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Non–technical Summary

The relationship between technological change and employment has been controversially discussed for a long time. But, on the basis of the persistently high rate of unemployment in several Western European countries, innovation is still a key issue in the current debates on employment creation. From a theoretical point of view the effects of innovation on employment are not clearly determined. There are several mechanisms through which innovations can destroy existing jobs or create new ones (displacement versus compensation effects). The overall impact depends on a number of firm–, sector– as well as country–specific factors. Thus, the empirical answer to this long–standing question is more topical than ever.

Using the theoretical, multi–product framework recently proposed by Jaumandreu (2003), this paper reports new results on the relationship between the growth rate in total employment and innovation activities for German manufacturing firms. Furthermore, it is the first to provide empirical evidence for German service firms. The data set used is derived from the third Community Innovation Surveys (CIS 3) launched in 2001 and includes information on more than 2,200 German manufacturing and service sector firms observed in the period 1998–2000. The model establishes a link between the employment growth rate and the innovation output in terms of sales growth stemming from innovative products and process innovations. It allows to disentangle some of the theoretical employment effects and is highly applicable in analysing firm–level employment impacts of innovation activities using the specific information provided by CIS data.

Although employment effects are likely to differ according to the type of innovation, there is still a dearth of studies that focus on different innovation output indicators at the firm level. Using the above–mentioned new model framework, I am therefore extending the analysis in a second step by distinguishing between (i) two different product innovations according to their novelty degree (sales growth generated by market novelties and sales growth stemming from product innovations only new to the firm) and (ii) two different process innovation indicators (rationalisation and other process innovations respectively).

The econometric results confirm that successful product innovations have a positive impact on net employment at the level of the innovating firm. The impact tends to be larger in manufacturing firms than in the service sector, although the difference is statistically not significant. The results further provide evidence that the employment does grow one–for–one with the sales growth accounted for by new products. In addition to that, the estimation results indicate that new jobs are not only created in firms launching market novelties, but also in firms which successfully

pursue product imitation strategies. Moreover, the coefficients of both indicators of product innovation success were not significantly different. This holds for manufacturing and service firms. Hence, this result contradicts the hypothesis that employment effects depend on the degree of product novelty and stands in contrast to previous conclusions drawn by Falk (1999).

The impact of process innovations on employment growth turns out to be variable. In manufacturing firms, displacement effects outweigh compensation effects, resulting in a negative employment effect. But, as expected, the estimation results also reveal that not all process innovations are associated with employment reduction. Jobs are merely significantly deteriorated through rationalisation innovations, but not as a consequence of other process innovations. In contrast, process innovations are not responsible for a significant reduction in labour demand in service firms in the period 1998–2000.

Employment Effects of Different Innovation Activities: New Microeconometric Evidence

Bettina Peters*

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Abstract: Extending a recently developed multi–product model and distinguishing between different product and process innovation activities, this paper reports new results on the relationship between innovation and employment growth in manufacturing and service firms in Germany. The model is tailor-made for analysing firm–level employment effects of innovations using specific information provided by CIS data. It establishes a theoretical link between employment growth and innovation output. The econometric analysis confirms that product innovations have a positive impact on employment. In contrast to previous studies, this effect is independent of the novelty degree. Moreover, different employment effects between manufacturing and service firms regarding process innovations were found. Finally, from a cross country perspective the results for Germany are similar to those found for Spain and the UK.

Keywords: Innovation, employment, applied econometrics, manufacturing, services

JEL Classification: O33, J23, L60, L80, C21, O32

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1 Introduction

The question how technological progress affects the employment situation is an old one and has long been the focus of theoretical and empirical industrial organisation research as well as lively public discussions.[1] The controversial debates on this issue mainly result from the fact, that from a theoretical point of view different channels exist through which innovations can destroy existing jobs (displacement effects), but that there are also several mechanisms through which innovations may create new jobs (compensation effects). And in addition, product and process innovations influence employment via different channels. The overall impact depends on a number of firm–, sector– as well as country–specific factors.

The empirical answer to this long–standing question, however, is more topical than ever. This is based on the incessantly high rate of unemployment not only in Germany, but in several other Western European countries as well. High unemployment induces severe problems such as those facing the German social security system or public budgets. In addition to mere economic recovery, politics hope that innovations could provide an important contribution to strengthen the competitiveness of firms and consequently to the preservation or creation of new jobs. Policies to stimulate innovation activities are therefore high on the list of priorities. For instance, the German government proclaimed 2004 as the "year of innovation".

Recently, Jaumandreu (2003) proposed a new simple multi–product model well–suited for analysing the employment impacts of innovations using the specific information provided by Community Innovation Surveys (CIS) data. Further details of the model were worked out in a joint paper by Harrison, Jaumandreu, Mairesse and Peters (2004). One interesting aspect of the approach is that it establishes a theoretical link between employment growth and innovation output in terms of the sales growth generated by new products as well as efficiency gains attributable to process innovations. As far as employment is concerned it seems especially useful to lean on indicators that emphasise the economic success because they also incorporate the demand situation which is an important factor to the firms' employment decision (see Blechinger et al. 1998). The second advantage is that it allows to disentangle some of the theoretical employment effects under certain assumptions.

The first aim of this paper is to empirically analyse the employment effects caused by innovations in Germany using this theoretical multi–product model. The investigation reports new results on the relationship between innovation and employment growth for German manufacturing firms and is the first to provide empirical evidence for German service firms, using data from the third Community Innovation

[1] For a historical overview see Petit (1995) or Freeman and Soete (1997).

Surveys (CIS 3). The sample includes data on more than 2,200 German manufacturing and service sector firms observed in the period 1998–2000. Despite the dynamic development of the service sector in highly industrialised countries within the last two decades and the fact that new employment was especially created within this sector, firm–level evidence on displacement and compensation effects of innovation activities scarcely exists for the service sector.

As a second stage, further insights into the innovation–employment nexus are gained by considering different types of product as well as process innovations, as employment effects are expected to differ according to the type of innovation. In case of product innovations, they are likely to depend on the product novelty degree. Falk (1999) has found evidence that new jobs are mainly created in firms that have positioned themselves on the cutting edge by launching products that are new to the market (market novelties), while no significant employment effects can be found in enterprises pursuing an imitation (follower) strategy. That is, in firms which offer new products that are new to the firm, but not new to the market (firm novelties). However, the latter firms are important for the diffusion of new technologies and the structural change within an economy. Moreover, most theoretical as well as empirical studies assume that process innovations work on the supply side by reducing unit cost. But, the implementation of new production methods is not necessarily intended to afford increased productivity and reduced costs (rationalisation innovations); it can also be a result of product innovations or legal regulations, or serve to improve product quality. Displacement effects are assumed to be stronger for firms which introduce new processes for rationalisation reasons, while for example process innovations aimed to improve the product quality should have an effect similar to product innovations. Despite the large body of empirical work discussing the innovation–employment link, there is still a dearth of studies that focus on different innovation indicators at the firm level. Using the above mentioned multi–product framework, I am therefore extending the model and the analysis by distinguishing between (i) two different product innovations according to their novelty degree (sales growth generated by market novelties and sales growth stemming from product innovations only new to the firm) and (ii) two different process innovation indicators (rationalisation, respectively other process innovations).

To sum up, four questions are addressed in the paper:

1. Do product and process innovations spur or diminish employment at the level of the innovating firm in Germany?
2. Can a pattern common to industry and service firms be perceived regarding this topic?

3. Do employment effects differ between different kinds of process innovations?

4. Do firm–level employment effects differ between products new to the firm and those new to the market?

The outline of this chapter is as follows: Section 2 sketches some theoretical considerations about the channels through which innovations affect employment and section 3 summarises the main empirical firm–level results so far. The basic theoretical and econometric model developed as well as its extension is explored in section 4. Section 5 describes the data set used for the empirical analysis and holds some descriptive statistics. The econometric results are presented in section 6. And finally, section 7 draws some conclusions on the relation between innovation and employment growth.

2 Theoretical Considerations

From a theoretical viewpoint, the impact of innovation activities on employment is not clearly determined. There are different channels through which technological change can destroy or create new labour: the overall impact depends on several factors and might differ in short– and long–run perspectives. First of all, it depends on the existing production technology and the nature of the technological progress itself, i.e., the type (product or process innovation), direction (labour– or capital–saving, neutral, skill–biased etc.), dimension (radical or incremental innovation) and manifestation (disembodied or factor–embodied) of the technological change. Moreover, consumer preferences, the competition on commodity and labour markets and the qualification structure of the labour force are of importance to the employment impact. The link between innovation and employment can be analysed on different levels: firm, sector and aggregate level. The following empirical analysis is restricted to employment effects at the level of the innovating firm, representing one of the main instances where the according mechanisms are more or less explicitly supposed to work. On a sector or aggregate level, technological progress is associated with further impacts on firms' labour demand, which are beyond the scope of the present study.

Both product and process innovations influence employment via different channels (see, for instance, Stoneman 1983, Katsoulacos 1984 or Blechinger et al. 1998).

If process innovations lead to an increase in productivity (rationalisation innovations), firms are able to produce the same amount of output with less input and ceteris paribus lower costs. The immediate extent of the employment effect in the innovating firm depends on the current production technology and thus the substitutability between input factors, as well as on the direction of the technological change. As a rule, this effect negatively affects employment in the short run and is thus called the displacement effect of process innovations. At the same time, the innovative firm can pass on the cost reduction to output prices which results – from a dynamic perspective – in a higher demand for and output of the product. This compensating price effect depends on the amount of price reduction, the price elasticity of demand, the degree of competition as well as the behaviour and relative strength of different agents within the firm. The more intense the competition on the commodity market, the higher the extent to which cost reductions are passed to output prices. On the other hand, managers may be tempted to use market power to increase profits, while unions may seek to transform any gains from innovations into higher wages which lessen the size of compensation effects (see Nickell 1999). The compensating mechanism enhances labour demand, and thus the overall employment change at the level of the innovating firm is not clear. Unlike rationalisation innovations, process innovations directed to improve the quality of an existing product or process innovations which accompany the introduction of new products should work more explicitly on the demand side and their employment effects should essentially correspond to those pertaining to product innovations.

Additional employment effects may occur in upstream or downstream firms, e.g., if the innovative firm is able to increase its output, its suppliers also benefit and may boost their labour demand. On the other hand, competitors which cannot keep pace with the technological progress will lose market share or even disappear, implying a deterioration of jobs in those firms. Furthermore, the competition on commodity and labour markets have to be taken into account when analysing employment effects on a sector or aggregate level.

Employment impacts of product innovations are essentially a result of demand effects. If a new product has successfully been launched to the market, it creates new demand for the firm. The demand effect is likely to be the result of a market expansion as well as a business–stealing effect (crowding–out effect, that is, the innovating firm's extension of its market share at the expense of its competitors). As a consequence, product innovations increase the labour demand of the innovating firm. The amount and sustainability of such compensation effects resulting from demand increases depend on the competition and the way and delay with which competitors react (see Garcia et al. 2002). If the innovating firm produces more than one good, the amount also depends on synergies in production. The higher synergy effects are, the lower, ceteris paribus, the effect on labour demand is, as common production implies economies in input factors. Additionally, indirect employment effects occur which depend on the substitutability between the old and new products. If the new product (partially or totally) replaces the old one, labour demand for the old product will decrease and the overall effect is again not clear for the innovating firm. However, in the case of complementary demand relationships, the innovation in question causes the demand for previously existing products to rise as well and employment will increase. Product innovations may also have productivity effects, even if they are not associated with simultaneous process innovations. The new or improved product may imply a change in production methods and input mix, which could either reduce or increase labour requirements. The extent and direction of the effect must be determined empirically (see Harrison et al. 2004).

Employment effects of product innovations are also likely to depend on the product novelty degree. From a theoretical point of view, the product life cycle theory of Vernon (1966), which states that each product or sector follows a life cycle, provides one explanation. By definition, market novelties initiate the cycle of the product or even the sector. According to this theory, younger sectors are less mature as consumers are not yet well equipped and thus, they experience higher demand increases (see Greenan and Guellec 2000). As a consequence, market novelties should, ceteris paribus, result in higher output and employment growth.

On the other hand, firms develop innovations to alter market structures and to reduce the competitive pressure. This intended change is an important incentive for innovation activities. If firms are successful, i.e., if the own price elasticity for their commodity is diminished, then product innovations should, ceteris paribus, result in higher prices and decreasing output and employment (see, e.g., Smolny 1998). This effect should be more pronounced in case of market novelties as they define an at least temporary monopoly. Moreover, market novelties are usually associated with a higher uncertainty and a higher risk of failure which might also lead to a lower employment growth.

In summary, it is suggested that the total effect of process as well as product innovations is not explicitly inferable, and therefore must ultimately be ascertained on the basis of empirical analysis.

3 Previous Empirical Findings

The large body of empirical work discussing the innovation–employment link has concentrated on two major questions: The first one is related to the impact of technological change on total employment, mainly on aggregate or industry level, but there is also a growing number of firm–level studies. The second strand of empirical literature focuses on the question whether innovation activities induce a change in the skill structure of employees, referred to as the technological skill bias, as it is hypothesised that technological changes increase the demand for high skilled labour and reduce that for low skilled persons.[2] In what follows, only studies dealing with the first question will be taken into account. For an overview of empirical studies on technological skill bias, see, for instance, Chennels and Van Reenen (1999) or Kaiser (2000, 2001) and Falk and Seim (2000, 2001) and the references cited therein.

For a long time, empirical innovation research has focused on input–oriented innovation indicators when measuring aspects of innovation, i.e., mainly productivity but also employment effects (see, for instance, Griliches 1995). This means that, traditionally, conditional labour demand functions are estimated using factor prices, output and a measure of innovation input (like R&D capital stock, R&D expenditure or IT investment) as explanatory variables. R&D is often found to be positively correlated with employment growth (see, for example, Blechinger et al. 1998 and Regev 1998), although not always (see Brouwer et al. 1993 and Klette and Forre 1998). However, the innovation input transforms into product as well as process innovations and both affect labour demand via different channels. In the nineties, the focus changed to more output–oriented innovation indicators.[3] One obvious reason for this trend is connected to the greater availability of large firm data bases and especially the development of the Oslo Manual (OECD and Eurostat 1992, 1997) and the release of new, internationally harmonised survey data, known as the Community Innovation Surveys (CIS), which began in the first half of the 1990s.

Reviewing previous econometric firm–level studies which explicitly focused on the distinction between employment impacts of product and process innovations, we can ascertain that the majority of them have found a stimulating effect of product innovations on labour demand in manufacturing. For Western Germany, this was shown in the studies of Entorf and Pohlmeier (1990), König et al. (1995), Blechinger et al. (1998), Rottmann and Ruschinski (1998) or Smolny (1998, 2002).[4] The same qualitative result was confirmed by Van Reenen (1997) for the UK, by Garcia et al. (2002) for Spain or by Greenan and Guellec (2000) for France.

As Falk (1999) pointed out, this effect depends on the novelty degree. Using German CIS 2 manufacturing data covering the period 1994–1996, he showed that firms

[2] Closely related to the aspect of the shift in the labour demand from low to high skilled personnel is the increasing inequality of the relative wages across skill groups (see, e.g., Fitzenberger 1999).

[3] Traditionally, patents have been used as an indicator to measure innovation output. However, patent–based indicators have been heavily criticised as being a poor measure of innovative outcome (see Griliches 1990).

[4] The result of Zimmermann (1991) is an exception.

launching market novelties expected an increase in labour demand. Contrarily, no significant employment effects were found in enterprises which had solely launched imitative products that are new to their own firm, but not to the market. However, Falk (1999) analysed the expected instead of the realised employment change. Brouwer et al. (1993) found that firms with a high share of product–related R&D experienced an above average growth of employment. They interpret their innovation indicator as a proxy of R&D related to industrial activities in an early stage of the life cycle. All in all, there is currently little empirical evidence of how employment effects depend on the degree of product novelty.

Moreover, there is no clear evidence of a robust effect of process innovations on jobs in manufacturing. In the studies of Van Reenen (1997) and Entorf and Pohlmeier (1990) the impact of process innovations turned out to be small and not significant at all, while König et al. (1995), Smolny and Schneeweis (1999), Smolny (2002) or Greenan and Guellec (2000) reported that process innovators experienced significantly higher employment growth rates. The latter study even found evidence that process innovations, compared to product innovations, are of greater importance to create new employment at the firm level.[5] Contrarily, Blechinger and Pfeiffer (1999) found evidence that the introduction of new production technologies led to a reduction in employment in manufacturing firms in Western Germany in the mid nineties – the effect being more pronounced in larger firms.

With the exception of Van Reenen (1997), who used the number of major innovations, the above mentioned studies estimated reduced form equations including dummy variables for product and process innovations.

So far, there is hardly any econometric evidence on the overall employment effects of technological change for service firms, Jaumandreu (2003) being an exception. Using the model described in the next section, he found some indication that the net outcome of process innovation was employment displacement in the Spanish service sector, although the effect was not significant. Like in manufacturing, product innovations were associated with employment growth.

4 Model

The model developed by Jaumandreu (2003) allows to disentangle some of the theoretical employment effects mentioned above and is highly applicable in analysing firm-level employment impacts of innovation activities using the specific information provided by CIS data. The share of sales due to product innovations serves as the

[5] However, the reverse relationship was detected on the sectoral level.

key output indicator in this data. One interesting aspect of the approach is that it establishes a theoretical relationship between employment growth and results of innovation activities at the firm level. That is, it postulates a link between the employment growth rate and the innovation output in terms of sales growth stemming from innovative products. The latter can be directly calculated by means of CIS data.

4.1 Basic Model

The model is based on the idea that firms can produce different products. At the beginning of the reference period, a firm i produces one or more products which are aggregated to one product and the corresponding output is Y_{i1}. In what follows, this aggregate product is called the "old product". In the period under consideration, the firm can decide to launch one or more new (or significantly improved) products, with the aggregate output of the new products at the end of the reference period being Y_{i2}. We assume in the remainder of the text that the innovation decision is predetermined to the employment decision, i.e., we do not model the firm's choice to innovate or not.[6] The new product can (partially or totally) replace the old one if they are substitutes, or enhance the demand of the old product if complementarity exists. Thus, in the same period, the output of the unchanged product increases or declines by $\triangle Y_{i1}$.[7]

To produce the different outputs, it is assumed that firms must replicate the conventional inputs labour L_i and capital C_i and that the production function F is linear-homogeneous in these conventional inputs. To keep the model as simple as possible, we assume that labour is a homogenous input factor. However, a knowledge capital exists which is a non-rival input to the production processes, and which drives specific efficiencies for each process and its evolution over time. Assuming that (i) knowledge proportionally raises the marginal productivity of all conventional inputs by an efficiency parameter θ_j, for $j = 1, 2$, (ii) the efficiency in the productive process for the old product can increase by $\triangle\theta_1$, e.g. due to process innovations, learning effects or exogenous technological progress, and (iii) economies of scope are absent,

[6] The possible simultaneous determination of innovation and employment might induce an endogeneity problem in the estimation.

[7] This set-up does not mean that the model is only restricted to firms that change their status from non-innovator to innovator. The label "old product" is justified viewed from the end of the reference period (here, the reference period is 1998-2000), because the OSLO Manual defines innovators as enterprises that have successfully completed at least one innovative project within a three-year period. That is, new products introduced, for example by firm i in 1997 define said firm as an innovator at the beginning of the reference period in 1998, but are not viewed as innovations in 2000 any longer.

this leads to the following equations (1) and (2) for the old product's output Y_i at the beginning and the end of the reference period, respectively:

$$Y_{i1} = \theta_1 \cdot F\left(L_{i1}, C_{i1}\right) \qquad \forall\ i \qquad \text{and} \tag{1}$$

$$Y_{i1} + \triangle Y_{i1} = \left(\theta_1 + \triangle\theta_1\right) \cdot F\left(L_{i1} + \triangle L_{i1}, C_{i1} + \triangle C_{i1}\right) \qquad \forall\ i. \tag{2}$$

The corresponding end-of-period output of the new product is given by (3):

$$Y_{i2} = \theta_2 \cdot F\left(L_{i2}, C_{i2}\right) \qquad \forall\ i. \tag{3}$$

According to the duality theorem and the assumptions of linear-homogeneity and separability, these production functions correspond to the cost function:

$$C_i^* = \begin{cases} c\left(w_i, r_i\right) \cdot \frac{Y_{i1}}{\theta_1} & \text{at the beginning of the period} \\ c\left(w_i, r_i\right) \cdot \frac{Y_{i1}+\triangle Y_{i1}}{\theta_1+\triangle\theta_1} + c\left(w_i, r_i\right) \cdot \frac{Y_{i2}}{\theta_2} & \text{at the end of the period} \end{cases} \tag{4}$$

with the input prices wage w and interest rate r and $c\left(.\right)$ stands for marginal costs. Denoting $c_L\left(w_i, r_i\right) = \partial c\left(w_i, r_i\right)/\partial w_i$ and applying Shephard's Lemma we can derive the labour demand functions for the different products for each period. Assuming that the input prices are constant, the labour demand for product 1 and thus the firm's overall employment at the beginning of the reference period is (for ease of presentation, firm indices i are suppressed in the following terms) $L_1 = c_L \cdot (Y_1/\theta_1)$. At the end of the period, firm i demands $L_1 + \triangle L_1 = c_L \cdot \left[\left(Y_1 + \triangle Y_1\right)/\left(\theta_1 + \triangle\theta_1\right)\right]$ for the old and $L_2 = c_L \cdot (Y_2/\theta_2)$ for the new product. Thus, the employment growth is given by equation (5):

$$\frac{\triangle L}{L} = \frac{\triangle L_1 + L_2}{L_1} = \frac{c_L \cdot \left(\frac{Y_1+\triangle Y_1}{\theta_1+\triangle\theta_1}\right) - c_L \cdot \left(\frac{Y_1}{\theta_1}\right) + c_L \cdot \left(\frac{Y_2}{\theta_2}\right)}{c_L \cdot \left(\frac{Y_1}{\theta_1}\right)}, \tag{5}$$

which can be rearranged to

$$\frac{\triangle L}{L} = \left(\frac{Y_1 + \triangle Y_1}{\theta_1 + \triangle\theta_1}\right) \cdot \frac{\theta_1}{Y_1} - 1 + \frac{\theta_1}{\theta_2} \cdot \frac{Y_2}{Y_1}. \tag{6}$$

Using a first order (linear) approximation for the first fraction, employment growth can be written as

$$\frac{\triangle L}{L} \simeq \frac{-\triangle\theta_1}{\theta_1} + \frac{\triangle Y_1}{Y_1} + \frac{\theta_1}{\theta_2} \cdot \frac{Y_2}{Y_1}. \tag{7}$$

According to equation (7), employment growth stems from three different well-known sources: (i) from the efficiency increase in the production of the old product, which negatively affects labour demand; (ii) from the rate of change in the production of the old product (which is provoked by the new product to a certain degree, the induced change being negative for substitutes and positive for complements); and (iii) from starting production of the new product (positive sign). The employment effect of the latter depends on the efficiency ratio between both production technologies.

Transforming the economic model in an econometric model and taking into account that efficiency gains are likely to be different between process innovators and non-process innovators, we arrive at equation (8):

$$l = \alpha_0 + \alpha_1 \, d + y_1 + \beta y_2 + u \tag{8}$$

with

l	:	employment growth rate
α_0	:	(negative) average efficiency growth for non-process innovators
α_1	:	average efficiency growth for process innovators
d	:	dummy variable indicating process innovations
y_1	:	real output growth due to old products $\frac{\triangle Y_1}{Y_1}$
y_2	:	real output growth due to new products $\frac{Y_2}{Y_1}$
u	:	error term with $E\left(u \mid d, y_1, y_2\right) = 0$

Equation (8) implies that even non-process innovators can achieve efficiency gains, possibly due to exogenous technological progress, organisational changes, improvements in human capital, learning or spill-over effects.

One problem in estimating equation (8) is that we do not observe real output growth but nominal sales growth. However, we can split the firm's (observed) sales growth rate into the sales growth due to old (g_1) and new products (g_2) and using the following definitions we can derive equation (10) in nominal variables, which serves as the basic estimation equation. Concerning the nominal rate of sales growth due to old products, the relation $g_1 = y_1 + \pi_1$ holds approximately, where p_1 is the price of the old product at the beginning of the reference period and π_1 represents the corresponding inflation rate over the period. g_2 is defined as the ratio of sales of new products to sales of old products measured at the beginning of the period:

$$g_2 = \frac{p_2 \, Y_2}{p_1 \, Y_1} = y_2 + \pi_2 \, y_2 \quad \text{with } \pi_2 = \frac{p_2 - p_1}{p_1} \tag{9}$$

This leads to the following estimation equation[8] :

[8] If the inflation rate π_1 has a non-zero mean, one could include $-E(\pi_1)$ in the intercept and $-(\pi_1 - E(\pi_1))$ in the error term.

$$l - g_1 = \alpha_0 + \alpha_1\, d + \beta\, g_2 + v \tag{10}$$

with

$g_1 = y_1 + \pi_1$	:	nominal rate of sales growth due to old products
$g_2 = \frac{p_2\, Y_2}{p_1\, Y_1} = y_2 + \pi_2 y_2$	:	sales ratio of new to old products
π_1	:	price growth of old products
π_2	:	ratio of the price difference between the new and old products to the price of the old product
$v = -\pi_1 - \beta\pi_2 y_2 + u$	:	error term,

where we assume that $E\left(\pi_2 | y_2\right) = 0$. Then $E\left(\pi_2 y_2\right) = 0$ and $\pi_2 y_2$ is uncorrelated with y_2.

Note that $l - g_1$ is used as right-hand variable as new products cannibalise the old ones to some extent and are thus to a certain degree responsible for the old products' change in sales. This implies that we are estimating a net employment effect.

The relationship (10) implies endogeneity as well as identification problems for the estimation. The endogeneity problem occurs because, by definition, g_2 is correlated with the error term v. The identification problem results from the fact that we cannot observe firm-level price changes, which leads to π_1 being included in the error term. As a consequence, it is not possible to identify the gross employment effect of efficiency (productivity) gains but merely the net employment effect which has been accounted for indirect price effects. If efficiency rises by the factor a, marginal costs decline by the same factor. Depending on competition and market power, firm i passes on the cost reduction to its clients by the factor δ so that the price is reduced by δa. As long as we cannot control for firm-level price changes of the unchanged product, we are only able to estimate the net effect $-a - \pi_1 = -(1-\delta)a$. To overcome this hindrance, Jaumandreu (2003) proposed to use the disaggregate price indices $\widetilde{\pi}_1$ and $l - (g_1 - \widetilde{\pi}_1)$ as dependent variable (see also footnote 8). This method leads to an identification of the average gross productivity effect if firms behave according to the sector average. However, the identification problem is still valid for firms that deviate from the average price behaviour. In the empirical analysis, I will rely on equation (10), using $l - g_1$ or $l - (g_1 - \widetilde{\pi}_1)$ as dependent variable in a first step.

4.2 Extended Model

It is expected that employment effects may not only depend on the type (product or process) but also on the dimension of technological change. Therefore, the analysis is simply broadened in a second step by distinguishing between different kinds of product as well as process innovations.

I use the the above mentioned multi–product framework and assume that, depending on its innovation strategy, firm i decides upon the product novelty degree by launching new products that are new to the market (market novelties) and/or by introducing products which are new to the own firm, but not to its relevant market (firm novelties), with the aggregate output of the respective products at the end of the reference period being Y_{i2m} and Y_{i2f}. The innovation decision is still assumed to be predetermined.

Most theoretical as well as empirical studies assume that process innovations reduce unit cost. However, the introduction of new production technologies may have several different purposes. Process innovations may aim to improve the quality of products or to assure that products or production processes meet new legal requirements; firms also introduce new technologies simply to be able to produce a new product. Last but not least, process innovations may be intended to rationalise in terms of reducing average production costs. I allow for the fact, that efficiency and thus employment effects may differ according to the type of process innovation.

Both considerations lead to the following estimation equation in the second step:

$$l - (g_1 - \widetilde{\pi}_1) = \alpha_0 + \alpha_c\, d_c + \alpha_{nc}\, d_{nc} + \beta_m\, g_{2m} + \beta_f\, g_{2f} + v \tag{11}$$

with g_{2m} and g_{2f} denoting the sales growth generated by market novelties and firm novelties respectively and d_c meaning a rationalisation innovation and d_{nc} other process innovations. The hypothesised relationship is $\alpha_c < \alpha_{nc}$, because we expect that the displacement effects are higher for firms with rationalisation innovations. As was set forth in section 2 the employment consequences of introducing new products are likely to depend on the product novelty degree. But from a theoretical point of view, the expected relationship between β_m and β_f is ambiguous.

5 Data Set and Descriptive Statistics

The data set used is based on the 2001 official innovation survey in the German manufacturing and service industries, which was the German part of the Community Innovation Surveys CIS 3.[9] Firms were observed for the reference period 1998–2000. The survey collected data on 4,611 firms, 1,922 of which are in manufacturing (NACE 15–37), 2,433 in services (NACE 50–90) and the rest in mining,

[9] A more detailed data description is given in the appendix.

quarrying, electricity, gas and water supply and construction. In Germany, the innovation survey covers firms with at least 5 employees, but to facilitate comparison of my results with those of Jaumandreu (2003), I include only firms with 10 or more employees.[10] Furthermore, I restrict the sample to manufacturing and to those service sectors which are covered by CIS 3, i.e., wholesale trade (NACE 51), transport/storage (60–63), post and telecommunication (64), financial intermediation (65–67), computers and related activities (72), research & development (73) and technical services (74.2+74.3).

For estimation purposes, I further exclude (i) firms established during 1998–2000 (i.e., if employment or sales are zero or missing for 1998) and (ii) firms which experience an increase or decrease in turnover of more than 10 per cent due to mergers or due to the sale or closure of a part of the enterprise. Besides that, a few outliers (in which employment growth or labour productivity growth turned out to be higher than 300 per cent) were eliminated and firms with incomplete data for any of the relevant variables were dropped. The total number of observations remaining for the empirical analysis is 1,319 for manufacturing and 849 for services. An overview of the sectors and the distribution of innovating and non–innovating firms is given in Table 12 in the appendix A. Table 13 contains information on the distribution by size classes in the estimation sample.

To compute price growth rates, I use producer price indices on a 3–digit NACE level for manufacturing. For a few 3–digit NACE classes no indices are published; here, the producer price indices on the corresponding 2–digit NACE level are used as proxy.[11] For service firms, I am only able to apply 7 different price indices.[12] All indices are elaborated and published by the German Statistical Office (Destatis).

In general, employment consists of the number of employees and the number of hours they work. Here, employment is measured as the number of employees in full–time equivalents, where we assume that part–time employees are represented by halves of full–time worker. The definition of other variables derived from the econometric model as well as of some of the other control variables subsequently

[10] However, estimations for the whole sample, including firms with at least 5 employees, show that the results do not substantially differ from those reported for the restricted sample. These estimation results are available on request.

[11] In Germany, producer price indices are available for 87 3–digit NACE classes in manufacturing. However, no producer price indices are published for the classes 17.3, 18.3, 20.5, 21.1, 22.3, 23.3, 28.5, 28.6, 29.6, 33.3, 35.3, 35.4, 35.5, 37.1, 37.2.

[12] Producer price indices are available for wholesale trade, shipping and air as well as railway transport, which were applied for NACE 51, 61, 62 and 60.1. For NACE 60 (except 60.1) and 63 I use the transport component of the consumer price index, for 64 the corresponding telecommunication component. For all other service sectors, price growth rates are computed from the services component of the consumer price index.

used are given in the Tables 1 and 2. Regarding the descriptive statistics, Table 3 introduces the means and standard deviations for the major variables used in the study. It further shows descriptive statistics for the instrumental variables (see Table 5 in section 6.1 for their definition). Additionally, Table 4 depicts the growth rates of employment, sales and prices of the sampled firms by their innovation status in the period 1998–2000. Since mean values can, of course, be strongly influenced by lone outliers, the median is also presented for comparison.

Some interesting similarities and differences between the two total samples, i.e., samples including both innovative and non–innovative firms, for manufacturing and services are displayed. Starting with the differences, the average employment growth rate between 1998 and 2000 is nearly two times higher in the service sector (10.2) compared to the manufacturing sample (5.9). However, we find that in both sectors the average employment growth is higher in innovative firms. Yet, this does not clearly indicate a causal relationship in that innovations lead to more employment. These statistics could, for example, be attributable to industry effects. The correlation between employment development and innovation activities at the firm level will thus be investigated using multivariate methods in the following section. The average employment growth rates exceed the official figures released by the German Federal Statistical Office (labour force growth rate in Germany between 1998–2000: 4.7 per cent, i.e., average growth rate of 2.3 per cent p.a.; see http://www.destatis.de). But of course, these figures are not directly comparable due to (i) different definitions and calculation methods, (ii) the sample restriction and (iii) a selectivity problem. The latter is due to the fact that only surviving firms as of 2000 are covered by the survey. However, the figures are consistent with the stylised fact that services in Germany have gained in importance since the mid eighties, and that employment shifts from manufacturing to the service sector (see Statistisches Bundesamt or Peters 2003).[13] Similar differences between manufacturing and service firms can be found in sales and price growth rates. On average, nominal sales mounted by 15 per cent in manufacturing between 1998 and 2000, while prices increased by 1.3 per cent. The corresponding figures for services are 18 and 4 per cent. However, this implies that real sales grew roughly by 7 per cent p.a. in both sectors.

Concerning the innovation behaviour, our sample reflects quite well such characteristics as on the national scale and does not give any obvious cause for selectivity concerns in this respect. About 60 per cent of the manufacturing enterprises introduced at least one product or process innovation in the reference period, compared to only 50 per cent of the service firms. New products were launched by 48 per cent

[13] Moreover, we observe an employment shift within the manufacturing as well as service sector to more knowledge–intensive branches; see Pfeiffer and Falk (1999).

Table 1: Definition of Qualitative Variables

Variable	Model	Type	Definition
PROD		0/1	Product innovation: Introduction of at least one new or significantly improved product during 1998–2000.
FIRM		0/1	Firm novelty: Introduction of at least one new or significantly improved product during 1998–2000 which was new for the firm but not for the market.
MARK		0/1	Market novelty: Introduction of at least one new or significantly improved product during 1998–2000 which was new to the firm's market.
PROC	d	0/1	Process innovation: Introduction of new or significantly improved production technologies or methods of supplying and delivering products or procedures during 1998–2000.
RATION	d_c	0/1	Introduction of at least one process innovation intended for rationalisation purposes in terms of reducing production costs in 1998–2000.
OTHER_PROC	d_{nc}	0/1	Dummy variable being 1 if PROC=1 and RATION=0.
PROD_ONLY		0/1	Dummy variable being 1 if PROD=1 and PROC=0.
PROC_ONLY		0/1	Dummy variable being 1 if PROD=0 and PROC=1.
PROD&PROC		0/1	Dummy variable being 1 if PROD=1 and PROC=1.
RATION_ONLY		0/1	Dummy variable being 1 if PROD=0 and PROC=1 and RATION=1.
OTHER_PROC_ONLY		0/1	Dummy variable being 1 if PROD=0 and PROC=1 and RATION=0.
RATION&PROD		0/1	Dummy variable being 1 if PROD=0 and PROC=1 and RATION=1.
NON_INNO		0/1	Dummy variable being 1 for non–innovators between 1998–2000.
SIZE		0/1	System of 3 size class dummies: Firms with 10–49, 50–499 and 500 and more employees.

of all firms in manufacturing. In the service sector just 40 per cent of the enterprises supplied new services to their clients. However, in both samples two out of three product innovators launched at least one market novelty. Process innovations are less common with 38 and 31 per cent in manufacturing and services, respectively.

Table 2: Definition of Quantitative Variables

Variable	Model	Type[a)]	Definition
EMPLOY	l	c	Growth rate of the firm's overall employment for period 1998–2000 (in full time equivalents).
SHARE_NEWPD		c	Share of sales in 2000 due to new products introduced between 1998–2000.
SHARE_MARK		c	Share of sales in 2000 due to market novelties introduced between 1998–2000.
SHARE_FIRM		c	Share of sales in 2000 due to firm novelties introduced between 1998–2000.
SALES		c	Growth Rate of the firm's turnover for the period 1998–2000.
SALES_NEWPD	g_2	c	Growth rate of the firm's turnover due to product innovations for the period 1998–2000. Computed as: [*SHARE_NEWPD * (sales in 2000/sales in 1998)*].
SALES_MARK	g_{2m}	c	Growth rate of the firm's turnover due to market novelties for the period 1998–2000. Computed as: [*SHARE_MARK * (sales in 2000/sales in 1998)*].
SALES_FIRM	g_{2f}	c	Growth rate of the firm's turnover due to firm novelties for the period 1998–2000. Computed as: [*SHARE_FIRM * (sales in 2000/sales in 1998)*]
SALES_OLDPD	g_1	c	Growth rate of the firm's turnover due to unchanged products for the period 1998–2000. Computed as: [*SALES - SALES_NEWPD*].
PRICE	$\widetilde{\pi}_1$	c	Price growth for the period 1998–2000 on a 3– or 2–digit level.
LAB_COSTS		c	Rate of change of the firm's average labour costs (total remuneration plus social contributions) per employee during 1998–2000.
INVEST		c	Sum of investments in tangible assets in 1998, 1999 and 2000 per employee in 1998.

Notes:
[a)] c: continuous variable.

The German CIS data set provides an additional distinction between firms applying rationalisation innovations and those utilising other process innovations. Just 26 per cent of all manufacturing firms, that is nearly three out of four process innovators, introduced new production technologies to rationalise processes. However, amongst service sector firms only one half of all process innovators experienced cost reductions due to new processes. In both sectors nearly one half (45 %) of all inno-

Table 3: Descriptive Statistics for Total and Innovative Sample

	Manufacturing				Services			
	Total sample		Innovative sample[a]		Total sample		Innovative sample[a]	
Variables	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.
Quantitative								
Employment	275	1168	389	1506	531	8044	990	11515
EMPLOY	5.9	24.7	8.4	27.3	10.2	34.9	14.9	35.7
SALES	15.2	34.4	18.2	36.2	18.5	51.0	22.8	48.9
SHARE_NEWPD[b]	–		23.5	23.4	–		25.0	27.7
SHARE_MARK[b]	–		8.5	14.9	–		9.3	16.2
SHARE_FIRM[b]	–		14.9	19.1	–		15.7	22.8
INNO_INTENS	–		6.3	8.8	–		10.7	20.2
RD_INTENS	–		2.7	4.9	–		6.0	14.1
EXP_INTENS	21.8	24.5	26.3	25.4	5.9	15.9	7.9	17.9
INVEST[c]	26.3	47.8	29.8	50.3	39.6	17.6	40.7	18.5
Qualitative[d]								
Innovator	58.5	0.493	100.0	0.000	48.6	0.500	100.0	0.000
PROD	48.4	0.499	82.6	0.379	39.3	0.488	80.8	0.394
PROD_ONLY	21.0	0.407	35.9	0.480	17.7	0.381	0.363	0.482
PROD&PROC	27.4	0.446	46.8	0.499	21.7	0.412	44.6	0.498
MARK	31.8	0.465	54.3	0.498	24.8	0.432	51.1	0.500
PROC	37.5	0.484	64.1	0.478	30.9	0.463	63.6	0.482
PROC_ONLY	10.1	0.302	17.4	0.379	9.3	0.291	19.1	0.394
RATION	27.0	0.444	46.1	0.499	16.4	0.371	33.9	0.474
CONT_RD	38.5	0.489	61.2	0.486	25.9	0.438	48.4	0.500
PATENTS	26.5	0.444	39.9	0.490	9.9	0.300	18.2	0.386
RANGE	48.9	0.500	78.5	0.411	39.5	0.389	76.3	0.426
QUALITY	52.2	0.499	83.8	0.368	43.2	0.496	81.6	0.388
MARKET	44.9	0.498	72.0	0.449	32.8	0.470	61.7	0.487
CLIENT	46.8	0.499	73.2	0.443	33.6	0.473	60.8	0.489
SCIENCE	7.7	0.266	12.0	0.325	6.7	0.250	13.1	0.338
# of observations	1319		772		849		413	

Notes:
[a] Innovative firms are defined as firms with product and/or process innovations.
[b] As percentage share of sales in year 2000.
[c] In thousand .
[d] As share of firms.
Source: Own calculations.

vative firms introduced new products as well as new production technologies, while amongst the other half, one third concentrated solely on process innovation and the remaining two thirds on pure product innovation activities.

Looking at the innovation performance, we find that in both sectors innovative firms earned approximately 25 per cent of their turnover in 2000 with product innovations introduced during 1998–2000, including about 9 per cent with market novelties. This corresponds to a sales growth rate due to product innovations of nearly 35 per cent in manufacturing: 33.6 per cent for firms only launching new products and 35.2 per cent for firms introducing both new products and processes. In the service sector these growth rates are even a little higher, at 37 and 45 per cent, respectively. Thus, product innovations are important for sales growth in both sectors, and firm novelties contributed more to sales growth than market novelties. At the same time, sales for old products decreased substantially for product innovators, revealing that the new products replaced the old ones to a large extent. All in all, this induced the sales growth rate of product innovators to be roughly 11 and 14 percentage points higher than that of non–innovative firms or pure process innovators in the service sector. Note that the sales growth recorded by non–innovators and firms innovating only with respect to processes must be attributed to old products. Furthermore, it should be mentioned that the German economy experienced a considerable upswing in economic activity during this period, the peak being in the year 2000.

Table 4: Employment and Sales Growth Rates for Innovators and Non–innovators, 1998–2000[a)]

Type[b)]	Employment growth			Sales growth															Price growth		
				Total			Old product			New product											
										Total			Firm novelty			Market novelty					
	m	s.d.	md	m	s.d.	md	m	s.d.	md	m	s.d.	md	m	s.d.	md	m	s.d.	md	m	s.d.	md
Manufact.																					
NON_INNO	2.4	20.0	0.0	10.8	31.2	6.0	10.8	31.2	6.0	–	–	–	–	–	–	–	–	–	1.1	4.8	1.2
PC_ONLY	6.0	22.7	2.3	21.7	44.1	11.4	21.7	44.1	11.4	–	–	–	–	–	–	–	–	–	2.4	7.0	1.6
PROD	9.0	28.0	3.5	17.5	34.3	10.8	-17.0	32.9	-14.8	34.5	35.3	24.0	21.4	24.6	14.2	13.1	26.6	5.3	1.3	4.5	1.8
thereof																					
PD_ONLY	8.1	28.2	2.6	15.2	31.8	8.7	-18.4	31.5	-16.1	33.6	35.1	22.6	21.6	25.8	12.6	12.0	23.6	4.3	1.4	5.5	1.8
PD&PC	9.4	28.2	4.1	19.3	36.0	12.5	-15.9	34.0	-13.9	35.2	35.5	25.3	21.2	23.6	14.8	14.0	28.7	5.6	1.2	3.4	1.8
Total	5.9	24.7	1.6	15.2	34.4	8.7	-1.5	36.9	-1.2	16.7	30.0	0.0	10.3	20.2	0.0	6.4	19.6	0.0	1.3	4.9	1.7
Services																					
NON_INNO	5.9	33.7	0.0	14.4	52.8	4.6	14.4	52.8	4.6	–	–	–	–	–	–	–	–	–	5.0	5.8	4.2
PC_ONLY	6.1	28.8	0.0	11.2	32.6	5.4	11.2	32.6	5.4	–	–	–	–	–	–	–	–	–	4.7	5.8	1.8
PROD	16.9	36.9	7.1	25.6	51.6	13.3	-15.9	44.3	-11.9	41.5	48.4	24.0	25.1	34.8	11.9	16.4	33.9	6.0	3.0	2.9	1.8
thereof																					
PD_ONLY	17.9	34.3	8.8	25.8	55.8	12.5	-11.3	49.2	-11.9	37.2	42.4	23.0	22.1	31.9	10.1	15.1	29.1	6.6	3.2	3.1	1.8
PD&PC	16.1	38.9	5.9	25.4	48.1	13.4	-19.6	39.6	-11.6	45.0	52.8	25.7	27.5	36.9	15.9	17.5	37.4	5.7	2.8	2.8	1.8
Total	10.2	34.9	0.0	18.5	51.0	8.0	2.2	50.1	0.0	16.3	36.5	0.0	9.9	25.0	0.0	6.5	22.7	0.0	4.2	5.0	1.8

Notes:
[a)] Rates of growth for the entire period 1998–2000. Entrants and firms affected by merger, sale or closure are excluded, as are firms with less than 10 employees in 2000 or those lacking complete information.
[b)] For lack of space PROD_ONLY is abbreviated as PD_ONLY, PROC_ONLY as PC_ONLY, and PROD&PROC as PD&PC.
Source: Own calculations.

6 Empirical Analysis

6.1 Estimation Procedure

As mentioned above, the relationship (10) implies an identification and an endogeneity problem. To address the identification problem, industry price growth rates were subtracted from the nominal sales growth of unchanged products, i.e., $l - (g_1 - \widetilde{\pi}_1)$ was used as the dependent variable.

Due to the likely endogeneity problem, applying OLS to equation (10) would yield biased and inconsistent parameter estimates. Based on the first regressions in Tables 6 and 7, the estimates for the coefficient of sales growth due to new products appeared to be downward biased.[14] The Durbin–Wu–Hausman (DWH) test confirmed the endogeneity problem and rejected the null hypothesis that the OLS estimator is consistent.[15] Hence, the model is estimated applying the instrumental variable (IV) method.

Instruments for the endogenous right–hand–side variable sales growth due to new products (SALES_NEWPD) should be correlated with the real rate of sales growth stemming from innovations, but should be uncorrelated with the change in relative prices. Factors which have been found to be important in explaining the success of product innovations in the theoretical as well as empirical literature are, among others: R&D and innovation input (see, for instance, Crépon et al. 1998, Lööf and Heshmati 2001, Love and Roper 2001 or Janz et al. 2004), technological opportunities (see Cohen and Levinthal 1989), technological capabilities (see, e.g., Dosi 1997 or König and Felder 1994), absorptive capacity (see, e.g., Becker and Peters 2000), market demand (see, e.g., Crépon et al. 1998), network relationships, especially with costumers (see, e.g., Hippel 1988 or Beise and Rammer 2003), corporate governance structure (see, e.g., Czarnitzki and Kraft 2004), or knowledge capital of employees (see Love and Roper 2001). Thus, the success of product innovations in terms of sales growth is likely to be correlated to the following factors, where the variables in parentheses are tried as instruments in the empirical analysis to measure these factors (see Table 5 for a more detailed definition):

[14] Notice, in general, the downward bias may show up because of the endogeneity or as a result of weak instruments. The problem of weak instruments will be further discussed at the end of this subsection.

[15] The DHW test is based on an artificial regression by including the predicted value of the endogenous right–hand–side variable (as a function of all exogenous variables) in a regression of the original model and applying an F test for significance of the additional regressor (see Davidson and MacKinnon 1993). For example, using the instruments proposed in regression (2), the DWH statistic was 44.74 (p–value: 0.000) in manufacturing and 8.60 (0.003) in services; using the preferred instruments of regression (6) the corresponding figures were: 4.46 (0.035) and 7.14 (0.008).

- innovation input (RD_INTENS or INNO_INTENS),
- effects of product innovations (RANGE, QUALITY or MARKET),
- degree of product novelty (SHARE_MARK; only attempted in the basic model),
- appropriability conditions (PATENT),
- technological capabilities (CONT_RD),
- technological opportunities (SCIENCE),
- integration of costumers into the innovation process (CLIENT),
- competitiveness (EXP_INTENS).

However, it is not clear how these factors are linked to price changes, so instrument validity has to be checked for which was done by performing the Sargan–Hansen overidentification test.[16] Additionally, subsets of instruments are tested using a "difference–in–Sargan" statistic, which is also called the C statistic. This means, the C statistic allows a test of the exogeneity of one or more instruments and is defined as the difference of the Hansen statistics of the unrestricted equation (with the smaller set of instruments) and the restricted equation (with the larger set of instruments). Under the null hypothesis that both the restricted and unrestricted equations are well–specified, the C statistic is distributed as chi–squared in the number of instruments tested. The acceptance of the null hypothesis, i.e., that the subset of orthogonality conditions is valid, requires that the full set of orthogonality conditions to be valid (see, e.g., Wooldridge 2002).

For Spanish firms, Jaumandreu (2003) proposed the variables RD_INTENS, RANGE and MARK_SHARE as instruments. To compare results, I used the same instruments in regressions (2)–(3) of Tables 6 and 7. However, in several regressions the test of overidentifying restrictions rejected the null hypothesis of valid instruments for the German data set. Using the difference–in–Sargan statistic, I found that it is the RD_INTENS, which is often rejected as a valid instrument. In regression (4) the INNO_INTENS, was used instead, but Hansen's J statistic again rejected the null hypothesis of the validity of the moment restrictions. After testing the different above–mentioned instruments, CONT_RD, PATENT, CLIENT, SCIENCE and, in addition, RANGE in manufacturing were used as instruments in specifications (5) and (6) of Tables 6 and 7 and in all estimations of Tables 8 and 9. Using this

[16] It is well–known that the Sargan test statistic is not consistent if heteroskedasticity is present. This problem was addressed through the use of the heteroskedasticity–consistent Hansen statistic.

Table 5: Definition of Alternative Instruments

Variable	Type[a)]	Definition
CONT_RD	0/1	Firm was engaged continuously in intramural R&D activities during 1998–2000.
CLIENT	0/1	Clients have been a high to medium–sized source of innovation.
SCIENCE	0/1	Science (universities, public research institutes) has been a high to medium–sized source of innovation.
PATENT	0/1	Firm applied for a patent during 1998–2000.
RANGE	0/1	Innovations has had a high to medium–sized impact on an increased range of goods.
MARKET	0/1	Innovations has had a high to medium–sized impact on increased market or market share.
QUALITY	0/1	Innovations has had a high to medium–sized impact on improved quality in goods or services.
RD_INTENS	c	Total R&D expenditure / sales in 2000.
INNO_INTENS	c	Total innovation expenditure / sales in 2000.
SHARE_MARK	c	Share of turnover in 2000 due to market novelties introduced during 1998–2000.
EXP_INTENS	c	Export / sales in 1998.

Notes:
[a)] c: continuous variable.

set of instruments, the null hypothesis regarding the validity of the orthogonality restrictions was accepted for all estimations.

The search for appropriate instruments is essential for estimation. As mentioned above, appropriateness here refers to the instruments' *validity* in terms of zero correlation ($\rho = 0$) between the instruments and the error term of the structural model as well as *strength* as in showing strong partial correlation with the endogenous right–hand–side variable. In recent years, several authors have been emphasising that particular problems and pitfalls in inference arise if the instruments are weak and conventional (first–order) asymptotic inference techniques are used, for instance, the Sargan test or the traditional Hausman specification test (see, e.g., Bound et al. 1995, Staiger and Stock 1997, Shea 1997, Hausman 2001 or Hahn and Hausman 2002). A situation of weak instruments can emerge when the instruments have a low explanatory power for the endogenous right–hand–side variable or when the number of instruments becomes large (Hahn and Hausman 2002).

The first problem associated with weak instruments is that they can cause large finite sample biases: Regardless of whether the instruments are valid or not, the

IV estimator is likewise biased (in the same direction as OLS) in finite samples because the parameters of the reduced form are unknown and have to be estimated. Bound et al. (1995) already showed that assuming instrument validity, the bias of the IV relative to the OLS estimator is approximately inversely related to the F–statistic F of the first stage regression.[17] That is, when the instruments have a high degree of explanatory power for the jointly endogenous variable and thus F is sufficiently large (a value of at least 10 was put forward in the literature as a rule of thumb), IV performs better than OLS and should be given preference. And even when instruments are weak, yet still valid, IV nevertheless has a smaller bias compared to OLS as long as the number of instruments is sufficiently small in proportion to sample size (see Hahn and Hausman 2003). First–step regression results for the preferred set of instruments are presented in Table 14 in the appendix A. The instruments are positively and significantly correlated with the endogenous variable(s) and, throughout, F is evidently greater than 10. However, as may be applicable with the instruments identified here, larger problems can emerge when instruments are not truly exogenous. Both IV as well as OLS are then biased in finite samples and inconsistent. Hahn and Hausman (2002) demonstrate that the finite sample bias of the IV is monotonically increasing (i) in the correlation between the error terms of the structural and reduced form (ρ), (ii) in the number of instruments and decreasing (iii) in the sample size and (iv) in the $R2$ of the reduced form. Hahn and Hausman (2003) found that IV does still better than OLS under a wide range of conditions, but if instruments are weak, even a small correlation between the instruments and the stochastic disturbance of the structural model can produce a large finite sample bias in the IV estimator, potentially even larger than in OLS. A similar result was shown for the inconsistency of the IV estimator in such a case by Bound et al. (1995).

The second problem of weak instruments is that conventional asymptotic theory breaks down, because it treats the coefficients of the first stage regression as nonzero and fixed (see Staiger and Stock 1997). That is, the classical asymptotic distributions are not only very poor approximations for the exact finite distributions, but even if the sample size is large they are poor approximations.

Thus, IV–based inference can be highly misleading in a particular application when weak instruments are a problem. Recently, Hahn and Hausman (2002) suggested a new specification test for the validity of IV which jointly addresses exogeneity and weakness. The general approach is that of the well–known Hausman–type

[17] More precisely, if there are no exogenous variables in the structural model, the F–statistic of the first stage regression is applied. If the structural equation contains exogenous variables, the latter have to first be partialled out by premultiplying with an appropriate projection matrix. In this case the partialled out reduced form regression delivers the correct F–statistic.

specification test, comparing two different estimators for the same parameter(s). Here, the forward (standard) IV and reverse IV (by exchanging the endogenous variables) estimators are used. Under the null hypothesis that conventional first order asymptotics provide a reliable guide, the two estimators should be very similar. However, when second order asymptotic distribution theory is used, the two estimators will differ due to second order bias terms. Thus, if the null hypothesis is rejected, one cannot trust the conventional inference techniques. Rejection can occur due to false orthogonality assumptions of the instruments and / or due to weak instruments. The proposed test statistic HH is shown to have a normal distribution under the null hypothesis.[18] Using the set of preferred instruments, the estimated test statistics are 1.211 (p–value: 0.226) in manufacturing and 1.432 (p–value: 0.152) in the service sector (see Tables 6 and 7). Thus, this test clearly indicates that the problem of endogenous or weak instruments doesn't exist here and that reliance on the IV estimates is not misleading.[19] The interpretation of the results in section 6.2 below will be based on this preferred set of instruments.

On a final note it needs to be addressed that the conventional IV estimator, though consistent, is inefficient if heteroskedasticity is present. When facing heteroskedasticity of unknown form, efficient estimates can be obtained by applying General Method of Moments (GMM) techniques. I test the null hypothesis of homoskedasticity performing the test proposed by Pagan and Hall (1983) (see also Baum et al. 2003). Using two different sets of indicator variables that are hypothesised to be related to the heteroskedasticity (levels, squares and cross–products of the instruments or levels only), both statistics PH_{all} and PH_{lev} did not reject the null hypothesis of homoskedasticity. Thus, IV was considered as an appropriate method and corresponding results are reported in the next section. Nonetheless, a comparison of GMM and IV results was carried out and can be found in Table 15 in the appendix A. As expected, the GMM results are more or less the same compared to IV.

6.2 Econometric Results

The empirical results revealing the relationship between employment growth and product and process innovations are reported in Tables 6 and 8 for manufacturing and in 7 and 9 for services, respectively.

[18] See Hahn and Hausman (2002), p. 166–169, for the calculation of the test statistic.

[19] Hahn and Hausman (2002) suggest that a similar specification test based on second–order unbiased Nagar–estimators should be carried out if the null hypothesis has been rejected. If the second test has not led to a rejection of the null hypothesis, the LIML estimator as the optimal combination of Nagar–estimators should be applied. If the second test has also failed, none of these estimators should be used.

Table 6: Employment Effects of Product and Process Innovations for Manufacturing Firms, 1998–2000 (Basic Model)

Basic Model: $l - (g_1 - \widetilde{\pi}_1) = \alpha_0 + \alpha_1\, d + \beta\, g_2 + v$

Regression	(1)	(2)	(3)	(4)	(5)	(6)
Method	OLS	IV	IV	IV	IV	IV
Expl. Variable	coeff. (s.e.)	coeff. (s.e.)	coeff. (s.e.)	coeff. (s.e.)	coeff. (s.e.)	coeff. (s.e.)
Constant	-5.492***	-7.605***	-7.301***	-7.282***	-6.414***	-6.433***
	(1.101)	(1.261)	(1.792)	(1.768)	(1.804)	(1.786)
PROC	-1.251	-3.943**	—	—	—	—
	(1.673)	(1.763)				
PROC_ONLY	—	—	-5.881**	-5.898**	-6.712**	-6.684**
			(2.967)	(2.963)	(2.905)	(2.910)
PROC&PROD	—	—	-2.697	-2.658	-0.851	—
			(2.349)	(2.322)	(2.592)	
SALES_NEWPD	0.883***	1.071***	1.077***	1.075***	0.993***	0.980***
	(0.064)	(0.085)	(0.101)	(0.100)	(0.085)	(0.063)
Adj. R2	0.483	0.462	0.463	0.464	0.478	0.480
Root MSE	27.3	27.8	27.6	27.6	27.2	27.2
W_{IND} (p–value)	—	—	0.160	0.160	0.245	0.238
W_β (p–value)	0.069	0.407	0.447	0.452	0.936	0.747
PH_{all} (p–value)	—	—	—	—	0.950	0.745
PH_{lev} (p–value)	—	—	—	—	0.140	0.120
HH (p–value)	—	—	—	—	0.221	0.226
Hansen J	—	3.52	4.17	6.10	1.11	1.08
(df)		(2)	(2)	(2)	(4)	(4)
p-value		0.172	0.125	0.047	0.893	0.897

Notes:
$***$, $**$ and $*$ indicate significance on a 1%, 5% and 10% level, respectively (standard errors robust to heteroskedasticity in brackets). Number of firms: 1319. Regressions (3)–(6) include 10 industry dummies and Suits' method is used to calculate the overall constant (see text). Instruments: RD_INTENS, RANGE and SHARE_MARK in (2)–(3), INNO_INTENS instead of RD_INTENS in (4). CONT_RD, RANGE, PATENT, CLIENT and SCIENCE in (5)–(6). The Wald test statistic W_{IND} tests for the null hypothesis that the industry dummies are jointly equal to zero and is asymptotically $\chi^2\,(10)$ distributed under H_0. W_β is the Wald test statistic of the test $H_0 : \beta = 1$ and is asymptotically $\chi^2\,(1)$ distributed under H_0. PH_{all} and PH_{lev} test the null hypothesis of homoskedasticity. In (5) $PH_{all} \sim \chi^2\,(107)$ and $PH_{lev} \sim \chi^2\,(17)$ and in (6) $PH_{all} \sim \chi^2\,(91)$ and $PH_{lev} \sim \chi^2\,(16)$ under H_0. HH is the Hahn–Hausman specification test. Here, only the corresponding p–values are reported. J reports the test statistic of a test of overidentifying restrictions. Under H_0, J follows a $\chi^2\,(m)$ distribution with m as the number of overidentifying restrictions. Testing the orthogonality of RD_INTENS in (3), we yield a C statistic of 4.158 (p–value: 0.041). For (6) the corresponding C statistics are: $C_{CONT\_RD} = 0.031$ (p–value: 0.861), $C_{RANGE} = 0.705$ (0.401), $C_{PATENT} = 0.000$ (0.998), $C_{CLIENT} = 0.552$ (0.458), $C_{SCIENCE} = 0.104$ (0.747).

Table 7: Employment Effects of Product and Process Innovations for Service Firms, 1998–2000 (Basic Model)

Basic Model: $l - (g_1 - \widetilde{\pi}_1) = \alpha_0 + \alpha_1\, d + \beta\, g_2 + v$

Regression	(1)	(2)	(3)	(4)	(5)	(6)
Method	OLS	IV	IV	IV	IV	IV
Expl. Variable	coeff. (s.e.)	coeff. (s.e.)	coeff. (s.e.)	coeff. (s.e.)	coeff. (s.e.)	coeff. (s.e.)
Constant	-1.402	-2.403	-6.010	-5.903	-7.814	-7.870
	(1.521)	(1.611)	(6.711)	(6.709)	(7.243)	(7.261)
PROC	4.777	2.472	—	—	—	—
	(2.387)	(2.392)				
PROC_ONLY	—	—	1.353	1.273	2.724	2.792
			(2.959)	(2.958)	(2.982)	(2.989)
PROC&PROD	—	—	3.041	3.283	-1.057	—
			(3.256)	(3.257)	(4.081)	
SALES_NEWPD	0.746***	0.851***	0.833***	0.825***	0.965***	0.955***
	(0.054)	(0.074)	(0.090)	(0.090)	(0.098)	(0.075)
Adj. R2	0.402	0.395	0.416	0.417	0.391	0.394
Root MSE	34.0	34.1	33.4	33.4	34.1	34.0
W_{IND} (p–value)	—	—	0.013	0.013	0.016	0.013
W_{β} (p–value)	0.000	0.046	0.064	0.053	0.721	0.547
PH_{all} (p–value)	—	—	—	—	1.000	1.000
PH_{lev} (p–value)	—	—	—	—	0.714	0.714
HH (p-value)	—	—	—	—	0.150	0.152
Hansen J	—	7.95	9.84	10.21	0.11	0.12
(df)		(2)	(2)	(2)	(3)	(3)
p-value		0.019	0.007	0.006	0.990	0.990

Notes:
$***$, $**$ and $*$ indicate significance on a 1%, 5% and 10% level, respectively (standard errors robust to heteroskedasticity in brackets). Number of firms: 849. Regressions (3)–(6) include 6 industry dummies and Suits' method is used to calculate the overall constant (see text). Instruments: RD_INTENS, RANGE and SHARE_MARK in (2)–(3), INNO_INTENS instead of RD_INTENS in (4). CONT_RD, PATENT, CLIENT and SCIENCE in (5)–(6). The Wald test statistic W_{IND} tests for the null hypothesis that the industry dummies are jointly equal to zero and is asymptotically $\chi^2(6)$ distributed under H_0. W_β is the Wald test statistic of the test $H_0 : \beta = 1$ and is asymptotically $\chi^2(1)$ distributed under H_0. PH_{all} and PH_{lev} test the null hypothesis of homoskedasticity. In (5) $PH_{all} \sim \chi^2(59)$ and $PH_{lev} \sim \chi^2(12)$ and in (6) $PH_{all} \sim \chi^2(48)$ and $PH_{lev} \sim \chi^2(11)$ under H_0. HH is the Hahn–Hausman specification test. Here, only the corresponding p–values are reported. J reports the test statistic of a test of overidentifying restrictions. Under the null hypothesis, J follows a $\chi^2(m)$ distribution with m as the number of overidentifying restrictions. Testing the orthogonality of each instrument in (6), we yield the following C statistics: $C_{CONT\_RD} = 0.099$ (p–value: 0.753), $C_{PATENT} = 0.001$ (0.977), $C_{CLIENT} = 0.036$ (0.849), $C_{SCIENCE} = 0.033$ (0.857).

All in all, I arrive at plausible and, in the first part, very similar estimates for the employment effects of product innovations compared to the results for Spain, France and the UK; however, there are discernible differences concerning the impact of process innovations (see Jaumandreu 2003 and Harrison et al. 2004.)

The main result, which is quite robust to different specifications, is that successful product innovations have a significantly positive employment impact, i.e., the higher the sales growth rate due to product innovations, the higher the employment growth rate. This impact tends to be larger in manufacturing than in services. Recall that β measures the relative efficiency across production processes, i.e., if new products are produced more efficiently than the old ones, then this ratio is less than unity and employment does not grow one–for–one with the sales growth accounted for by new products. Jaumandreu (2003) found a unit elasticity of employment with respect to innovative output in terms of sales growth due to new products for Spanish firms. The t–tests show that the null hypothesis of a unit elasticity cannot be rejected for German firms in all estimations, even in the service sector. At the same time, one must consider that product innovations can displace existing products to a considerable extent; this also leads to downsizing. An estimation of the net employment effect of product innovations will be undertaken in the following section 6.3.

Furthermore, the estimation results of the extended model, given in Tables 8 and 9, suggest that new jobs are created not only in firms with market novelties, but also in those which successfully pursue imitation strategies. Both variables are significant, and using an F–test, the null hypothesis that both coefficients are equal cannot be rejected. This result suggests that the employment effects do not vary significantly with the product novelty degree. This conclusion is valid for manufacturing as well as service firms. Hence, at least for the German manufacturing sector, this result is partly in contrast to previous conclusions drawn by Falk (1999).[20]

Note that industry dummies are included in most of the regressions. The estimation equation is specified in growth rates, i.e., in first differences. This implies that time–invariant firm–specific (observable and unobservable) effects in the employment levels are already eliminated. However, the inclusion of industry dummies enlarge the flexibility of the specification by allowing for an unspecified form of heterogeneity in the growth rates between industries.

[20] Using CIS 2 data covering the period 1994–1996, Falk (1999) showed that only market novelties have stimulated the expected labour demand. The expected employment change was an ordinal variable in the data set which required a different estimation method (ordered probit model). Furthermore, he used dummy variables for both kinds of product innovations. Replacing the continuous variables in equation (11) with their dummy counterparts, however, did not alter the qualitative results.

Based on the theoretical model the constant can be interpreted as the average real productivity growth (with negative sign) in the production of old products in the reference period that is not traceable to own process innovation activities of that period, but, e.g., to organisational changes, sales of less productive parts of the firm, acquisitions of higher productive firms, improvements in human capital, learning or spill–over effects).[21] Inclusion of industry dummies of course implies that the constant term cannot be interpreted as average real productivity growth since it is related to the respective reference industry. To get an estimate of the average value, we thus use Suits' method. Suits (1984) suggested that once the equation has been estimated, one can choose a value k and add it to each of the coefficients of the industry dummies (including of course the zero coefficient of the dropped–out industry) and substract it from the constant term. The value k is chosen so that the resulting new industry dummy coefficients average zero.[22] Estimating the equation with all industry dummies and this restriction would yield identical statistical properties as the original estimation. The estimates show the expected negative sign of the constant and reasonable magnitudes for a two–year period (about 3.2 per cent p.a. average real productivity growth in manufacturing and 3.9 per cent in the service sector). In any case, this kind of productivity advances in the service sector seem to broadly differ from manufacturing for any firm (innovators and non–innovators). The constant is not significant and less robust.

In the theoretical model, the process innovation dummy should pick up additional efficiency gains and thus employment changes due to changes in the production process of the old product. However, the information in the data set does not allow to distinguish between process innovations applied to old or new products. To partially address this problem, we divide process innovators up into two groups: firms with process innovations only (corresponds by definition to old products) and firms with both product and process innovations, where changes in the production technology could be related to both old or new products.

The empirical analysis shows differences between the manufacturing and service sectors regarding the impact of process innovations: Process innovations were responsible for an employment reduction in the period 1998–2000 in the manufacturing, but not in the service sector. From a theoretical point of view, this can be interpreted in a way that displacement effects outweigh compensation effects in manufacturing, resulting in a negative employment effect. Conversely, the results suggest that service firms tend to react more aggressively and pass on to prices the

[21] Since we control for (industry) price changes of the old product, the value of the constant is an estimate of average real productivity growth, after any compensating price effects.

[22] Since the new coefficients are linear combinations of the original coefficients, their variance can easily be calculated from the original variance–covariance matrix.

Table 8: Employment Effects of Different Types of Product and Process Innovations for Manufacturing Firms, 1998–2000 (Extended Model)

$$\text{Extended Model: } l - g_1 - \widetilde{\pi}_1 = \alpha_0 + \alpha_c\, d_c + \alpha_{nc}\, d_{nc} + \beta_m\, g_{2m} + \beta_f\, g_{2f} + v$$

Regression	(8)	(9)	(10)	(11)	(12)	(13)
Expl. Var.	coeff. (s.e.)	coeff. (s.e.)	coeff. (s.e.)	coeff. (s.e.)	coeff. (s.e.)	coeff. (s.e.)
Constant	-6.823*** (1.602)	-6.822*** (1.602)	-6.488*** (1.803)	-6.484*** (1.801)	-6.467*** (1.809)	-7.157*** (2.332)
PROC	-2.891 (1.903)	—	—	—	—	—
RATION	—	-3.075 (1.951)	—	—	—	—
OTHER_PROC	—	-2.459 (3.222)	—	—	—	—
PROC_ONLY	—	—	-6.614** (2.897)	—	—	—
RATION_ONLY	—	—	—	-8.081** (3.452)	-8.102** (3.449)	-7.621** (3.368)
OTHER_PROC_ ONLY	—	—	—	-3.179 (4.956)	-3.203 (4.959)	-3.193 (4.975)
RATION&PROD	—	—	—	—	-0.362 (2.269)	—
SALES_FIRM	1.055*** (0.177)	1.052*** (0.178)	1.045*** (0.168)	1.044*** (0.168)	1.042*** (0.170)	1.006*** (0.175)
SALES_MARK	0.986*** (0.277)	0.992*** (0.278)	0.877*** (0.265)	0.878*** (0.265)	0.891*** (0.278)	0.990*** (0.268)
SIZE: 10-49	—	—	—	—	—	0.995 (1.415)
SIZE: 50-499	—	—	—	—	—	1.263 (1.102)
SIZE: 500+	—	—	—	—	—	-2.258 (1.849)
INVEST	—	—	—	—	—	-0.013 (0.037)
Adj. R2	0.472	0.472	0.478	0.478	0.478	0.477
Root MSE	27.4	27.4	27.2	27.2	27.2	27.2
W_{IND} (p–val)	0.229	0.226	0.243	0.240	0.239	0.167
W_{SIZE} (p–val)	—	—	—	—	—	0.236
$W_{\beta_f=\beta_m}$ (p–val)	0.872	0.889	0.685	0.687	0.718	0.970
Hansen J	1.30	1.32	0.96	0.95	0.97	1.17
(df)	(3)	(3)	(3)	(3)	(3)	(3)
p–value	0.729	0.726	0.810	0.814	0.808	0.760

Notes:
$***$, $**$ and $*$ indicate significance on a 1%, 5% and 10% level, respectively (standard errors robust to heteroskedasticity in brackets).
Number of firms: 1319. Instruments: CONT_RD, RANGE, PATENT, CLIENT and SCIENCE. Regression (13) include size dummies and Suits' method is used to calculate the overall constant and the 3 size dummies (see text). See also the notes of Table 6.

Table 9: Employment Effects of Different Types of Product and Process Innovations for Service Firms, 1998–2000 (Extended Model)

Extended Model: $l - g_1 - \widetilde{\pi}_1 = \alpha_0 + \alpha_c\, d_c + \alpha_{nc}\, d_{nc} + \beta_m\, g_{2m} + \beta_f\, g_{2f} + v$

Regression	(8)	(9)	(10)	(11)	(12)	(13)
Expl. Var.	coeff. (s.e.)	coeff. (s.e.)	coeff. (s.e.)	coeff. (s.e.)	coeff. (s.e.)	coeff. (s.e.)
Constant	-7.682	-7.498	-7.796	-7.777	-7.730	-8.563
	(9.037)	(8.574)	(10.361)	(10.360)	(10.252)	(21.214)
PROC	0.411	—	—	—	—	—
	(3.995)					
RATION	—	1.810	—	—	—	—
		(3.202)				
OTHER_PROC	—	-1.596	—	—	—	—
		(5.606)				
PROC_ONLY	—	—	2.746	—	—	—
			(3.152)			
RATION_ONLY	—	—	—	2.500	2.495	2.780
				(3.399)	(3.393)	(3.946)
OTHER_PROC_ ONLY	—	—	—	2.411	2.403	2.712
				(4.664)	(4.656)	(5.027)
RATION&PROD	—	—	—	—	2.291	—
					(4.012)	
SALES_FIRM	0.948**	0.941**	0.939**	0.941**	0.919**	0.957**
	(0.470)	(0.448)	(0.410)	(0.409)	(0.407)	(0.415)
SALES_MARK	0.953**	0.952**	0.971**	0.969**	0.960**	0.979**
	(0.449)	(0.449)	(0.454)	(0.454)	(0.450)	(0.431)
SIZE: 10-49	—	—	—	—	—	0.752
						(7.800)
SIZE: 50-499	—	—	—	—	—	3.263
						(5.047)
SIZE: 500+	—	—	—	—	—	-4.015
						(20.411)
INVEST	—	—	—	—	—	-0.006
						(0.005)
Adj. R2	0.394	0.395	0.392	0.391	0.394	0.389
Root MSE	34.0	34.0	34.1	34.1	34.0	34.1
W_{IND} (p–val)	0.020	0.023	0.019	0.019	0.018	0.019
W_{SIZE} (p–val)	—	—	—	—	—	0.243
$W_{\beta_f=\beta_m}$ (p–val)	0.996	0.991	0.970	0.974	0.961	0.979
Hansen J	0.11	0.10	0.11	0.11	0.12	0.18
(df)	(2)	(2)	(2)	(2)	(2)	(2)
p–value	0.949	0.950	0.945	0.945	0.943	0.916

Notes:
$***$, $**$ and $*$ indicate significance on a 1%, 5% and 10% level, respectively (standard errors robust to heteroskedasticity in brackets).
Number of firms: 1319. Instruments: CONT_RD, PATENT, CLIENT and SCIENCE. Regression (13) include size dummies and Suits' method is used to calculate the overall constant and the 3 size dummies (see text). See also the notes of Table 7.

productivity gains derived from innovations to a larger extent which may be a result of less market power of service firms on average. However, the results for services should be interpreted with more care as innovation processes in the service sector exhibit substantial differences compared to the manufacturing sector. In the service sector, the distinction between old and new services or processes is hindered by the fact that services are more often customized to specific demands, and that in many cases a clearly structured production process is lacking. Innovations in services are therefore more difficult to identify than in the manufacturing sector (see, e.g., Hempell 2003).

Moreover, the estimates show that only manufacturing firms which solely carried out process innovations experienced negative employment effects, while this was not the case for firms that introduced both new products and new processes. This result leads to the conclusion that different innovation strategies appear to be associated with different price behaviour. However, column (11) of Table 8 further reveals that this is not true for all firms that exclusively introduced process innovations, but rather only for those firms which merely concentrated on rationalisation innovations. These varying effects of different types of process innovations may be one explanation as to why there is no clear empirical evidence of a robust (negative or positive) effect of process innovations on employment. The aims associated with the introduction of new production technologies (and thus, the composition of process innovations in the sample under consideration) may, for instance differ according to the level of economic activity or to different industries.[23]

Employment changes might be influenced by many other economic factors. Besides the technological progess and the industry structure, wages, investment or firm size[24] might be important in explaining employment growth. Labour supply factors like preferences for leisure or the qualification level of the labour supply may also have an influence on the employment. Due to data limitations we cannot control for the latter ones. But, firm size (proxied by three different size classes according to employment in the base year 1998) and investment were controlled for in the last columns of Tables 8 and 9. Firm size, however, as well as the investment variable turned out to be not significant.

Equation 10 was derived under the assumption of constant factor prices. Table

[23] König et al. (1995) found a significant positive effect of process innovations for the boom period 1990–1992, while Blechinger and Pfeiffer (1999) reported a significant negative effect for the recession period 1993–1995.

[24] According to Gibrat's law, firms grow (in terms of employment or sales) proportionally and independently of their size, see Gibrat (1934). In constrast to that, Jovanovic (1982), for instance, stressed the importance of managerial efficiency and learning by doing, and developed a model in which surving young and small firms grow faster than older and larger ones.

Table 10: Effects of Innovations and Labour Costs on Employment, 1998–2000 (Reduced Sample)

Basic Model: $l - (g_1 - \widetilde{\pi}_1) = \alpha_0 + \alpha_1 \, d + \beta \, g_2 + v$

	Manufacturing			Services		
	coeff. (s.e.)	coeff. (s.e.)	coeff. (s.e.)	coeff. (s.e.)	coeff. (s.e.)	coeff. (s.e.)
Constant	-6.162*** (2.100)	-6.020*** (2.253)	-5.484** (2.257)	-7.696 (7.208)	-1.857 (25.337)	-2.197 (20.878)
PROC_ONLY	-6.475** (2.857)	-5.893* (3.249)	-6.169* (3.212)	2.628 (2.986)	-7.252 (5.587)	-9.412* (4.903)
SALES_ NEWPD	0.984*** (0.063)	0.981*** (0.072)	0.977*** (0.071)	0.958*** (0.076)	0.843*** (0.217)	0.857*** (0.195)
INVEST	-0.013 (0.039)	-0.027 (0.036)	-0.028 (0.035)	-0.006 (0.005)	0.009 (0.017)	0.003 (0.014)
LAB_COSTS	—	—	-0.091** (0.045)	—	—	-0.296*** (0.070)
Adj. R2	0.480	0.473	0.476	0.393	0.519	0.564
Root MSE	27.2	23.6	23.5	34.1	22.7	21.6
W_{IND} (p–val)	0.228	0.085	0.072	0.012	0.020	0.008
W_{β} (p–val)	0.797	0.795	0.751	0.580	0.471	0.463
Hansen J	1.15	0.72	0.71	0.14	2.55	2.71
(df)	(4)	(4)	(4)	(3)	(3)	(3)
p–value	0.887	0.949	0.951	0.987	0.467	0.439
# of firms	1319	701	701	849	257	257

Notes:
$***$, $**$ and $*$ indicate significance on a 1%, 5% and 10% level, respectively (standard errors robust to heteroskedasticity in brackets).
Instruments: CONT_RD, RANGE (only in manufacturing), PATENT, CLIENT and SCIENCE.
Hansen J reports the test statistic of a test of overidentifying restrictions. Under the null hypothesis, J follows a $\chi^2\,(m)$ distribution with m as the number of overidentifying restrictions.

10 shows some further robustness checks of the basic model by relaxing this assumption and controlling for changes in average labour costs. The sample had to be reduced remarkably for this exercise because the labour cost growth rate could only be constructed by merging the German innovation surveys of 2001 and 1999 and the intersection of firms came to 55 per cent in manufacturing and 30 per cent in services.[25] The negative sign of the estimator associated with the labour costs variable is what we expected (see for instance Blechinger et al. 2004 or Smolny 1998) while the coefficients associated with the innovation variables are little affected. The

[25] The core CIS questionnaire did not provide information on labour cost. The latter is an additional information in the German data set.

coefficient of the sales growth due to new products has slightly declined in manufacturing and has decreased to a larger extent in services, however, this seemed to be the result of the reduced sample itself.

6.3 Decomposition of Employment Growth

Based on the basic model estimation, the following decomposition holds for each firm (see Harrison et al. 2004):

$$\begin{aligned} l &= \widehat{\alpha}_0 + \widehat{\alpha}_1 \, d + [1 - 1(g_2 > 0)] \, (g_1 - \widetilde{\pi}_1) \\ &\quad + 1(g_2 > 0) \, (g_1 - \widetilde{\pi}_1 + \widehat{\beta} \, g_2) + \widehat{u}, \end{aligned} \tag{12}$$

where $1(\cdot)$ denotes the indicator function. The first term shows the change in employment due to productivity gains which are not attributable to own process innovations in the respective period, but to organisational changes, sales of less productive firm components, acquisitions of higher productive firms, improvements in human capital endowment, learning or spill–over effects, etc. Notice, that incremental changes in the production process are likewise counted here since they are not covered by the definition of process innovation. This term is referred to as a general productivity trend. The second term presents the net contribution made by process innovations related to the old product. Here, net contribution is understood as the result of displacement effects brought about by process innovations and the compensatory demand effects owing to cost and price reductions. The third component registers so called general output effects seen in the production of the old product for non–product innovators. That is, the third component accounts for changes in employment growth due to shifting demand for the existing product. This shift in demand can be the result of cyclical impacts, rivals' product innovations, changes in consumers' preferences, etc. Finally, the fourth term summarises the net contribution of product innovations on employment for product innovators. In this case, this effect constitutes the result of increases in demand for the new product and possible shifts in demand for the old one. $\widehat{u}$ is the residual term. In the case of the extended model, the enlargement and interpretation of the decomposition is straightforward:

A dissection of the average employment growth can be obtained by inserting the average shares of innovators from the sample and the estimated coefficients into the equation.[26] Table 11 displays the results of the employment growth component dissection separately for the manufacturing and the service sector. As an advance

[26] This is equal to calculate separately the four terms and the residual for each firm and then take the average of each term. Note, that the mean of $\widehat{u}$ is zero by construction.

disclaimer, it should be mentioned that this decomposition presents the average effect of innovation activities on the employment growth of firms which survived, i.e., were active in the market at the beginning and end of the phase. Since no information on newly founded or withdrawing firms enter into the analysis, macroeconomic conclusions are limited.

Table 11: Decomposition of Average Employment Growth, 1998–2000[a)]

	Manufacturing		Services	
	Basic Model	Extended Model	Basic Model	Extended Model
Employment Growth	**5.9**	**5.9**	**10.2**	**10.2**
Decomposed into:				
Productivity trend in prod. of old products[b]	-6.9	-6.9	-3.6	-3.5
Net contribution of process innovation	-0.7	—	0.3	—
Net contribution of rationalisation innovation	—	-0.6	—	0.1
Net contribution of other process innovation	—	-0.1	—	0.1
Output growth of old products	6.0	6.0	5.4	5.4
Net contribution of product innovations	7.5	7.5	8.2	8.1
thereof:				
output reduction of old products	-8.8	-8.8	-7.4	-7.4
output increase of new products	16.4	—	15.6	—
output increase of market novelties	—	5.6	—	6.3
output increase of firm novelties	—	10.8	—	9.3

Notes:
a) Rates of growth (in %) for the whole period 1998–2000. Decomposition is based on Tables 4, 3 and on regressions (6) in Tables 6 and 7 in the basic model and regressions (11) in Tables 8 and 9 in the extended model. The sum of decomposition values may differ slightly from employment growth because of rounding.
b) Productivity trend is the weighted sum of industry dummy values and hence differs from the constant of the regression.
Source: Own calculations.

It is apparent that employment growth in manufacturing results primarily from product innovations. In the period 1998–2000, general productivity gains, process innovations and output effects related to old products would have led to an overall decrease in employment of 2 per cent. This deterioration of labour was, however, more than compensated for by product innovations, even considering the fact that new products replace previously offered goods by product innovators to some extent. The net effect of product innovation is about 7.5 per cent. The observed employment growth was thus based mostly on the introduction of new products. Looking at the extended model, we can infer that the contribution of firm novelties to employment growth is higher than that of market novelties. Given that the estimated coefficients for both kinds of product innovations are very similar, this result is mainly driven by the different means of the sales growth rates which in part also reflect the fact that market novelties are less common than firm novelties across product innovating firms. The net impact of process innovations on employment growth is negative in manufacturing, but is of secondary importance when observed quantitatively (-0.7 per cent). However, it should be noticed, that using PROC_ONLY, the significance of process innovations may be slightly underestimated. But as mentioned above, with the data at hand it is not possible to distinguish which process innovations of product innovators relate to the old and which to the new products.

The general picture in the service sector is similar, however, with some interesting differences. Most obviously, based on the estimates the general productivity trend in the production of old products in the service sector is merely about half of that in manufacturing. On the other hand and similarly to manufacturing, product innovations contribute the most to employment growth, with the absolute value here being higher for services (8.2 per cent in the basic model). Their relative influence, however, is weaker than in manufacturing. In other words, in the service sector general productivity effects, process innovations and demand effects related to old products also contributed positively to employment growth, that is, led overall to a labour expansion. As in manufacturing, firm novelties contribute more to employment growth than market novelties. And all in all, the net effect of process innovations is negligible in the service sector.

7 Conclusion

Using the multi–product approach recently proposed by Jaumandreu (2003) and Harrison et al. (2004), this study investigates to what extent employment growth in the German manufacturing and service sector between 1998–2002 can be explained by output growth of existing products, output of newly introduced products, and the productivity growth both attributable and not attributable to process innovation. In a second step, I contribute to the literature by analysing different types of both product and process innovations according to the theoretical considerations that their employment effects may differ.

The econometric results confirm that successful product innovations have a positive impact on gross employment in the innovating firm. Furthermore, there is no evidence of labour displacement effects associated with product innovation and the results provide evidence that gross employment does grow one–for–one with the sales growth accounted for by new products. The impact tends to be larger in manufacturing than in service firms, although the difference is statistically not significant. That is, an increase in the success of product innovations (measured in terms of sales growth due to new products) by one per cent lead to an increase in gross employment by one per cent. At the same time, new products can displace existing ones within the innovating firm to a considerable extent which leads to downsizing. But, the decomposition of employment growth provides evidence that the net effect is positive and that product innovations have been the major driver of employment growth in the period under consideration. This result turns out to be very robust with respect to different specifications, the business cycle and methods used. Various specification tests further show that the preferred instrumental variable estimation is appropriate and does not suffer from endogenous or weak instruments which could heavily bias the complete results.

In addition to that, the estimation results indicate that new jobs are not only created in firms launching market novelties, but also in firms which successfully pursue product imitation strategies. Moreover, the coefficients of both indicators of product innovation success were not significantly different. This holds for manufacturing and service firms. Hence, this result contradicts the hypothesis that employment effects depend on the degree of product novelty.

The impact of process innovations on employment growth turns out to be variable. In manufacturing firms, results indicate that process innovations are labour–saving. That is, labour displacement effects outweigh compensation effects, leading to a fall in employment. But, as expected, the estimation results also reveal that not all process innovations are associated with employment reduction. Jobs are merely significantly deteriorated through rationalisation innovations, but not as a consequence of other process innovations, e.g., as those intended to improve product quality. In the service sector, however, a different picture emerges. Here, process innovations are not responsible for a significant downsizing in labour. Various reasons could explain this difference between manufacturing and service. The first explanation is related to the specific nature of services and its production. The provision of services is typically strongly geared towards customer preferences, and clearly structured production processes are often lacking complicating the distinction between new and existing products (services) and processes. If this is true, this could imply that a part of the effects of new processes is attributed to product innovations and this could also explain why the coefficient of this variable is a bit lower than in manufacturing (assuming process innovations have likewise a negative impact in the service sector). An alternative explanation might be that service firms are smaller on average than manufacturing firms and have thus less market power on average which forces them to pass on efficiency gains derived from innovations to costumers to a larger extent. Unfortunately, with the data at hand it is not possible to distinguish between these alternative explanations. All in all, the decomposition of the employment growth provides evidence that the net effect of process innovation is only small in both manufacturing and the service sector.

Finally, from an international perspective the results for the employment effects of product innovations are very similar to those found for Spain, UK and France, thus supporting a discernible international pattern in the firm–level association between innovation and employment. However, the empirical analysis reveals different impacts of process innovations.

The potential employment effects of innovations may even be underestimated for the boom period 1998–2000 because a growing number of firms reported for that period that they could not meet their demand for qualified personnel (see Ebling et al. 2000).

Furthermore, we consider a three–year period to analyse the impact of innovation activities on labour. Admittedly one might ask whether this is enough to assess the entire employment consequences. While it is sensible to assume that displacement effects of process or product innovations won't be lagging much to the time of their introduction, compensation effects especially of process innovations may appear with a certain delay. Given that this assumption is true, this would imply that I may even overestimate the negative, respectively underestimate the presumably positive employment impact of process innovations. Estimating the time period in which compensation effects of product innovations arise is further complicated by the fact that the amount and sustainability of such compensation effects resulting from demand increases depend on the competition and the way and delay with which competitors react. A full assessment of long–term employment effects would require a panel data analysis which is on the agenda of future research.

These empirical findings on employment effects are restricted to the level of the innovating firm, while neglecting the wider consequences. On a sector or aggregate level, technological change may be associated with further impacts on firms' labour demand, which are beyond the scope of the present study.

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Data Appendix

The data set used is based on the 2001 official innovation survey in the German manufacturing and service industries, which was the German part of the Community Innovation Surveys CIS 3. In Germany, the survey was conducted by the Centre for European Economic Research (ZEW) on behalf of the German government. The survey covers legally independent German firms from the sectors mining and quarrying, manufacturing, electricity, gas and water supply as well as construction (NACE classes 10–14, 15–37, 40–41 and 45) and from various service sectors (NACE 50–52, 60–64, 65–67, 70–74, 90). The sample of the innovation survey is drawn as a stratified random sample. Firm size (8 size classes according to the number of employees), sector (according to two-digit NACE classes) and region (East and West Germany) serve as stratifying variables. The innovation survey is performed voluntarily by mail. For a detailed description of the survey methodology as well as the surveyed information, see Janz et al. (2001).

Tables

Table 12: Sample by Industry

Industry	Nace	Total		NON–INNO		PROC_ ONLY		PROD_ ONLY		PROD& PROC	
		#	%$^{a)}$	#	%$^{b)}$	#	%$^{b)}$	#	%$^{b)}$	#	%$^{b)}$
Manufact.											
Food	15–16	113	*8.6*	72	*63.7*	7	*6.2*	13	*11.5*	21	*18.6*
Textile	17–19	77	*5.8*	48	*62.3*	7	*9.1*	16	*20.8*	6	*7.8*
Wood	20–22	112	*8.5*	58	*51.8*	21	*18.8*	11	*9.8*	22	*19.6*
Chemicals	23–24	92	*7.0*	28	*30.4*	10	*10.9*	21	*22.8*	33	*35.9*
Plastic	25	116	*8.8*	39	*33.6*	10	*8.6*	28	*24.1*	39	*33.6*
Glass	26	78	*5.9*	39	*50.0*	4	*5.1*	14	*18.0*	21	*26.9*
Metals	27–28	227	*17.2*	113	*49.8*	40	*17.6*	23	*10.1*	51	*22.5*
Machinery	29	184	*14.0*	58	*31.5*	14	*7.6*	55	*29.9*	57	*31.0*
Elec. eng.	30–33	214	*16.2*	46	*21.5*	9	*4.2*	75	*35.1*	84	*39.3*
Vehicles	34–35	53	*4.0*	21	*39.6*	4	*7.6*	11	*20.8*	17	*32.1*
Furniture	36–37	53	*4.0*	25	*47.2*	8	*15.1*	10	*18.9*	10	*18.9*
Total		**1319**	***100***	**547**	***41.5***	**134**	***10.2***	**277**	***21.0***	**361**	***27.4***
Services											
Wholesale	51	204	*24.0*	131	*64.2*	16	*7.8*	28	*13.7*	29	*14.2*
Transport	60–63	204	*24.0*	143	*70.1*	20	*9.8*	18	*8.8*	23	*11.3*
Post/tele.	64	26	*3.1*	19	*73.1*	1	*3.9*	2	*7.7*	4	*15.4*
Bank/ins.	65–67	97	*11.4*	36	*37.1*	10	*10.3*	12	*12.4*	39	*40.2*
Computer	72	80	*9.4*	16	*20.0*	4	*5.0*	33	*41.3*	27	*33.8*
R&D.	73	75	*8.8*	15	*20.0*	8	*10.7*	20	*26.7*	32	*42.7*
Tec. serv.	74.2 –74.3	163	*19.2*	76	*46.6*	20	*12.3*	37	*22.7*	30	*18.4*
Total		**849**	***100***	**436**	***51.4***	**79**	***9.3***	**150**	***17.7***	**184**	***21.7***

Notes:
$^{a)}$ As percentage share of total firms in manufacturing and services, respectively.
$^{b)}$ As percentage share of firms in the relevant branch of industry.
Source: Own calculations.

Table 13: Sample by Size Class

Size Class	Total		NON_ INNO		PROC_ ONLY		PROD_ ONLY		PROD& PROC	
	#	%$^{a)}$	#	%$^{b)}$	#	%$^{b)}$	#	%$^{b)}$	#	%$^{b)}$
Manufacturing										
10 – 19	193	*14.6*	115	*59.6*	18	*9.3*	35	*18.1*	25	*13.0*
20 – 49	321	*24.3*	177	*55.1*	30	*9.4*	63	*19.6*	51	*15.9*
50 – 99	244	*18.5*	109	*44.7*	23	*9.4*	53	*21.7*	59	*24.2*
100 – 199	198	*15.0*	74	*37.7*	25	*12.6*	44	*22.2*	55	*27.8*
200 – 499	221	*16.8*	47	*21.3*	25	*11.3*	54	*24.4*	95	*43.0*
500 – 999	91	*6.9*	17	*18.7*	10	*11.0*	18	*19.8*	46	*50.6*
1000+	51	*3.9*	8	*15.7*	3	*5.9*	10	*19.6*	30	*58.8*
Total	**1319**	***100***	**547**	***41.5***	**134**	***10.2***	**277**	***21.0***	**361**	***27.4***
Services										
10 – 19	266	*31.3*	159	*59.8*	21	*7.9*	48	*18.1*	38	*14.3*
20 – 49	257	*30.3*	153	*59.5*	20	*7.9*	46	*17.9*	38	*14.8*
50 – 99	127	*15.0*	59	*46.5*	18	*14.2*	21	*16.5*	29	*22.8*
100 – 199	87	*10.3*	35	*40.2*	7	*8.1*	15	*17.2*	30	*34.5*
200 – 499	46	*5.4*	18	*39.1*	5	*10.9*	8	*17.4*	15	*32.6*
500 – 999	33	*3.9*	7	*21.2*	5	*15.2*	8	*24.2*	13	*39.4*
1000+	33	*3.9*	5	*15.2*	3	*9.1*	4	*12.1*	21	*63.4*
Total	**849**	***100***	**436**	***51.4***	**79**	***9.3***	**150**	***17.7***	**184**	***21.7***

Notes:
a) As percentage share of total firms in manufacturing and services, respectively.
b) As percentage share of firms in the relevant branch of industry.
Source: Own calculations.

Table 14: First Step Estimation Results

Sample	Manufacturing			Services		
Endog. Var.	SALES_ NEW PD	SALES_ FIRM	SALES_ MARK	SALES_ NEW PD	SALES_ FIRM	SALES_ MARK
Regression	(6)	(11)	(11)	(6)	(11)	(11)
	coeff. (s.e.)	coeff. (s.e.)	coeff. (s.e.)	coeff. (s.e.)	coeff. (s.e.)	coeff. (s.e.)
Constant	0.168	−0.178	0.345	2.521	0.947	1.503
	(2.467)	(1.704)	(1.788)	(2.298)	(1.656)	(1.550)
PROC_ ONLY	−18.053***	—	—	−18.186***	—	—
	(2.395)			(3.749)		
RATION_ ONLY	—	−11.805***	−6.000***	—	−11.691***	−7.324**
		(1.930)	(2.026)		(3.694)	(3.457)
OTHER_ PROC_ ONLY	—	−12.690***	−5.949**	—	−10.947***	−6.796*
		(2.880)	(3.023)		(3.789)	(3.546)
CONT_RD	10.482***	3.689***	6.797***	15.231***	9.205***	6.057***
	(1.952)	(1.348)	(1.415)	(3.145)	(2.268)	(2.123)
RANGE	11.922***	9.992***	1.936	—	—	—
	(1.928)	(1.332)	(1.398)			
CLIENT	7.597***	5.350***	2.244*	9.897***	5.301***	4.632***
	(1.937)	(1.338)	(1.404)	(2.673)	(1.927)	(1.804)
SCIENCE	7.418***	6.033***	1.381	15.437***	13.284***	2.151
	(2.782)	(1.921)	(2.016)	(4.920)	(3.546)	(3.318)
PATENT	2.055	−1.626	3.679***	20.677***	4.539	16.119***
	(1.873)	(1.293)	(1.357)	(4.465)	(3.219)	(3.012)
Adj. R2	0.27	0.23	0.10	0.26	0.19	0.13
Partial R2	0.199	0.169	0.075	0.154	0.089	0.093
Shea R2	0.199	0.051	0.023	0.154	0.021	0.022
Partial F	83.74	55.14	30.10	20.10	20.48	21.42
p-value	0.000	0.000	0.000	0.000	0.000	0.000
# of firms	1319	1319	1319	849	849	849

Notes:
$***$, $**$ and $*$ indicate significance on a 1%, 5% and 10% level, respectively (standard errors robust to heteroskedasticity in brackets).
Industry dummies are included in all regressions. Partial F is the F statistic of the partialled out reduced form regression. Under the null hypothesis F follows asymptotically a $\chi^2(5)$ and $\chi^2(4)$ distribution in manufacturing and services respectively. Partial R2 reports the R2 of the partialled out reduced form regression. Shea R2 denotes Shea's Partial R2 for two endogenous variables.
Source: Own calculations.

Table 15: Robustness of Estimation Results: Instrumental Variable versus General Method of Moments Estimation

Basic Model: $l - (g_1 - \widetilde{\pi}_1) = \alpha_0 + \alpha_1 \, d + \beta \, g_2 + v$

	Manufacturing		Services	
Method	IV	GMM	IV	GMM
Expl. Variable	coeff. (s.e.)	coeff. (s.e.)	coeff. (s.e.)	coeff. (s.e.)
Constant	-6.433***	-6.573***	-7.870	-7.877
	(1.786)	(1.756)	(7.261)	(7.195)
PROC_ONLY	-6.684**	-6.780**	2.792	2.816
	(2.910)	(2.882)	(2.989)	(2.981)
SALES_NEWPD	0.980***	0.985***	0.955***	0.952***
	(0.063)	(0.062)	(0.075)	(0.073)
Adj. R2	0.480	0.480	0.394	0.395
Root MSE	27.2	27.2	34.0	34.0
W_{IND} (p-value)	0.238	0.231	0.013	0.013
W_{β} (p-value)	0.747	0.812	0.547	0.517
PH_{all} (p-value)	0.745	—	1.000	—
PH_{lev} (p-value)	0.120	—	0.714	—
Hansen J	1.08	1.08	0.12	0.12
(df)	(4)	(4)	(3)	(3)
p-value	0.897	0.897	0.990	0.990
# of firms	1319	1319	849	849

Notes:
$***$, $**$ and $*$ indicate significance on a 1%, 5% and 10% level, respectively (standard errors robust to heteroskedasticity in brackets).
Instruments: CONT_RD, RANGE (only in manufacturing), PATENT, CLIENT and SCIENCE. Regressions include industry dummies and Suits' method is used to calculate the overall constant (see text). The Wald test statistic W_{IND} tests for the null hypothesis that the industry dummies are jointly equal to zero and is asymptotically $\chi^2\,(10)$ distributed under H_0 in manufacturing and $\chi^2\,(6)$ in services . W_β is the Wald test statistic of the test $H_0 : \beta = 1$ and is asymptotically $\chi^2\,(1)$ distributed under H_0. PH_{all} and PH_{lev} test the null hypothesis of homoskedasticity. $PH_{all} \sim \chi^2\,(91)$ and $PH_{lev} \sim \chi^2\,(16)$ under H_0 in manufacturing and $PH_{all} \sim \chi^2\,(48)$ and $PH_{lev} \sim \chi^2\,(11)$ in services. Here, only the corresponding p–values are reported. J reports the test statistic of a test of overidentifying restrictions. Under H_0, J follows a $\chi^2\,(m)$ distribution with m as the number of overidentifying restrictions.