the form of new products and new marketing techniques are also analyzed. We demonstrate that marketing innovations are conducive to firm growth if they complement product innovations, but they are less likely to foster growth when applied in isolation.

Keywords: innovation, firm growth, services, innovation complementarities, services taxonomy

JEL codes: O31, O32, O33, J23, C81

1 Introduction

The relationship between the innovation performance and growth of firms shows empirical regularities that need to be qualified by a number of factors, such as the kind of innovation activities (i.e., whether they are product, process or organizational innovation; see, e.g., Dachs and Peters, 2014), the characteristics of the innovator (i.e., whether it is a small or big firm, or a persistent or occasional patentee; see Demirel and Mazzucato, 2012), and the level of analysis (i.e., firm or industry level; see Bogliacino and Pianta, 2010). This paper addresses the problem of firm growth in terms of employment, following, for example, the work of Evangelista and Vezzani (2012) and Harrison *et al.* (2008).

In this paper we analyze Community Innovation Survey (CIS) data for Poland to assess the employment effects of innovation in services firms in 2004-2009.[1] We have chosen to focus on the service sector because it is by far the largest sector in today's advanced economies but has traditionally been under-researched, in comparison to manufacturing, in the literature on innovation, and innovation in the sector is relatively poorly understood (Tether, 2005; Miles, 2007; Leiponen, 2012). This applies also to the studies of the link between innovation and firm growth, even if some of the recent contributions have started to change this trend (cf. Evangelista and Vezzani, 2012; García-Manjón

[1] Firm-level data from the Polish CIS are rarely made available to researchers, resulting in Poland being absent in most cross-country comparisons (e.g., OECD, 2009).

and Romero-Merino 2012; Dachs and Peters 2014). Thus, while our primary concern is with the relationship between innovation and firm growth, we also hope to make a contribution to the literature on innovation in the service sector.

We offer a rigorous analysis of innovation activities in service firms and related growth effects. Our contribution consists not only in extending the research on the innovation-firm growth link in the services sector of a catching-up country, but most of all in addressing new aspects of the problem, such as the sector-specific character of employment outcomes and the synergies between the varieties of innovation.

The rest of the paper is structured as follows. In section 2 we review theoretical approaches to the link between innovation and firm growth, as well as some previous empirical studies, and we specify our research questions. Section 3 includes the presentations of our dataset and of the methodology adopted, while the empirical results are discussed in section 4. In Section 5 we offer conclusions.

2 Innovation and firms' employment growth: Theory and empirical evidence

Historically, before the link between innovation and firm growth was investigated, the study of the relationship between technological innovation and firm *size* was already advanced. Schumpeter (1934, 1942) argued that either growth of the firm results from its successful technological innovations, which allow it to acquire market share (i.e., innovation causes firms to become large), or innovation is a very costly and capital-intensive process that only larger firms are able to afford (i.e., high innovativeness or R&D intensity is only possible for large firms). In either case, there should be a positive relationship between size and (successful) technological innovation. However, the empirical evidence for such a relationship between size and innovativeness or R&D intensity is far from clear (see the review of the relevant literature in Subodh, 2002). Another question is how firm size affects the relationship between its innovativeness and growth. This is one of the problems we will investigate in this paper.

Two of the earliest empirical pieces on the link between innovation and firm growth (using employment growth as their growth measure) are Brouwer *et al.* (1993) and Audretsch (1995). The former study found a generally insignificant effect of innovation-related variables on employment growth in Dutch manufacturing during the 1980s; the only significant effect was that of the growth in R&D intensity, and this effect was negative. Audretsch (who was more interested in firm survival than firm growth, though his study deals with both) found growth and innovation to be positively related, with growth rates differing across industries and tending to be higher in more innovative industries.

Later studies have contributed more theoretical understanding to the issue. In a review of the literature on innovation and employment, Pianta (2005) contrasts the theoretical approaches of neoclassical economists, who regard innovation as opening up investment opportunities and therefore leading to employment expansion, with those of (neo-)Schumpeterians, who see it as leading to the more complex process of creative destruction. A more detailed exploration of these conflicting tendencies began with the literature on the distinction between product and process innovation. With regard to product innovation, Utterback and Abernathy (1975) argued in their now classic article that a high rate of product innovation would tend to be found in young firms, which are in their rapid growth phase. For Harrison et al. (2008), the employment growth or decline resulting from both product and process innovations depends on the combination of two factors, the displacement effect (in which labor is displaced by increasing productivity – the destructive element of creative destruction), and the compensation effect (in which cost reductions result in price reductions, which stimulate demand, leading to increased employment – the creative element).

In addition to this theoretical ambiguity in the relationship between innovation and the growth of firms, some empirical studies also suggest ambiguity in the direction of causality. Like us, Cainelli *et al.* (2006) looked at CIS data (from Italy), analyzing sales growth rather than employment growth, and found that sales growth in the past leads to greater innovation in the present (although this applies to process innovation, and not product innovations). Innovation positively affects productivity, but there is no effect on sales growth. Similarly, Coad and Rao (2010) find a positive but weak effect of R&D

spending on the subsequent growth of sales and employment but a strong positive effect of sales and employment growth on R&D spending. One possible reason is that if firms are credit-constrained then their sales must grow in order to finance their R&D expenditure.[2]

Examining empirical evidence, Harrison et al (2008) find that employment is positively affected by innovation, particularly product innovation, with compensation effects being quite significant (they characterize the employment effects of process innovations as negligible). They also find that these effects are weaker in the service sector (employment growth is stronger in services than in manufacturing, but the proportion of it resulting from product – or rather service – innovation is lower), but there is no evidence for displacement effects resulting from process innovation. The empirical studies of firm-level panel data reviewed by Pianta (2005) have varying results, although there is a tendency for product innovation to be associated with better employment results than process innovation (see also the industry-level study by Bogliacino and Pianta, 2010). Recent firm-level studies covering the services sector confirm the positive relationship between product innovations and employment growth (Dachs and Peters, 2014; Falk, 2014). Again, the impact of process innovations is less straightforward: while Falk found it insignificant for the employment dynamics of Austrian firms, Dachs and Peters identified a negative effect for manufacturing in 16 European countries but no significant effect for services, in

[2] The authors are grateful to Michal Brzozowski for this observation.

line with the results of Harrison *et al.* (2008).[3] Given these results we would thus expect the relationship between product innovation and firm growth to be positive, while the effect of process innovations might be ambiguous: this is one of the questions to be examined in this paper.

We will also seek to contribute to the research on the link between process innovations and employment growth by exploring the under-investigated industry specific effects. To this end we will apply Castellacci's (2008) extension of the classic Pavitt (1984) taxonomy, which divides the service industries in four groups. The first is composed of physical infrastructure services (PhIS) industries, such as wholesale trade, transportation and storage. These industries provide supporting infrastructure services for other sectors, and are characterized by a low level of technological opportunity. Firms in the second group, network infrastructure services (NIS), also offer supporting infrastructure, but they rely on physical and business networks and make an extensive use of ICT; examples include telecommunications or finances. These industries are characterized by a medium level of technological opportunity. The third industry group is composed of knowledge-intensive business service (KIBS) firms, operating in industries such as R&D, engineering, design, consulting, or software development. This group includes the most knowledge-intensive services sectors. Finally, Castellacci defined a supplier-dominated

[3] Evangelista and Vezzani (2010) report positive relationships between sales growth and product, process, and organizational innovations, but their methodology essentially consists in comparing firms undertaking these activities with non-innovators.

services (SDS) group, analogous to Pavitt's supplier-dominated goods producers. The SDS group includes mainly personal services, hotels and restaurants; these industries show a low level of technological opportunity.

According to Castellacci different types of innovation activities carry different weights in the four groups (cf. Table 1). We will examine whether the postulated pattern is confirmed in our data; i.e., whether, for a given taxonomy group, firms that innovate in the way suggested by Table 1 grow faster than firms that do not. To the extent that firm growth is an indicator of firm performance, this can be regarded as a verification of the taxonomy. This does not necessarily apply to process innovations, which, as argued above, might have an ambiguous effect on employment. However, it is also possible that this relationship is actually moderated by the level of technological opportunity; it might be the case that in less knowledge-intensive service sectors process innovations lead to displacement, while in more knowledge-intensive industries they can actually promote employment growth. On the other hand – given that in low-tech industries process innovation in the form of new equipment and machinery is the principal kind of innovation – the reverse might also be the case: less knowledge-intensive services firms are more likely to grow as a result of the introduction of process innovation than more knowledge-intensive service businesses. These are the possibilities we will seek to explore.

INSERT TABLE 1 HERE

On a different note, it is worth remembering that notions such as product and process innovations have a specific meaning in the context of service industries. Services are usually intangible and often produced in an interaction with the client. Consequently, marketing innovations – which can be regarded as innovations in the relationship between the firm and its clients – might be particularly important in service firms. Indeed, some authors argue that changes in the ‘client interface’ (the way the consumer participates in service design, production and consumption) *are* a service innovation (den Hertog, 2000). Empirical evidence confirms that marketing and organizational innovations are a strong focus of service firms (see, e.g., the review by Kanerva *et al.*, 2006). We would like to learn more about the role of marketing innovations in services firms, in particular whether they complement product innovations or can they actually replace them?

Before examining the relationship between innovation and firm growth we take account of one empirical regularity: in most empirical studies smaller firms grow faster than larger ones (e.g. Lotti *et al.*, 2009). This is especially the case if firms’ exits are not observed and controlled for. Smaller firms are, ceteris paribus, more likely to disappear from the market than bigger ones, so those small firms that survive exhibit above-average growth rates. By implication, if one only observes the same cohort of firms over years, then the small ones are likely to excel in growth. As explained in the next section, since we do not control for firms' exits we expect this regularity to be confirmed in our case too.[4]

3 *Data, methodology, and variables*

3.1 Dataset and variables

We use the data on service firms from the 2006, 2008 and 2009 runs of the Community Innovation Survey. In the part of the Polish CIS dedicated to the services sector the coverage is approximately 25% of the population. There are 3879 observations for CIS 2006, 4256 for CIS 2008 and 4262 for CIS 2009. For the reasons specified in the next section, we compare the innovation performance in the period *preceding* the dates between which the change in employment is observed. As a result we are particularly interested in the intersection of the datasets: CIS 2006 and 2008 (1683 observations) and 2008 and 2009 (1662 observations). The scope of CIS implies that 40 NACE-Rev-2 service industries are represented (out of 103 3-digit industries in the NACE classification) representing the following broad sectors: wholesale trade, transport and warehousing, ICT, financial and insurance services, and some

[4] Note that as long as one cannot observe firms' exits this stylized fact does not contradict Gibrat's Law, which states that the firm's rate of growth is independent of its initial size; see the review by Sutton, 1997, as well as Lotti et al., 2009. On the other hand, empirical evidence on Gibrat's law is quite mixed; in addition to the aforementioned literature reivews, see recent studies by Bentzen, Madsen & Smith, 2012, and Daunfeldt & Elert, 2013.

other industries (incl. consulting). Applying Castellacci's taxonomy we divide the industries in the following three groups:

PhIS Physical infrastructure services (NACE Rev 2 codes: 46, 49, 50, 51, 53),

NIS Network infrastructure services (NACE Rev 2 codes: 61, 63, 64, 65, 66), and

KIBS Knowledge-intensive business services (62, 71, 581).

We note that supplier-dominated services (SDS) are absent from our database.

A well-known characteristic of the Community Innovation Survey is that the bulk of the questionnaire is answered only by firms that introduced product- or process innovation, while the general part of the questionnaire, answered by all the firms, is rather short. Consequently, we will use the following variables for which we have data for all the companies. All of them are dummy variables.

NEWPRODUCT – equals 1 for service firms that introduced new products in the form of new goods or services during the period in question. [5]

NEWPROCESS – equals 1 if the firm introduced process innovations.

NEWORG0406 – equals 1 if the firm introduced organizational innovations between 2004 and 2006. The definition of 'organizational innovation' is different in CIS-2006 and CIS-2008 (more restrictive in the latter period). This

[5] We do not consider new services and new goods separately. Unlike manufacturing firms, which routinely offer e.g. after-sales services, in the case of services industries it is hard to determine what the goods offered by such firms could be (in fact, the difference might be blurred, as in the case of software development). Therefore we decided to stick to a more general category of product innovations.

change forces us to create two different variables for organization innovation in both subperiods.

NEWORG0608 – equals 1 if the firm introduced organizational innovations between 2006 and 08

NEWMARKT0406 – equals 1 if the firm introduced innovations in marketing between 2004 and 2006. Again, the definition of marketing innovation changed from CIS-2006 to CIS-2008, rendering it necessary to construct two separate variables.

NEWMARKT0608 – equals 1 if the firm introduced innovations in marketing between 2006 and 2008.

SMALL – equals 1 for firms with less than 50 employees.

GROUP – equals 1 if the firm is a member of group of enterprises (where group is a set of firms owned by the same entity or person).

Note that the limited information on firm size (the *SMALL* variable) is caused by the confidentiality policy of the Polish Central Statistical Office, which would not disclose the data on the exact number of employees. The distributions of the dummies listed above are presented in Table 2. The percentage of firms that introduced product innovations (22.6-26.9%, depending on the period) was slightly smaller than those implementing process innovations (27-33%). The percentage of firms declaring marketing and/or organizational innovation dropped significantly, but this was probably due to the introduction of more restrictive definitions in CIS-2008. As for the firms' characteristics, group members constitute about one-quarter of the sample and small firms about 25-30%, depending on the period.

INSERT TABLE 2 HERE

The distribution of firms by industry groups in 2006 and 2009 is presented in Table 2. Physical infrastructure services (PhIS) are the biggest group, with more than 50% belonging to this group in both periods. Network infrastructure services (NIS) come second and knowledge-intensive business services (KIBS) third in both datasets, but there is a considerable difference between 2006 and 2009. While in the former period both industry groups have similar shares, in the latter period the KIBS share shrank to a mere 8.47%, which is probably a result of the sampling technique employed by the Polish Central Statistical Office.

INSERT TABLE 3 HERE

Finally, we will be observing the growth of firms in three subperiods 2004-2006, 2006-2008, and 2008-2009.[6] To ensure the comparability of estimated parameters in both subperiods, we square the latter rate of growth and treat it as an approximate rate of growth in 2008-2010. Key statistics of employment dynamics are presented in Table 4. Note that means and standard deviations are not particularly interesting in this context, because of the quite extreme upper

[6] Audretsch (1995) studies employment growth, utilizing the percentage growth rate (not annualized) in various periods (of 2, 4, 6, 8, and 10 years in duration). Harrison *et al.* (2008) look at the rate of employment growth over a 3-year period. Brouwer *et al.* (1993) look at the annualized rate of employment growth over a 5-year period.

outliers. More insight can be obtained from the measures of position. Apparently, while the distribution of growth indicators in 2004-2006 and 2006-2008 seems to a large extent similar (at least for firms between zero and the 75 percentile), a decline in employment dynamics can be observed between 2008 and 2010. We keep the outliers in the datasets, because they will not affect our empirical techniques (see below).

INSERT TABLE 4 HERE

3.2 Methodology

In the baseline version of our analysis we estimate parameters of the following model:

$$\begin{aligned} GR_{it} &= \alpha_0 + \alpha_1 U2008\_2010_t + \alpha_2 GR_{it-1} + \alpha_3 NEWPRODUCT_{it-1} \\ &+ \alpha_4 NEWPROCESS_{it-1} + \alpha_5 NEWORG0406_{it-1} + \alpha_6 NEWORG0608_{it-1} \\ &+ \alpha_7 NEWMARKT0406_{it-1} + \alpha_8 NEWMARKT0608_{it-1} + \alpha_9 SMALL_{it-1} \\ &+ \alpha_{10} GROUP_{it-1} + \alpha_{11} NIS_{it-1} + \alpha_{12} KIBS_{it-1} + \varepsilon_{it}, \end{aligned} \tag{1}$$

where i indexes firms and $t-1$ refers to one of the two subperiods: 2004-2006, 2006-2008. Consequently t refers to the subperiods 2006-2008 and 2008-2010 (the growth rate for the latter is derived from 2009-2010).

GR is the difference of logs of the employment levels between the ends of the respective subperiods. Although we do not have the exact levels of employment, we have the ratios for the subperiods; GR variable is the log of a given ratio. Since we consider logarithms, squaring the 2009-2010 growth rates is equivalent to doubling the dependent variable in (1) and has no effect on the statistical significance of the estimated parameters. We use the variable $U2008\_2010_{t}$ to identify the period effect. The remaining variables are described in the previous section. Note the particular character of the variables describing innovations in firm organization and marketing: for instance, $NEWORG0608_{it-1}$ is automatically zero whenever $t-1$ is the first subperiod (2004-2006).

Our reference group is PhIS – physical infrastructure services. Note that we test the relationship between the growth in the given period and the innovation performance in the period *before*, so as to allow for the measures taken by the companies to take effect. By doing so, we also avoid a possible endogeneity problem.

Like Coad and Rao (2008), we control for the employment growth in the previous period. Moreover, given that most of our research questions refer to relationships in individual sectors, equation (1) is also estimated for the subsets of our data defined by the industry groups PhIS, NIS and KIBS (while excluding industry dummies). Finally, in addition to the full-sample estimation, equation (1) is estimated separately for small firms and for medium and large ones, to investigate how the relationship between a firm’s innovation performance and its growth is moderated by its size.

When we estimate the parameters of the dynamic model, we have the problem of the endogeneity of the lagged dependent variable for the second subperiod (parameters of the model with this variable treated as the dependent one are estimated for the first subperiod). In other words, in equation (1), GR_{it-1} is correlated with the error term. Moreover, the number of periods is extremely small, and we have an unbalanced panel, making the application of dynamic panel techniques (see Arellano and Bond, 1991, and Baltagi, 2008) problematic. Therefore, after estimation of parameters for the first subperiod, we calculate theoretical values of the growth variable; that is, we estimate the parameters of model (1) using cross-sectional data for two subperiods, 2004-2006 and 2006-2008. The theoretical values GR_{it-1} for subperiod 2006-2008 calculated in this manner are then substituted for the empirical ones in the matrix of observations of explanatory variables when we estimate the parameters of the entire panel. This is a standard approach, used, for example, in estimation with 2SLS (see Greene, 2003). Since for some firms the variable *GR* takes on non-typical values, and we expect the problem of outliers in our regression, we apply robust regression methods instead of OLS (see, e.g., Verardi and Croux, 2009; Rousseeuw and Leroy, 2003).

We estimate the parameters of model (1) using the MM-estimator (one of a wider class of M-estimators), proposed by Yohai (1987). In a regression model, the presence of outliers can significantly distort the classical OLS estimator, and lead to unreliable results. To solve this problem, a number of robust-to-outliers methods are available. One such method is quantile regression, frequently applied in firm growth studies (e.g., Falk, 2014). An example is Edgeworth's (1887) median regression estimator, which is a special case of the quantile regression estimator. However, this estimator has an efficiency of 64% at a normal error distribution (see Huber, 1981), and though it protects against vertical outliers and makes it possible to describe the relationship between explanatory variables and the dependent variable at different points in the conditional distribution of the dependent variable, it does not protect against bad leverage points (a more detailed discussion of different types of outliers can be found in Verardi and Croux, 2009). By contrast the MM-estimator can reach a considerably higher efficiency (see below), while being robust to bad leverage points and eliminating the problem of outliers, and for this reason the method is suggested by Verardi and Croux (2009). Moreover, had we applied quantile regression, the nature of our dataset would have made it necessary to estimate the relationship between the innovation performance and firm growth in two subperiods separately, which, given our focus on sectoral effects, would have made the presentation of our results considerably less transparent.[7]

Our estimation procedure consists of two steps. In the first step the robust S-estimator of the standard deviation of the error term is calculated, based on the formula:

[7] Nevertheless, we did try quantile regressions as well. The results (available upon request), were qualitatively similar to those presented in this paper; however, there are no evident patterns across quantile groups. Statistically significant effects were more likely to be observed in 2006-2008 than in 2008-2010, possibly because of the economic slowdown in the latter period.

$$\frac{1}{N_1 + N_2} \sum_{t=1}^{2} \sum_{i=1}^{N_t} \rho \left\{ \frac{(GR_{it} - \mathbf{x}_t \boldsymbol{\alpha})}{\hat{\sigma}^S} \right\} = b \,, \tag{2}$$

where $b = E\{\rho(Z)\}$ with $Z \sim N(0,1)$, $\mathbf{x}_t$ consists of all explanatory variables and $\rho(u)$ is the Tukey biweight function defined as:

$$\rho(u) = \begin{cases} 1 - \left\{ 1 - \left(\dfrac{u}{k} \right)^2 \right\}^3 & if \quad |u| \le k, \\ 1 & if \quad |u| > k. \end{cases} \tag{3}$$

Parameter k reflects the trade-off between efficiency and robustness. After calculating $\hat{\sigma}^S$, in the second step, the MM-estimator of parameters is obtained:

$$\hat{\boldsymbol{\alpha}}^{MM} = \arg\min_{\boldsymbol{\alpha}} \sum_{t=1}^{2} \sum_{i=1}^{N_t} \rho \left\{ \frac{(GR_{it} - \mathbf{X}\boldsymbol{\alpha})}{\hat{\sigma}^S} \right\}. \tag{4}$$

In our calculations, we set constant k to 1.547 for the S-estimator and to 4.685 for the second-step MM-estimator which guarantees a 95% efficiency of the final estimator (see Verardi and Croux, 2009, p. 443).

As explained in section 2, we would like to investigate the complementarities between product and marketing innovations, which seem particularly interesting in the context of service industries.[8] To that end we define the following interaction variables:

[8] More generally, the literature suggests that the effect of the introduction of a particular type of innovation in isolation may differ from the effect that it has when introduced jointly with another type (see, for example, Damanpour, Walker and Avellaneda, 2009, and Leiponen and Helfat, 2010).

$PRODMARKT_{0406}01, PRODMARKT_{0406}10, PRODMARKT_{0406}11,$
$PRODMARKT_{0608}01, PRODMARKT_{0608}10, PRODMARKT_{0608}11.$ For instance, $PRODMARKT_{0608}10$ is a dummy variable equal to 1 whenever the firm introduced product innovation in 2006-2008 but did not introduce marketing innovations in the same period. We estimate another version of equation (1), namely

$$\begin{aligned} GR_{it} &= \beta_0 + \beta_1 U2008\_2010_t + \beta_2 GR_{it-1} + \beta_3 PRODMARKT_{0406}\,01_{it-1} \\ &+ \beta_4 PRODMARKT_{0406}\,10_{it-1} + \beta_5 PRODMARKT_{0406}\,11_{it-1} + \beta_6 PRODMARKT_{0608}\,01_{it-1} \\ &+ \beta_7 PRODMARKT_{0608}\,10_{it-1} + \beta_8 PPRODMARKT_{0608}\,11_{it-1} + \beta_9 NEWPROCESS_{it-1} \\ &+ \beta_{10} NEWORG0406_{it-1} + \beta_{11} NEWORG0608_{it-1} + \beta_{12} SMALL_{it-1} \\ &+ \beta_{13} GROUP_{it-1} + \beta_{14} NIS_{it-1} + \beta_{15} KIBS_{it-1} + \varepsilon_{it}. \end{aligned} \tag{5}$$

Equation (5), like equation (1), is estimated for the full sample as well as for the industry groups PhIS, NIS and KIBS. We use the same constant *k* as for the basic model.

4 Results

The results of our estimations are presented in Tables 5 and 6. The first observation one can make when analyzing the results is that the relationship between the innovation performance of firms and their growth is strongly sector-specific. Indeed, the aggregate-level results are quite weak, while each of the sector-level regressions tells a different story.

INSERT TABLE 5 HERE

In the KIBS and NIS industries, firms that implemented product innovation tended to grow faster; this is true for both our specifications (Tables 5 and 6) and consistent with Castellacci's (2008) characterization of this taxonomy group (cf. Table 1). Also consistent with that characterization is the positive effect of organizational innovation in KIBS, presented in Table 5. For the PhIS group it is process innovations that are followed by the growth in employment: again this is a result robust across our specification and consistent with Table 1 and the low-tech profile of the group.

However, the effects of process innovations are more complicated, because they are associated with with job cuts in NIS and KIBS firms (we note that while the coefficients are negative for both groups and both models, they are statistically significant for NIS in the estimation presented in Table 5 and for KIBS in Table 6). This can be explained by the differences in the level of technological opportunities. Physical infrastructure services (PhIS) consist of low-tech industries whose firms are strongly dependent on equipment suppliers in their innovation efforts, and are hence more likely to grow as a result of process innovations. In more technologically advanced NIS and KIBS groups, the displacement effect of process innovations is more likely to dominate.

Regarding the role of marketing innovations, positive and significant effects could be observed in the full sample and large firms, but not in any of the sectoral groupings. Here, however, key insights can be obtained from the results of the regressions that included interaction terms (Table 6). It turns out that marketing innovations are more likely to have a significant effect when they complement product innovations than when they are implemented alone. This was true for the whole sample, as well as for the NIS and KIBS groups, and the effect was significant in both subperiods. This is consistent with the nature of service innovations, which include changes not only to the critical characteristics of the service, but also to the way in which interaction with the client is organized, which is in turn the central concern of marketing.

INSERT TABLE 6 HERE

As expected, smaller firms grew faster: this was true for the whole sample and for PhIS, the biggest industry group (the effects for NIS and KIBS). We also ran regressions for small and medium-or-large firms separately, both for the whole sample and the three industry groups (PhIS, NIS and KIBS); the results are not reported here but are available from the authors on request. We found significant relationships between innovation performance and growth both in the small and medium-large firm subsamples, suggesting that the size of the firm does not necessarily moderate the relationship between innovation and firm growth.

5 Conclusions

Differences in the growth of firms remain a major topic in economics and strategy research. In this paper we have investigated the link between innovation performance and employment growth in the largely underresearched context of services firms. First we discussed the problem from the theoretical point of view, paying particular attention to the possible role of different innovation activities (introduction of new products, processes, marketing techniques, and organizational solutions) in different subsectors of the service sector distinguished by Castellacci (2008) based on two criteria: the role of the industry in the economic system and its level of technological opportunity. Then we analyzed the relationship between innovation performance and the dynamics of employment in Polish service firms in 2004-2009, investigating both the general population of firms and Castellacci's taxonomy groups: physical infrastructure services (PhIS), network infrastructure services (NIS) and knowledge-intensive business services (KIBS).

Our findings show that the effects of different varieties of innovation are strongly sector-specific and that they are largely consistent with the taxonomy applied; i.e., that the firms that implement innovations Castellacci postulated to be important for a given industry group tend to grow faster. This was the case for KIBS and NIS companies that introduced product innovations and PhIS companies that implemented process innovations. Especially the relationship between process innovations and employment growth seems to be moderated by the level of technological opportunity in the industry: while process innovations were conducive to employment growth in the low-technology PhIS industries, they were associated with zero growth or possibly even job cuts in NIS and KIBS.

Given the literature's stress on marketing innovations in the services sectors, we took a closer look at how this kind of innovation influence firm growth. The relationship is positive in the whole sample and in the KIBS and NIS groups, however marketing innovation matter only if they complement product innovations. Further firm-level research is needed to investigate what is really behind this finding, but it seems to offer support for authors who define service innovations broadly, to include such measures as changes to the client-interface (e.g., den Hertog, 2000).

Our study is obviously subject to some limitations, especially those related to the nature and the structure of our dataset. In particular, while a longer time series would have been preferable, we were only able to observe two periods. This is the shortcoming most CIS-based analyses share.[9] We also lacked data about the exact number of workers in any given year (data were only provided on the change in this number). The latter problem was partly circumvented by using the growth in the preceding period as a kind of instrument.

[9] Even the database available at the Eurostat safe-center in Luxembourg does not include unique identifiers for firms in different editions of the CIS, so that building a panel of companies is impossible.

To conclude, our results suggest that as far as services are concerned, the moderating effects of sectoral characteristics are a particularly promising line of research on the relationship between innovation performance and changes in firm employment. For it appears that depending on the industry's level of technological opportunity, different sets of innovation activities can matter for the growth of service companies.

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References

Arellano M., Bond, S. (1991) Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations, *Review of Economic Studies*, 58(2), pp. 277-297.

Audretsch, D. (1995) Innovation, growth and survival, *International Journal of Industrial Organization*, 13(4), pp. 441-457.

Baltagi, B. (2008) *Econometric analysis of panel data*, 4th edition, John Wiley and Sons, London.

Bentzen, J., Madsen, E. S. and Smith, V. (2012) Do firm's growth rates depend on firm size? *Small Business Economics*, 39(4), pp. 937-947.

Bogliacino, F. and Pianta, M. (2010) Innovation and Employment: a Reinvestigation using Revised Pavitt classes, *Research Policy*, 39(6), pp. 799–809.

Brouwer, E., Kleinknecht, A. and Reijnen, J.O.N. (1993) Employment Growth and Innovation at the Firm Level, *Journal of Evolutionary Economics*, 3(2), pp. 153–159.

Cainelli, G., Evangelista, R. and Savona, M. (2006) Innovation and economic performance in services: a firm-level analysis, *Cambridge Journal of Economics*, 30(3), pp. 435-458.

Castellacci, F. (2008) Technological paradigms, regimes and trajectories: Manufacturing and service industries in a new taxonomy of sectoral patterns of innovation, *Research Policy*, 37(10), pp. 978 – 994.

Coad, A. and Rao, R. (2008) Innovation and firm growth in high-tech sectors: A quantile regression approach, *Research Policy*, 37(4), pp. 633–648.

Coad, A. and Rao, R. (2010) Firm growth and R&D expenditure, *Economics of Innovation and New Technology*, 19(2), pp. 127-145.

Dachs, B. and Peters, B. (2014) Innovation, employment growth, and foreign ownership of firms, *Research Policy*, 43(1), pp. 214–232.

Damanpour, F., Walker, R.M., and Avellaneda, C.N. (2009) Combinative Effects of Innovation Types and Organizational Performance: A Longitudinal Study of Service Organizations, *Journal of Management Studies*, 46(4), pp. 650-675.

Daunfeldt, S-O., & Elert, N. (2013) When is Gibrat's law a law? *Small Business Economics*, 41(1), pp. 133-147.

den Hertog, P. (2000) Knowledge-Intensive Business Services as Co-Producers of Innovation, *International Journal of Innovation Management*, 4(4), pp. 491–528.

Demirel, P. and Mazzucato, M. (2012) Innovation and Firm Growth: Is R&D Worth It? *Industry and Innovation*, 19(1), pp. 45-62.

Edgeworth, F.Y. (1887) On observations relating to several quantities, *Hermathena*, 6, pp. 279-285.

Evangelista, R. and Vezzani, A. (2010) The economic impact of technological and organizational innovations. A firm-level analysis, *Research Policy*, 39(10), pp. 1253–1263.

Evangelista, R. and Vezzani, A. (2012) The impact of technological and organizational innovations on employment in European Firms, *Industrial and Corporate Change*, 21(4), pp. 871–899.

Falk, M. (2014) The Impact of New Goods and Service Products on Firm Growth: Evidence from Austrian Linked Firm-Level Data, *Economics of Innovation and New Technology* 23(4): 378-397.

García-Manjón, J.V. and Romero-Merino, M.E. (2012) Research, development, and firm growth. Empirical evidence from European top R&D spending firms, *Research Policy*, 41(6), pp. 1084-1092.

Greene, W., H. 2003. *Econometric analysis*. New York: Prentice Hall.

Harrison, R., Jaumandreu, J., Mairesse, J. and Peters, B. (2008) Does innovation stimulate employment? A firm-level analysis using comparable micro-data from four European countries. NBER Working Paper 14216.National Bureau of Economic Research: Cambridge, MA.

Huber, P.J. (1981) *Robust Statistics*, Wiley, New York.

Kanerva, M., Hollanders, H. and Arundel, A. (2006) Can We Measure and Compare Innovation in Services? 2006 TrendChart Report. European Commission: Brussels.

Leiponen, A. (2012) The benefits of R&D and breadth in innovation strategies: a comparison of Finnish service and manufacturing firms, *Industrial and Corporate Change*, 21(5), pp. 1255-1281.

Leiponen, A., and Helfat, C.E. (2010) Innovation objectives, knowledge sources, and the benefits of breadth, *Strategic Management Journal*, 31(2), pp. 224-236.

Lotti, F., Santarelli, E. and Vivarelli, M. (2009) Defending Gibrat's Law as a long-run regularity, *Small Business Economics* 32(1), pp. 31–44.

Miles, I. (2007) Research and development (R&D) beyond manufacturing: the strange case of services R&D, *R&D Management*, 37(3), pp. 249-268.

OECD (2009) Innovation in Firms: A Microeconomic Perspective, OECD Publishing, Paris.

Pavitt, K. (1984) Sectoral patterns of technical change: towards a taxonomy and a theory, *Research Policy* 13, pp. 343–373.

Pianta, M. (2005) Innovation and Employment, in J. Fagerberg, D.C. Mowery, and R.R. Nelson (eds), *The Oxford Handbook of Innovation*, 568-598. Oxford University Press: Oxford.

Rousseeuw, P.J., Leroy, A.M. (2003) *Robust regression and Outlier Detection*, Wiley and Sons, New York.

Schumpeter, Joseph A. (1934) *The theory of economic development: an inquiry into profits, capital, credit, interest, and the business cycle*. Harvard University Press, Cambridge.

Schumpeter, Joseph A. (1942), *Capitalism, socialism and democracy*, Harper and Brothers, New York.

Subodh, K. (2002) Market concentration, firm size and innovative activity: A firm-level economic analysis of selected Indian industries under economic liberalization, World Institute for Development Economics Research, Discussion Paper No. 2002/108, November. Helsinki: United Nations University.

Sutton, J. (1997) Gibrat's Legacy, *Journal of Economic Literature*, 35(1), pp. 40-59.

Tether, B. (2005) Do Services Innovate (Differently)? Insights from the European Innobarometer Survey, *Industry and Innovation*, 12(2), pp. 153-184.

Verardi, V. and Croux, C. (2009) Robust regression in Stata, *The Stata Journal*, 9(3), pp. 439-453.

Yohai, V.J. (1987) High breakdown-point and high efficiency robust estimates for regression, *Annals of Statistics*, 15, pp. 643-656.

Table 1. Selected characteristics of sectoral groups in Castellacci's taxonomy of serviuce industries

Taxonomy group	Level of technological opportunity	Type of innovation activities
Supplier-Dominated Services (SDS)	Low	Process innovations
Physical Infrastructure Services (PhIS)	Low	Process innovations
Network Infrastructure Services (NIS)	Medium	Process, product and organizational innovations
Knowledge-Intensive Business Services (KIBS)	High	Product and organizational innovations

Source: Own compilation based on Castellacci (2008), Table 1.

Table 2. The percentage of observations for which the variable is equal to 1

	NEW PRODUCT	NEW PROCESS	NEWORG	NEW_ MARKT	SMALL	GROUP
2006*	26.92	33.08	44.95	31.24	30.88	25.23
2008**	22.62	27.99	27.79	23.34	26.59	24.52

* intersection of CIS-2006 and CIS-2008 datasets

** intersection of CIS-2008 and CIS-2009 datasets

Table 3. Breakdown of the sample by Castellacci's (2008) groups

	PhIS	NIS	KIBS
2006*	55.14%	24.54%	20.32%
2008**	54.71%	36.82%	8.47%

* intersection of CIS-2006 and CIS-2008 datasets

** intersection of CIS-2008 and CIS-2009 datasets

Table 4. Statistics for employment dynamics

Statistics	Employment dynamics (starting year=100)			
	2004-2006*	2006-2008*	2006-2008**	2008-2010**
p5	79.31	74.83	79.12	59.71
p25	96.19	95.24	97.50	87.77
p50	106.11	105.56	108.82	100.00
p75	128.27	121.37	136.36	108.22
p95	228.57	173.33	284.21	147.79
mean	158.27	115.56	287.08	166.92
sd	812.01	59.98	2529.27	2407.02
min	6.09	13.49	10.08	0.24
max	30800.00	1397.96	67500.00	98177.77

* intersection of CIS-2006 and CIS-2008 datasets

** intersection of CIS-2008 and CIS-2009 datasets; growth in 2008-2010 is estimated based on the number for 2008-2009 (see explanation in the text)

Table 5. Results of estimation of parameters of model (1)

	Full sample	**PhIS**	**NIS**	**KIBS**	**Small**	**Medium and large**
GR_{it-1}	0.063*** (0.011)	0.061*** (0.012)	0.049 (0.032)	0.165 (0.107)	0.039** (0.020)	0.066*** (0.013)
U2008_2010	-0.038*** (0.006)	-0.032*** (0.008)	-0.063*** (0.013)	-0.045* (0.024)	-0.116*** (0.024)	-0.031*** (0.007)
NEWPRODUCT	0.008* (0.005)	-0.007 (0.009)	0.013** (0.006)	0.030* (0.018)	0.013 (0.012)	0.005 (0.006)
NEWORG0406	0.010 (0.010)	-0.004 (0.014)	-0.001 (0.015)	0.042* (0.025)	0.008 (0.036)	0.008 (0.010)
NEWORG0608	-0.006 (0.004)	-0.003 (0.007)	-0.006 (0.005)	0.004* (0.002)	-0.013 (0.010)	-0.006 (0.005)
NEWMARKT0406	0.020* (0.011)	0.020 (0.016)	0.014 (0.016)	-0.017 (0.028)	-0.010 (0.037)	0.019* (0.011)
NEWMARKT0608	0.004* (0.003)	0.006 (0.007)	-0.000 (0.005)	0.002 (0.013)	0.000 (0.010)	0.003* (0.002)
NEWPROCESS	0.000 (0.005)	0.013* (0.007)	-0.009* (0.006)	-0.024 (0.018)	0.003 (0.014)	-0.003 (0.006)
GROUP	-0.004 (0.004)	-0.001 (0.006)	-0.008* (0.005)	-0.008 (0.014)	0.015* (0.009)	-0.007* (0.004)
SMALL	0.015*** (0.004)	0.026*** (0.006)	0.004 (0.005)	0.012 (0.014)	-	-

NIS	0.020*** (0.004)	-	-	-	0.003 (0.006)	0.029*** (0.005)
KIBS	0.007 (0.005)	-	-	-	0.007 (0.008)	0.012** (0.006)
Intercept	0.015** (0.006)	0.008 (0.008)	0.059*** (0.013)	0.017 (0.020)	0.105*** (0.024)	0.010 (0.006)
No. of observations	3345	1837	917	591	704	2641
Pseudo R-squared	0.074	0.073	0.098	0.117	0.133	0.060

* $p< 0.10$; ** $p< 0.05$; *** $p< 0.01$.

Table 6. Results of estimation of parameters of model (5)

	Full sample	**PhIS**	**NIS**	**KIBS**	**Small**	**Medium and large**
GR_{it-1}	0.062*** (0.011)	0.061*** (0.012)	0.046 (0.031)	0.179** (0.090)	0.040* (0.023)	0.065*** (0.013)
$U2008\_2010_t$	-0.035*** (0.007)	-0.031*** (0.008)	-0.055*** (0.016)	-0.040* (0.022)	-0.113*** (0.027)	-0.028*** (0.007)
$PRODMARKT_{0406}01$	0.017 (0.013)	0.020 (0.017)	0.009 (0.028)	-0.028 (0.033)	-0.035 (0.059)	0.021 (0.014)
$PRODMARKT_{0406}10$	0.028** (0.014)	-0.004 (0.027)	0.034 (0.021)	0.044 (0.037)	0.012 (0.063)	0.025* (0.014)
$PRODMARKT_{0406}11$	0.041*** (0.014)	0.014 (0.023)	0.042** (0.020)	0.031* (0.017)	0.023 (0.058)	0.032** (0.014)
$PRODMARKT_{0608}01$	0.004 (0.005)	0.009 (0.007)	0.001 (0.009)	-0.019 (0.019)	-0.001 (0.013)	0.006 (0.006)

PRODMARKT$_{0608}$10	-0.003 (0.005)	-0.004 (0.011)	0.003 (0.066)	-0.000 (0.017)	0.001 (0.012)	-0.005 (0.006)
PRODMARKT$_{0608}$11	0.018*** (0.005)	-0.004 (0.009)	0.007* (0.004)	0.028* (0.016)	0.010 (0.013)	0.010* (0.006)
NEWORG0406	0.005 (0.010)	-0.004 (0.014)	-0.009 (0.016)	0.036 (0.027)	0.006 (0.044)	0.004 (0.010)
NEWORG0608	-0.003 (0.004)	-0.003 (0.007)	-0.005 (0.005)	0.008 (0.013)	-0.013 (0.010)	-0.003 (0.005)
NEWPROCESS	0.002 (0.005)	0.013* (0.007)	-0.006 (0.007)	-0.024* (0.015)	0.007 (0.015)	-0.002 (0.006)
GROUP	-0.003 (0.004)	-0.001 (0.006)	-0.007 (0.005)	-0.006 (0.013)	0.015* (0.009)	-0.007 (0.004)
SMALL	0.015*** (0.004)	0.026*** (0.006)	0.003 (0.004)	0.011 (0.013)	-	-
NIS	0.019 *** (0.004)	-	-	-	0.003 (0.007)	0.028*** (0.005)
KIBS	0.007 (0.005)	-	-	-	0.007 (0.009)	0.012** (0.006)
Intercept	0.012* (0.007)	0.007 (0.008)	0.052*** (0.015)	0.015 (0.020)	0.102*** (0.028)	0.007 (0.007)
No. of observations	3345	1837	917	591	704	2641
Pseudo R-squared	0.075	0.074	0.099	0.119	0.137	0.060

* p< 0.10; ** p< 0.05; *** p< 0.01.