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# Firm Growth, Innovation and the Business Cycle

Background Report for the 2014 Competitiveness Report

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# Chapter 1. INTRODUCTION

## 1.1. BACKGROUND

The impacts of the economic crisis, set off in 2008 and still ongoing in many European countries, have been far reaching on the ability of the EU economy to innovate, grow and create jobs. Overcoming the current economic crisis and ensuring long-term competitiveness and growth is thus a key challenge for European policy. Research, development (R&D) and innovation - the main sources of knowledge creation - are seen as key drivers for competitiveness of firms and, consequently, for economic growth. This is why R&D and innovation has been placed at the heart of the new ‘Europe 2020’ strategy for smart, sustainable and inclusive growth and job creation. Within the Europe 2020 strategy, the Innovation Union is one of the seven flagship initiatives in order to reach smart, sustainable and inclusive growth. With several action points, the Innovation Union aims to improve conditions and access to finance for research and innovation in Europe and to ensure that innovative ideas can be turned into products and services that create growth and jobs. All in all, policies to foster innovation activities are, therefore, high on the list of priorities within the Europe 2020 strategy in general and the EU Innovation Union in particular. A key question in the current debate, however, is to what extent countries hit by the crisis are able to develop new industries and seize growth opportunities offered by new technologies and ideas or whether they lack innovation dynamism. This greatly hinges upon firm’s innovation behaviour over the business cycle in general and during recessions in particular and how innovation affects long-term competitiveness and growth in times of economic boom or crisis. However, innovation, growth and employment and the business cycle are interlinked in a complex way. It is therefore essential to provide empirical evidence on the productivity and employment growth effects of innovation over the business cycle in order to improve our understanding about the interrelationship between them.

Quantifying the effects of innovation on productivity and employment growth has been one of the most challenging tasks in empirical economics for several decades. For a long time, empirical studies have focused on input-oriented innovation indicators when analysing the impact of innovation on productivity and employment growth. In particular, firms’ R&D expenditures have been employed as innovation indicator as they represent an important ingredient for the creation of new products and processes within firms. With respect to productivity and stimulated by the seminal work of Griliches, many empirical studies have shown that firms investing in R&D experience on average an increase in productivity (Griliches 1979, Griliches and Mairesse 1983, Griliches 1986, Mairesse and Sassenou 1991, Griliches 1995, 1998, Hall et al. 2010). In another seminal paper Crèpon et al. (1998) extended this kind of analysis and they showed that there is a positive link from innovation expenditure to product and process innovation output and from innovation output to productivity (see also Hall 2011). In addition to this direct effect, indirect productivity effects can occur as a result of knowledge spillovers. In fact, many empirical studies have found large positive spillover effects between firms within and across sectors from investments in innovation that are often at least as large as the direct effect (Hall et al. 2010).

However, firms are heterogeneous and they operate in different economic environments, e.g. related to different industries, technological regimes, locations or time. It is therefore likely that the returns to innovation differ between firms. As a consequence, even though the positive correlation between firm-level innovation and productivity growth is well documented, the relationship is likely to be more complex than suggested by standard economic theories. For example, productivity effects of innovation are potentially stronger for R&D-intensive firms than for firms with lower R&D intensity (e.g. Falk 2007). It might also be that the most efficient firms gain more from innovation than the least performing firms (Coad and Rao 2008, Falk 2012, Bartelsman et al. 2013). To put it more general, it is not clear from the existing literature how firms respond to direct and indirect gains in productivity growth due to innovation. A positive effect of innovation on productivity may translate into employment growth, or lead to 'jobless' growth or even to labour displacement. If process innovation, for instance, leads to an increase in productivity, firms are able to realize the same production volume with less labour input. However, they may also pass along these cost reductions to output prices and reduced prices should stimulate product demand and employment of the firm. The total effect is unclear a priori and has to be determined empirically.

Another open question is whether the business cycle matters for employment and productivity effects of innovation. For instance, it is likely that the business cycle matters for the extent to which firms' pass on cost reductions resulting from process innovations and for the extent to which they are able to stimulate demand. So far there is only scarce evidence whether the returns to innovation (on average or along the dimensions mentioned above) also vary with the business cycle. The literature studying the relationship between innovation and business cycles has mainly focussed on the question whether the business cycle has an impact on firms' innovation behaviour.

## 1.2. OBJECTIVES AND RESEARCH QUESTIONS

Against this background, the overarching aim of this background report which contributes to the 2014 European Competitiveness Report is to enhance our knowledge of the micro-dynamics of innovation and firm growth in Europe. Firm growth in this study is mainly focussed on firm-level employment growth as job creation of is of particular interest within the Innovation Union Flagship. Given the prevailing uncertainty over the effects of innovation on employment, we will employ firm sales growth as an alternative to firm employment growth. A special focus will be laid on the changing dynamics over the course of the business cycle. Thus, this background report will tackle the following main research questions:

- Are product, process and organizational innovation conducive to productivity growth?
- Do product and process innovation stimulate employment growth? Or does jobless growth take place?
- To what extent do productivity and employment effects of innovation depend on the business cycle?
    - For instance, do firms create less employment due to product innovation in recession periods?
    - Are labour-saving effects of process innovation larger during a cyclical fall?
    - Or does the basic relationship between innovation on employment remain stable during different phases of the business cycle and it is for instance only the fact that firms are less engaged in innovation during recession periods that lead to a lower contribution of innovation to employment growth during recessions?
    - Do industries differ in the way innovation creates employment growth in different phases of the business cycle?

## 1.3. STRUCTURE

The structure of this report is as follows: In section 2 we will take stock and provide a review of the existing theoretical and empirical literature. Based on the existing literature we derive hypotheses that we will investigate in the empirical analysis. The data sources that are underlying our empirical study will be explained in section 3. Section 4 will present empirical evidence on innovation activities over the business cycle in Europe. Section 5 investigates the dynamics of innovation on firms' employment growth in Europe over the business cycle. We will start by setting forth the empirical model that is used for the empirical analysis in section 5.1, followed by a description of its empirical implementation and estimation method in section 5.2. In section 5.3 we provide descriptive evidence on the growth performance of innovators and non-innovators over the business cycle, followed by the econometric analysis in section 5.4. Section 5.5 complements this section by using an alternative indicator for the size of economic growth. In Section 6 we will further investigate potential sector-level heterogeneity in the link between innovation, growth and the business cycle whereas section 7 studies whether small and medium-sized companies behave differently than large companies. Section 8 examines whether regional differences in employment creation of innovation over the business cycle can be found in Northern, Southern and Eastern European countries. Whereas sections 5 to 8 are based on European Community Innovation Survey (CIS) repeated cross-sectional data, section 9 will study the nexus on innovation, employment and business cycles in Germany. The German case is not only interesting because it provides panel data but also because Germany presents the largest single European economy and its economy had recovered relatively fast after the deep economic crisis in 2008/2009. Section 10 complements the empirical analysis by investigating productivity effects of innovation in different stages of the business cycle. Section 11 summarize our main finding and draws some policy conclusions.

# Chapter 2. LITERATURE REVIEW

## 2.1. INNOVATION, PRODUCTIVITY AND EMPLOYMENT GROWTH

Firms have two options to achieve real output growth; by putting more factors of production (labour and capital) at work, or by improving the ratio between the factors of production employed and the output. Improvements in the ratio between input and output are usually referred to as improvements in productivity. Productivity is central to all discussions on employment growth and output growth. Empirical evidence suggests that increases in productivity account for a considerable proportion of the growth in many sectors in the European Union, in particular high-technology sectors (Peneder 2009, p. 14). The slower growth of value added in Europe between 1995 and 2004 compared to the US can be attributed to a slower growth of productivity in Europe (Peneder 2009, p. 14). Two concepts or measures of productivity are found in the literature; labour productivity, which refers to output per unit of labour input, and total factor productivity (TFP), which refers to output per unit of capital and labour input. The correlation between the two measures at the sectoral level was 0.914 for the EU 25 during the period 1995 to 2004 (Rincon-Aznar et al. 2009), so it seems to be justified to regard labour productivity as a good proxy for total factor productivity.

Productivity is strongly connected to innovation and employment; innovation may lead to changes in labour productivity which in turn may lead to changes in employment. The linkage between innovation, productivity and employment, however, is not straightforward, and different forms of innovation may have different effects on employment growth (Edquist et al., 2001; Garcia et al., 2002; Pianta, 2005; Hall et al., 2008; Harrison et al., 2014).

To investigate the productivity and employment effects of innovation, it is useful to make a distinction between product innovation, the introduction of new products on the market, and process innovation, which is the implementation of new processes for the production of products (OECD 2005). The OECD considers both product and process innovation as technological innovation. In addition, firms may invest in non-technological innovation such as organisational innovations. Whereas process innovations apply to units of real capital (i.e. material goods) which have been improved through technical change, organisational innovations are new ways to organise work (Edquist et al. 2001), including for instance business processes and workplace organizations. The data sets used in the analysis distinguish between these three types of innovation.[1]

Firms can introduce new processes for several purposes which largely reflect their different innovation strategies. On the one hand, process innovations may be intended to promote rationalisation in terms of reducing average production costs. This type of process innovation allows firms to produce the same amount of output with less capital and/or labour input, leading to an increase in productivity. On the other hand, process innovations can be intended to improve the quality of products, to assure that products or production processes meet new legal requirements, or to produce or deliver new or significantly improved products. In the latter case, process innovations are not necessarily related to higher productivity.

[1] The CIS data further includes information on marketing innovation. It is defined as a new marketing method involving significant changes in product design or packaging, product placement, product promoting or pricing (e.g. discount system). However, we do neglect marketing innovations in our analysis.

The effect of product innovation on productivity is less straightforward. New products, on the one hand, may require less input of labour and capital than old ones, and give rise to scale economies, both leading to a higher productivity of the firm. On the other hand, new products may help firms to increase productivity by moving resources from the production of old products to new products with a higher value so that output per input and productivity increases.

There is a large empirical literature that has investigated the link between innovation and productivity. Hall et al. (2010) recently surveyed the literature in great detail. In a nutshell, the majority of studies have confirmed a positive impact of product innovation on productivity and thus confirmed positive rates of return to innovation. A bit surprisingly, the results for process innovation are more mixed.

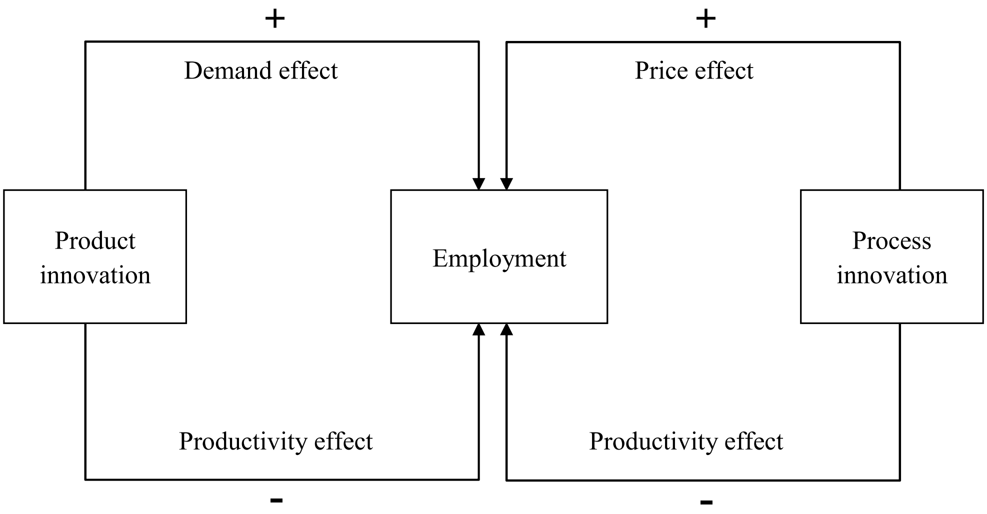
Even if it turns out that the effects of innovation on productivity are positive, it is unclear a priori how these effects transform into employment changes. To examine this question, we must further include reactions of market demand to product innovation, the price elasticity of demand and the existence of substitutes or complementary products into our considerations. Product innovation has a demand-creating effect which is likely to stimulate employment. Both, product and process innovation may be associated with a labour-saving effect which reduces employment (productivity effect). Additional price effects from process innovation may also enter into the equation (see Figure 2.1). We will explain these effects in more detail below.

If a new product has been introduced onto the market and if it provides a higher utility for consumers, it creates a new demand for the firm. This *direct demand effect* of product innovation spurs employment growth. This higher demand can either be the result of an overall market expansion, or it comes at the expense of demand for existing products. If the new product partially or totally replaces the old product of the innovating firm ('cannibalization effect'), labour demand for the production of the old product will decrease, and the overall effect is ambiguous for the innovating firm. However, in the case of complementarity between the old and the new product, the new product will cause demand for existing products to rise as well, and employment will increase further. Due to these indirect demand effects the overall effect is unclear, but more likely to be positive. Complementarity and substitution may also affect product demand of competitors. 'Business stealing' (Aghion and Howitt 1992, p. 338; see also Box 1) occurs when a new product has a negative substitution effect on demand for existing products of competitors. The degree of these indirect demand effects depends on the existence of substitutes and the reactions of competitors (see Garcia et al. 2002).

In contrast to product innovation, the main employment effects of *process innovation* are closely related to productivity changes if the introduction of new production processes allows firms to produce the same amount of output with less labour input (*productivity effect of process innovation*). As a consequence, process innovation most often leads to an increase in productivity and a negative effect on employment. The size of this negative effect depends on the current production technology and, thus, the rate of substitution between input factors as well as on the direction of the technological change. This labour-saving effect also varies significantly between sectors (Edquist et al. 2001).

In addition to these main effects, we may also see side effects of product and process innovation which may steer employment in the different direction. Product innovation can lead to a negative (*productivity*) effect on employment when the new product can be produced with less inputs and a higher productivity than the old product (see Harrison et al. 2014). Product innovation thus can lead to productivity changes, even if product innovation is not associated with simultaneous process innovation.

**Figure 2.1: Effects of product and process innovation on employment**




*Source: Harrison et al. (2014), own illustration.*

Process innovation leads to a reduction in unit costs which may allow the innovative firm to lower its product price. Lower prices, in turn, can lead to a higher demand for the product, thus increasing output. Thus, increased productivity may lead to increases in consumption. The magnitude of this *price effect* depends on the size of the price reduction, the price elasticity of demand, the degree of competition as well as on the behaviour and relative strength of different agents such as managers and unions within the firm (Garcia et al. 2002). The higher the market power of the innovating firm, for instance, the lower the extent to which cost reductions are passed to product prices.

Employment losses from the productivity effect of product and process innovation may be softened by two effects that lower productivity during downswings and recessions (Bhaumik 2011):

- First, firms show a tendency towards labour hoarding during downswings and recession periods, which means that firms only slightly reduce their staff as demand for their products falls. Labour hoarding results in a decrease of productivity during periods of economic downswings and therefore smaller employment losses. Leitner and Stehrer (2012) report that labour hoarding was widely used during the crisis in Central and Eastern European countries and particularly frequent among innovators. They explain this fact by high training and search costs for experienced R&D personnel which makes it rational to keep personnel even if it is underemployed. Pro-cyclical fluctuations of productivity are also reported by Rojas Pizarro (2013) who analyses data from Spain with a model similar to that of this project.

- Second, firms loos economies of scale in production during downswings when output shrinks. This is a second another explanation for lower productivity in an economic downturn.

**Box 2-1: Differences in productivity and employment growth between the firm-level and aggregate level**

Changes in productivity can be measured at the firm, the sectoral, or the macroeconomic level. Depending on the level of aggregation, diverse effects and mechanisms are observable, and the analysis may reveal different growth rates. These differences have to be kept in mind when one compares the results of this analysis with data at the macroeconomic level.

Aggregate productivity can be defined as a share-weighted sum of firm productivity levels. Hence, changes at the aggregate level are the result of two factors: on the one hand, changes in productivity at the firm-level (i.e. *within-firm effect*); on the other hand, the result of changes in the composition of industries (i.e. *between-firm effect*).

The *within-firm* effect subsumes restructuring within firms, such as the introduction of new products or changes in factor utilization resulting from process innovation. We describe within-firm effects of product and process innovation on productivity and employment below. The *between-firm* effect, in contrast, comprises the reallocation of resources among existing firms. An example for the between-firm effect is industrial restructuring. Aggregate productivity can increase even if productivity at the firm-level remains unchanged if more productive firms gain market share at the expense of less productive firms. 'Business stealing' (Aghion and Howitt 1992, p. 338) occurs when product innovation of one firm has a negative substitution effect on existing products of other firms. In the case of complementary demand, however, product innovation will stimulate demand for existing products of other firms as well. It may even trigger the development of new complementary products.

Between-firm effects also result from market entry and exit of firms (Foster et al. 2001). Average productivity rises when firms with lower levels of productivity than the average firm leave the market. Additionally, new firms entering the market may induce new products as well as new production methods, which raises aggregate productivity, but might also spur incumbent firms to improve their productivity (Aghion et al. 2004). The net entry effect may be attenuated through the existence of restrictive market entry regulations; see Aghion et al. (2004) for the firms' entry effects of policy reforms in the UK on productivity growth. The impact of exits and entries of firms on the aggregate productivity is highly sensitive to the method of decomposition and to the horizon over which the productivity is measured (Foster et al. 2001). Studies which focus on a longer time horizon often find a large contribution of net entry to aggregate productivity, whereas only a relatively small impact could be identified by studies which examine high frequency variation (Foster et al. 2001).

Regarding the cyclicality, the net entry component is found to have strong impact on productivity growth during periods of economic slowdown, while within-firm factors are more important during periods of economic growth (Bartelsman and Doms 2000). In the case of labour productivity, within-firm changes have a larger positive impact on labour productivity growth than net entry effects during both periods (Barnes et al. 2001). Findings of Baily et al. (2001) show that the within-plant component for incumbent firms exhibits greater pro-cyclicality than aggregate labour productivity, whereas the countercyclical patterns are exhibited by the between-firm component. This indicates that the share of less productive firms falls in economic slowdowns.

With respect to the analysis of the innovation-employment relationship presented in the subsequent chapters, these findings have important implications. It is not the goal of this project to explain aggregate employment or productivity changes, since the data do not allow us to consider all the effects that occur at the aggregate level. However, we will provide insights into the heterogeneity of the innovation-employment relationship at the firm-level that aggregate data cannot deliver.

The majority of empirical studies have found a positive relationship between product innovation and employment growth (demand effect) in manufacturing (Entorf and Pohlmeier 1990, König et al. 1995, Van Reenen 1997, Blechinger et al. 1998, Rottmann and Ruschinski 1998, Smolny 1998, Greenan and Guellec 2000, Garcia et al. 2002, Smolny 2002, Hall et al. 2008, Harrison et al. 2014). Empirical evidence on the employment effects of process innovations is less clear than for the demand effect. In the studies of van Reenen (1997) and Entorf and Pohlmeier (1990), the impact of process innovations turns out to be small and not significant at all. König et al. (1995), Smolny and Schneeweis (1999), Smolny (2002), Greenan and Guellec (2000) or Lachenmaier and Rottmann (2011), in contrast, report a significant positive effect of process innovations on employment growth. The latter two studies even establish that process innovation creates more new employment at the firm level than product innovation. On contrary, Blechinger and Pfeiffer (1999) find evidence of labour displacement by process innovation, the effect being more pronounced in larger firms.

## 2.2. BUSINESS CYCLES AND INNOVATION

The aim of this report is to investigate how firms transform innovation into employment growth in different stages of the business cycle. So far, however, the literature has mainly focussed on the question whether the business cycle has an impact on firms' innovation behaviour and this subsection briefly summarizes the main findings from the literature focussing on cyclicality of innovation.

Before we discuss this relationship, it is useful to make a basic distinction between business cycle effects on innovation input and innovation output. The OECD defines innovation as "… the implementation of a new or significantly improved product (good or service), or process, a new marketing method, or a new organisational method in business practices, workplace organisation or external relations." (OECD 2005, p. 46). Hence, innovation is related to the creation of new products and processes as well as to their success and market acceptance.

The creation of new products or processes (or input side) is usually measured by the efforts and resources the firm spends on innovation, in the form of R&D expenditure, expenditure for product design, new equipment for process innovation etc. Innovation output, in contrast, can be captured by the turnover the firm generates by new products and processes.

So far, most contributions on the relationship between innovation and the business cycle focussed on the input side. Empirical evidence suggests that innovation activity, at least at the aggregate level, tends to be pro-cyclical and clusters in upswings of the business cycle, while decreases in downswings (Himmelberg and Petersen 1994, Barlevy 2007, OECD 2012). This pattern also occurred during the global financial crisis of 2008-09.

The literature explains this observation by higher internal cash flows and easier access to external finance in an economic boom (Himmelberg and Petersen 1994, Aghion et al. 2012), and more confidence in future demand growth during times of economic prosperity (Cohen 1995, 2010 discusses the role of demand expecations for innovation in detail). Barlevy (2007, p. 1131) speaks of a 'dynamic externality inherent in R&D that makes entrepreneurs short-sighted and concentrate their innovation in booms', while they invest too little in R&D during recessions. During economic downturns innovators could expand their R&D activities to gain from an investment during economic upswings. This long-term focus, however, increases the risk of spillovers to rival innovators and of profit losses. As a result, innovators take up an orientation towards short-term profits and thus they will invest more heavily in innovation during an economic upswing.

Recent contributions examine the role of credit constraints for the cyclicality of R&D investment in more detail. Aghion et al. (2012) find evidence that credit-constrained firms reveal a higher share of R&D investment during periods of flourishing sales, underpinning the hypothesis of pro-cyclicality. However, if firms are not credit-constrained, the relationship turns to be countercyclical, i.e. firms invest more in R&D during recessions. Accordingly, the opportunity costs (in terms of foregone profits) of long-term R&D investment compared to short-term capital investment is lower in economic downturns than in economic upswings (see Aghion and Saint-Paul 1998). Bovha-Padilla et al. (2009) corroborate this finding. Moreover, Bovha-Padilla et al. estimate different forms of financial constraints. As a result, firms that are owned by foreign companies, or receive governmental subsidies or have a high asset endowment, do not reveal any significant pro- or countercyclical R&D behaviour.

Explanations for the relationship between business cycle and innovation output, in contrast to innovation input, are scarce. One may go back to Josef Schumpeter's (1911) notion of extra-normal, monopolistic profits as the main incentive for innovators. These 'Schumpeterian' profits may be highest in an economic boom, when strong demand growth limits competitive pressure, leading to a positive association between innovation output and the business cycle. Furthermore, Judd (1985) argued that markets have a limited capacity for absorbing new products, thus, firms are more likely to introduce new products in prosperous market conditions. A similar relationship suggests the model by Francois and Lloyd-Ellis (2003) where entrepreneurs introduce innovation in an economic boom, but develop them in recessions. Moreover, Barlevy (2007) argues that appropriability conditions vary over the business cycle and possible losses from involuntary spillovers to competitors are lower during economic prosperity, leading to a pro-cyclical behaviour of firms with respect to the introduction of innovation output. Geroski and Walters (1995) using UK data on patents and innovation counts find evidence for pro-cyclicality of innovation output.

The growing literature that analyses the effects of the financial crisis 2008-2009 on R&D and innovation reports a considerable degree of heterogeneity in terms of the impact of the crisis across countries, sectors, firms, and different innovation strategies (Cincera et al. 2012, OECD 2012, Paunov 2012, Rammer, 2012, Archibugi et al. 2013; Arvanitis and Wörter 2013). According to Cincera et al. (2012) the automotive industry and other medium-technology sectors were most severely affected, while high-tech and low-tech sectors faced only modest reductions. Rammer (2012) reveals that R&D-intensive sectors in Germany had larger decreases in innovation expenditure than all other sectors. Both sources indicate that R&D and innovation in services seems to have suffered less than in manufacturing.

Heterogeneity can also be observed in innovation strategies during the crisis; a considerable number of firms also followed a counter-cyclical strategy between 2008 and 2009: 34 percent of all German firms intensified innovation activities in this period (Rammer 2012). Archibugi et al. (2013) observe in the UK that the crisis led to increases in innovation expenditure in fast-growing new entrants and firms with high sales from market novelties before the crisis, which the authors regarded as a sign of high innovativeness. Arvanitis and Wörter (2013) find that 17% of the firms in their data set follow a counter-cyclical innovation behaviour, and 40% no systematic cyclical or counter-cyclical behaviour.

## 2.3. FIRM HETEROGENEITY, INNOVATION AND EMPLOYMENT GROWTH

A main advantage of the firm-level approach - compared to an analysis at the aggregate level - is that it allows us to consider differences between various sub-groups within the observed firm population, as well as isolate and observe the association of single factors with employment growth. This subsection will discuss some relevant sub-groups of the sample and their association with different rates of employment growth.

### 2.3.1. Firm Size

The effects of innovation, as a main driver for productivity growth as well as employment growth, differ between large and small-/medium-sized enterprise (SMEs). Here, many arguments go along the discussion on specific advantages and disadvantages of small and large firms in the innovation process (Kleinknecht 1989, Dogson and Rothwell 1994, Cohen 1995, 2010). The main argument in favour of small enterprises is their flexibility to react to new opportunities, their ability to survive in niche markets where large enterprises are not willing to operate, and the personal engagement of an entrepreneur who brings in his/her knowledge of technologies and markets. In addition, employment growth in SMEs is often argued to exceed the growth rates of large firms, that is, smaller firms, on average, create more jobs relative to size than large ones. Evidence shows that especially young SMEs exhibit high net employment growth rates, whereas large, old firms are found to have the lowest rates (Fort et al. 2013; Haltiwanger et al. 2013). In addition, start-ups are often seen as highly innovative businesses, especially in technology-based sectors. Nevertheless, it needs to be considered that young firms are highly volatile, with a high likelihood of exit, which results in job destruction. Fort et al. (2013) find cyclicality for young, small and medium-sized as well as for old, large firms, but net job creation rates for young SMEs declined substantially during times of recession. That also holds true for old, small businesses (Fort et al. 2013). This is mainly because (young) small firms have no reserves they can access in times of crisis and are more often credit constrained.

Large firms, in contrast, usually have large internal financial means and can raise external funds to finance innovation projects more easily than entrepreneurs and small businesses. They can manage risk more easily through diversification and distribution of the cost of failures over a larger number of projects. Large, diversified firms have more potential applications for new knowledge discovered by their R&D departments (Rosenberg 1990). Another advantage of size is specialisation and a more intense division of labour between different scientific disciplines and persons of different qualifications. In addition, large firms also often enjoy advantages from multinationality described in 2.2.3. Data from the financial crisis of 2008-2009 provides evidence that innovation activities in larger firms have been less affected by the recession (Paunov 2012, Rammer 2012, Archibugi et al. 2013). Credit constraints may have posed considerable problems for the funding of innovation projects in smaller firms; large firms, in contrast, have larger internal means to finance those activities. Moreover, younger firms, firms with no access to public funding and suppliers to foreign multinational firms were more likely to stop on-going innovation projects (Paunov 2012).

To sum up, the literature suggests advantages for both, large and small firms, in the innovation process. It delivers evidence that employment growth is faster in SMEs, but also demonstrates that SMEs suffer more than large firms during a recession. We may explain this by a better access to finance and more diversification in larger firms. With respect to the effects of the business cycle on employment growth rates, we may therefore assume that small firms exhibit higher growth in upswings, but also lose more than large firms in downswings.

### 2.3.2. Foreign Ownership

Foreign-owned firms account for a large share of R&D and innovation activities in a number of countries. In some small countries such as Austria, Ireland, or Hungary, foreign-owned firms even account for the majority of business R&D expenditure (Zahradnik 2014). In addition, foreign-owned firms reveal a better innovation performance than domestically owned firms (Sadowski and Sadowski-Rasters 2006, Frenz and Ietto-Gillies 2007, Dachs et al. 2008). The literature has explained the superior performance of foreign-owned firms by their characteristics; foreign-owned firms are, on average, larger, employ a larger share of staff with tertiary education, are more export oriented, embedded in intra-firm networks to knowledge and technology exchange, and operate more often in high-technology sectors.

Foreign-owned firms also differ in terms of employment creation from innovation. Dachs and Peters (2014) investigate employment creation and destruction of foreign-owned and domestically owned firms in Europe. They find that foreign-owned firms create more employment due to more product innovation and a stronger demand effect, but also lose more employment than domestically owned firms due to a stronger productivity effect of product and process innovation.

In a business cycle perspective, this result implies that foreign-owned firms, compared to their domestic counterparts, create disproportionally more employment in upswings and economic booms because of a higher demand effect, but also destroy more employment in downswings and recessions due to the productivity effect and shrinking market demand. Foreign-owned firms, on average, enjoy higher productivity gains from new production processes than domestically owned firms, because they benefit from internal technology transfer and learning effects in the corporate network between affiliates and the parent company.

Lessons from the financial crisis may also help to explain differences in employment creation between foreign-owned and domestically owned firms. Empirical evidence suggests that the crisis had a more severe impact on export-oriented firms (Paunov 2012, Rammer 2012, Archibugi et al. 2013). Exports dropped faster than domestic demand, so it seems feasible that exporters where hit hardest by the crisis. Foreign-owned firms reveal a much higher export orientation than the average domestically owned firm. On contrary, Kolasa et al. (2010) find for Poland that foreign ownership provided a higher degree of resilience against the crisis due to intra-firm lending.

To sum up, the evidence available suggests that foreign-owned firms may reveal faster employment growth in upswings, but also destroy more employment in downswings than domestically owned firms. An advantage of foreign-owned firms is internal borrowing. One may also add that multinational firms reveal a tendency to cut jobs more easily abroad than at home, which may further contribute to higher employment volatility due to innovation in foreign-owned firms.

### 2.3.3. Sectoral Affiliation of the Firm

The literature has also identified major differences between firms affiliated in different industries or economic sectors. One key dimension of these sectoral differences is technology intensity, the amount they spend on R&D and innovation relative to turnover or value added. Research on industrial dynamics (summed up by Dosi and Nelson, 2010) has revealed considerable differences in technology intensity at the sectoral level, which led to the notion of high- medium and low- technology sectors (Hatzichronoglou 1997) or different technological regimes at the sectoral level (Marsili 2001). The literature explains these sectoral differences in technology intensity by differences in demand expectations, different levels of technological opportunity and appropriability conditions (Cohen 1995, 2010). These factors also help to understand differences between sectors in employment creation in various phases of the business cycle.

A first determinant for technological intensity at the sectoral level is demand expectation, which may differ systematically between industries. Higher growth in the past may lead to more confidence. Between 1995 and 2004, high-technology sectors have been growing faster than any other type of sector (Rincon-Aznar et al. 2009, p. 127). This may indicate that high-technology sectors are also more confident in future demand growth, leading to faster employment growth in economic upswings and less employment losses in downswings.

Another determinant of technological intensity is the level of technological opportunity in a sector. Better technological opportunities may lead to a higher importance of radical innovations and product innovation in general in a given sector, which may turn into more employment growth, because these types of innovation are related to demand effects which drive employment growth. Large technological opportunities are typical for high-tech sectors, as we can see from the share of new-to-the market innovations on turnover. Innovation in low-tech-sectors, in contrast, is characterized to a higher degree by process innovation (von Tunzelmann and Acha 2005), which is rather related to employment-destroying productivity effects. As a consequence, we may expect a faster employment growth in high-technology sectors due to differences in innovation activities.

Another possible source for differences between high-technology and low-technology sectors are appropriablility conditions, which denotes the ability of a firm to reap the full benefits of an innovation and avoid involuntary spillovers of new knowledge to competitors. It has been noted above that a high level of appropriability is favourable for employment growth, because it allows firms to reap more profits from an innovation compared to low appropriability levels. Despite Barlevy's (2007) suggestion that appropriability conditions vary over the business cycle, we may assume that patent protection or secrecy work – to a large degree - in a recession as well as in an economic boom, and sectors with strong appropriability conditions (such as a number of high-technology sectors) perform better in all phases of the business cycle.

It has been argued in the past that service industries are laggards in terms of innovation and the application of new technologies. However, service industries increasingly use technologies such as information and communication technologies, and reveal a faster employment growth than manufacturing industries, in particular if one looks at knowledge-intensive business services (KIBS) (Miles 2005, Rubalcaba et al. 2008). Compared to manufacturing, however, technology intensity, product innovation and opportunity for labour-saving process innovation is still lower in the service sector. This leads to the assumption that innovation-related employment fluctuations in services are smoother than in manufacturing. Cincera et al. (2012) and Rammer (2012) indicate that R&D and innovation in services seems to have suffered less than in manufacturing.

In addition, economic sectors vary considerably in terms of their reaction to general business fluctuations measured by changes in output (Zislin and Barret 2009, p 254f). Particular sectors may be more volatile than the economy overall, and expand and contract less than the whole economy in a boom or recession. We refer to this observation as the cyclical sensitivity of sectors. Cyclical sensitivity is related to the price and income elasticities of the main products of a sector, but also to characteristics of production such as the time it needs to react to perceived changes in demand, the position in the value chain, or industrial organisation of the sector. Cyclical and non-cyclical sectors are not necessarily sectors with high or low growth rates; is it rather the degree of persistence of growth rates over the business cycle which characterizes cyclical sensitivity.

In the context of innovation and employment growth, cyclical sensitivity means that the demand effect and the price effect in this particular sector may be stronger than in other parts of the economy. Moreover, firms in non-cyclical sectors which face a more stable demand may be more confident about future demand growth in an upswing, and reveal less labour hoarding. Therefore, we assume that firms in cyclical sectors experience larger employment growth in upswings, but also larger losses in downswings compared to firms in non-cyclical sectors.

### 2.3.4. Key Relationships Between Employment Growth and Innovation

Based on the main arguments from the literature reviewed in the preceding sections, we expect to find the following relationships between employment growth and innovation in the data:

- For product innovation, we assume that market acceptance for new products and the potential for demand expansion and extra-normal profits is higher during upswings and booms of the business cycle. This leads to a stronger *demand effect* and larger employment creation from product innovation during upswings and booms than during downswing or recession. In addition, the business stealing effect may be smaller in a growing than in a stagnant market, and firms need to sacrifice less of their turnover from old products if they introduce an innovation. Moreover, firms may find it easier to overcome financial constraints related to innovation during upswings, which may lead to a higher success rate of innovations. In economic downswings or recessions, in contrast, the lack of demand dynamics may hamper the employment-creating demand effect of product innovation. In addition, firms may be less willing to take high risks and shift their innovation strategies during downswings and recessions. That is, they are more likely to postpone the introduction of market novelties but instead focus on firm novelties which might be less demand and hence employment creating. In these phases of the business cycle, in particular in recessions, it is more likely that product innovation is labour preserving instead of labour creating.

- Process innovation and the *productivity effect of process innovation* may affect employment the other way around; in a growing market during an upswing, firms may not find it necessary to fully use the potentials of new process technologies to cut cost, raise productivity and therefore dampen employment growth. Process innovation may target on expanding production capacity, rather than stabilize profit margins. Downswings and stronger competitive pressure in shrinking markets, in contrast, may force firms to improve their cost and profit situation through rationalization innovations, leading to larger job reductions during cyclical falls than process innovation would cause in an economic boom.

Employment losses from the productivity effect during downswings and recession periods may be softened by labour hoarding and lost economies of scale in production, which both decrease productivity in an economic downturn. Both effects can counteract the productivity effect, and may be larger in downswings and recessions than during economic upswings or booms. They are also major factors to explain the pro-cyclicality of productivity, the finding that productivity increases with rising GDP growth rates, and decreases with falling growth rates.

Moreover, we assume that firm heterogeneity has the following effects on the results:

- Employment changes related to the demand effect may be larger in small and medium sized firms than in large firms.
- Employment in foreign-owned firms may be more volatile due to differences in innovation behaviour and a larger demand effect compared to domestically owned firms.
- Finally, we expect that the empirical results reveal higher employment volatility in high-technology firms and manufacturing in general compared to low-technology firms and services. Moreover, we expect that firms in cyclical sectors experience larger employment growth, but also larger losses in downswings due to the demand effect compared to firms in non-cyclical sectors.

# Chapter 3.
# DATA SOURCES

The empirical analysis in this study is based on large data bases from different sources and this section describes the data sources in more detail. We start by briefly explaining the business cycle indicators in section 3.1. Section 3.2 describes our main data set, the Community Innovation Surveys (CIS) whereas section 3.3, explains the German counterpart, the Mannheim Innovation Panel (MIP).

## 3.1. BUSINESS CYCLE INDICATORS

The business cycle describes fluctuations in economic activity that an economy experiences over a period of time. In its simplest definition, a business cycle consists of two phases: economic expansion (upturn) and contraction (downturn). During expansions, the economy is growing in real terms (i.e. excluding inflation), as evidenced by increases in indicators like GDP growth, capacity utilization or growth in employment, industrial production, demand, producer prices and factor incomes such as interest rates and wages (Tichy 1994). A downturn is characterized by shrinking growth rates of these indicators of economic activity.

In the empirical study, we use GDP growth to determine the phases of the business cycle. Country-level data on real GDP growth is taken from Eurostat. Based on GDP growth, we define two different indicators for the business cycle.

The 2-phases business cycle indicator *BC2* distinguishes between

- *upturn*: GDP growth is positive and increasing and
- *downturn*: GDP growth is positive but decreasing or negative

The 4-phases business cycle indicator *BC4* distinguishes between

- *upturn*: GDP growth is positive and increasing
- *boom*: GDP growth is positive and increasing and it is the last period of increasing growth before a downswing starts
- *downturn*: GDP growth is positive but decreasing
- *recession*: GDP growth is negative

As an alternative, we make use of the WIOD data base and extract industry-level information on output growth. We employ the same 2- and 4-phase definition to define business cycles at the industry level.

One issue that has arisen in the empirical analysis is the time period used to calculate GDP growth. Statistical offices often use quarterly data to define business cycle. In empirical work, it is also common to employ one-year growth rates. However, as we will see in subsection 3.2, the CIS data covers a three-year period, in CIS 2010 for instance the period 2008-2010. Hence, we used a two-year GDP growth rate, i.e. in the example above the growth rate between 2008 and 2010. However, we also experimented and checked robustness using one-year GDP growth rates and average annual GDP growth in the three-year period.

## 3.2. COMMUNITY INNOVATION SURVEY (CIS)

The Community Innovation Survey (CIS) is the main basis for the empirical analysis of this study. CIS is a survey that is based on a common questionnaire administered by Eurostat and national statistical offices in all EU member states, Iceland and Norway. The methodology of CIS is based on the definition laid down in the OECD Oslo Manual (latest edition: OECD, 2005). CIS collects information at the firm level. The target population covers all legally independent enterprises with at least 10 employees in manufacturing, mining, energy and water supply and selected services.

CIS contains information about employment and sales in a given year t and in year t-2, thus allowing us to calculate employment and sales growth at the firm level. Since its main objective is to gather information on firms' innovation behaviour, it includes numerous innovation indicators such as if the firm has introduced product innovations new to the firm or new to the market, the share of sales due to new products, or the introduction of process innovation and organizational innovation. It additionally contains various variables that describe the innovation process of the firm such as the aim of innovation activities, innovation intensity, R&D engagement, type of information sources used, and so on.

Innovation surveys similar to CIS have found wide spread in a number of countries including the European Union, Canada, the US, and Latin America. The merits of this type of survey can best be seen in Europe (Smith 2005, p. 165 ff): CIS data delivered a rich dataset for analytical studies and provided robust empirical evidence on the level of innovative behaviour. The CIS results point to some persistent variety in innovative behaviour between countries, sectors and over time which also gave reason for policy intervention. Moreover, CIS has also shed light on the innovative activities of service firms for the first time.

The first CIS (CIS1) was conducted in 1993. Up to 2005 the survey was conducted every four years. From 2005 onwards the survey was conducted on a bi-annual base. Eurostat offers access to non-anonymized micro-level data from CIS3 onwards at is premises in Luxemburg. Hence, we employ 5 waves of CIS data covering the years 1998-2000 (CIS3), 2002-2004 (CIS4), 2004-2006 (CIS2006), 2006-2008 (CIS2008) and 2008-2010 (CIS2010). Each wave covers at about 20 member states. Table 3.1 gives an overview of the different CIS waves.

In total, 414,474 observations are available, whereof more than half of the observed firms operate in the manufacturing sector (i.e. 234,406) and 180,068 firms are active in the services sector. The distribution among the CIS waves shows that the first three CIS waves exhibit the smallest sample sizes, whereas almost half of the observations are in the CIS2008 and CIS2010 waves.

**Table 3.1: Distribution of CIS Sample by Waves**

| CIS | Observation Period | Total | | | Manufacturing | | Services | |
|---|---|---|---|---|---|---|---|---|
| | | N | % | Cum | N | % | N | % |
| CIS 3 | 1998-2000 | 68,033 | 16.41 | 16.41 | 43,640 | 18.62 | 24,393 | 13.55 |
| CIS 4 | 2002-2004 | 79,089 | 19.08 | 35.50 | 44,993 | 19.19 | 34,096 | 18.94 |
| CIS2006 | 2004-2006 | 65,357 | 15.77 | 51.26 | 37,479 | 15.99 | 27,878 | 15.48 |
| CIS2008 | 2006-2008 | 99,656 | 24.04 | 75.31 | 54,996 | 23.46 | 44,660 | 24.80 |
| CIS2010 | 2008-2010 | 102,339 | 24.69 | 100.0 | 53,298 | 22.74 | 49,041 | 27.23 |
| Pooled | 1998-2010 | 414,474 | 100.0 | | 234,406 | 100.0 | 180,068 | 100.0 |

*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

Regarding the country coverage of the single CIS waves, 12 out of 26 listed countries were participating in all five waves. In contrast, five countries were only taking part in one or two waves (see Table 3.2). This fact also becomes apparent in the number of observations, which are widely spread. Spain, France, Bulgaria and Italy, descending in the mentioned order, exhibit the highest numbers of participating firms over all waves.

**Table 3.2: Country Coverage and Distribution of CIS Sample by Country**

| Country | Country | Wave | | | | | Manu | Services | Total | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 | N | N | N | % |
| Belgium | BE | + | - | - | - | - | 652 | 499 | 1,151 | 0.3 |
| Bulgaria | BG | + | + | + | + | + | 26,716 | 19,838 | 46,554 | 11.2 |
| Cyprus | CY | - | - | + | + | + | 1,217 | 1,629 | 2,846 | 0.7 |
| Czech Republic | CZ | + | + | + | + | + | 11,726 | 8,239 | 19,965 | 4.8 |
| Germany | DE | + | - | - | + | + | 5,727 | 3,890 | 9,617 | 2.3 |
| Denmark | DK | + | + | + | - | - | 1,445 | 1,792 | 3,237 | 0.8 |
| Estonia | EE | + | + | + | + | + | 4,557 | 3,230 | 7,787 | 1.9 |
| Spain | ES | + | + | + | + | + | 52,306 | 34,895 | 87,201 | 21.0 |
| Finland | FI | + | - | - | - | - | 900 | 463 | 1,363 | 0.3 |
| France | FR | + | + | - | + | + | 26,560 | 24,212 | 50,772 | 12.2 |
| Greece | GR | + | + | + | - | - | 1,568 | 678 | 2,246 | 0.5 |
| Croatia | HR | - | - | - | - | + | 1,212 | 940 | 2,152 | 0.5 |
| Hungary | HU | + | + | + | + | + | 9,581 | 5,341 | 14,922 | 3.6 |
| Iceland | IS | + | + | - | - | - | 318 | 283 | 601 | 0.1 |
| Italy | IT | + | + | - | + | + | 25,930 | 17,962 | 43,892 | 10.6 |
| Lithuania | LT | + | + | + | + | + | 3,567 | 2,792 | 6,359 | 1.5 |
| Luxembourg | LU | + | + | + | + | + | 765 | 1,584 | 2,349 | 0.6 |
| Latvia | LV | + | + | + | + | + | 2,615 | 2,776 | 5,391 | 1.3 |
| Malta | MT | - | - | + | + | - | 472 | 985 | 1,457 | 0.4 |
| Netherlands | NL | + | - | - | + | + | 5,813 | 9,091 | 14,904 | 3.6 |
| Norway | NO | + | + | - | - | + | 3,931 | 3,618 | 7,549 | 1.8 |
| Portugal | PT | + | + | + | + | + | 11,629 | 8,396 | 20,025 | 4.8 |
| Romania | RO | + | + | + | + | + | 18,479 | 14,255 | 32,734 | 7.9 |
| Sweden | SE | + | + | + | + | + | 8,150 | 5,866 | 14,016 | 3.4 |
| Slovenia | SI | + | + | - | + | + | 4,055 | 3,359 | 7,414 | 1.8 |
| Slovakia | SK | + | + | + | + | + | 4,515 | 3,455 | 7,970 | 1.9 |
| Total | | 23 | 19 | 16 | 19 | 20 | 234,406 | 180,068 | 414,474 | 100.0 |

*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

Table 3.3 represents the distribution of the CIS sample, in total for all the five waves by industry. For our analyses, the manufacturing sector is divided into eleven, partly aggregated industries based on the NACE classifications[2], and similarly, the services sector comprises eight (aggregated) industries. Within the manufacturing sector, manufacturing of basic and fabricated metals, food and beverages as well as the textile industry hold the highest shares of observations. The vehicles industry along with the industries of chemicals, rubber and plastics as well as non-metallic mineral products, are relatively underrepresented with low shares of observations.

**Table 3.3: Distribution of CIS Sample by Industry**

| Industry | Variable | NACE Rev. 1.1 | NACE Rev. 2 | Observations | |
|---|---|---|---|---|---|
| | | | | N | % |
| **Manufacturing** | | | | | |
| Food / beverages / tobacco | FOOD | 15-16 | 10-12 | 32,810 | 14.00 |
| Textile / wearing apparel / leather | TEXT | 17-19 | 13-15 | 32,085 | 13.69 |
| Wood / paper / printing | WOOD | 20-21, 22.2-22.3 | 16-18 | 26,932 | 11.49 |
| Chemicals | CHEM | 24 | 20-21 | 12,654 | 5.40 |
| Rubber / plastics | PLAS | 25 | 22 | 12,959 | 5.53 |
| Non-metallic mineral products | NONM | 26 | 23 | 13,662 | 5.83 |
| Basic and fabricated metals | BASM | 27-28 | 24-25 | 33,006 | 14.08 |
| Machinery | MACH | 29, 33.3 | 28, 33 | 23,854 | 10.18 |
| Electrical engineering | ELEC | 30-32, 33.2, 33.4-33.5 | 26-27 | 17,692 | 7.55 |
| Vehicles | VEHI | 34-35 | 29-30 | 11,352 | 4.84 |
| Nec | NEC | 36, 33.1 | 31-32 | 17,400 | 7.42 |
| Total | | | | 234,406 | 100 |
| **Services** | | | | | |
| Wholesale | WHOLE | 51 | 46 | 60,766 | 33.75 |
| Transport/storage/post | TRANS | 60-62, 63.1-63.2, 63.4, 64.1 | 49-53 | 38,298 | 21.27 |
| Telecomm. / computer program. / information services | TELE | 64.3, 72.1-72.3, 72.6 | 61-63 | 18,061 | 10.03 |
| Banks / insurances | BANK | 65-67 | 64-66 | 14,350 | 7.97 |
| Technical services | TECH | 74.2-74.3 73 | 71-72 | 18,675 | 10.37 |
| Consultancies | CON | 74.1, 74.4 | 69-70, 73 | 9,113 | 5.06 |
| Other business related services | OBRS | 74.5-74.8, 70.3 | 74, 78, 80-82 | 13,181 | 7.32 |
| Media | MEDIA | 22.1, 92.1-92.2 | 58-60 | 7,624 | 4.23 |
| Total | | | | 180,068 | 100 |

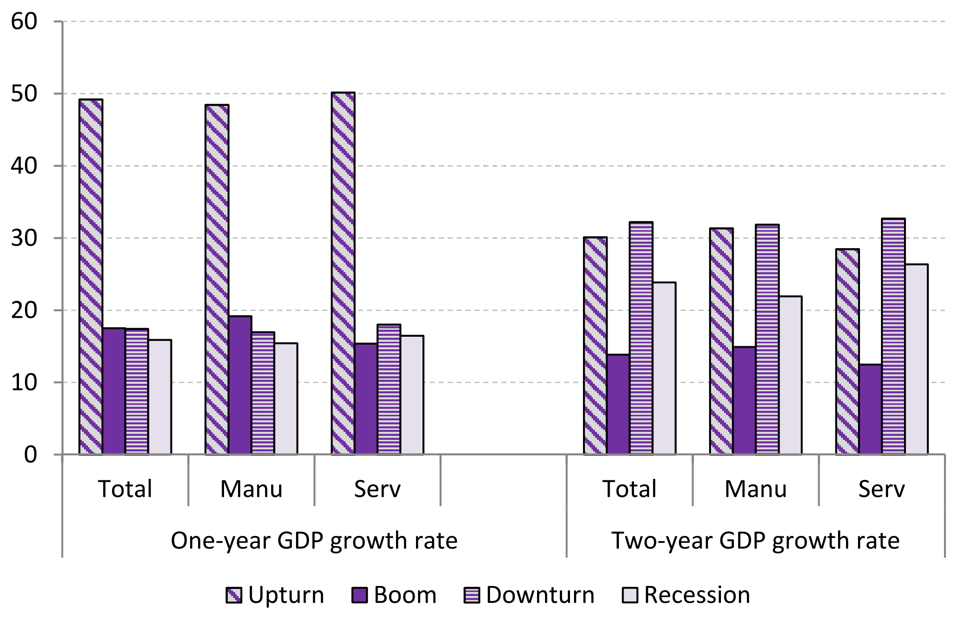
*Notes: Up to CIS2006 the industry classification was based on NACE Rev. 1.1 (NACE: Nomenclature générale des activités économiques dans les Communautés Européennes), since CIS2008 NACE Rev. 2 has been used as industry classification system.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation*

2 Note that for CIS3, CIS4 and CIS2006 information on industry classification was based on NACE Rev. 1.1. From CIS2008 onwards CIS data uses NACE 2 for classifying industries. A concordance has been used to define 11 and 8 industries in manufacturing and services, respectively.

Within the services sector, the observation shares are more dispersed than in manufacturing. Wholesale, with a share of 33.75% by far exceeds the other industries. Subsequently, transport, technical services and telecommunication/information technology have observation shares ranging from approximately 10% to 21%.

The number of observations for each business cycle phase is displayed in Table 3.4. In order to assign the firms observations from CIS to a distinct business cycle phase, we reported both one- and two-year GDP growth rates. For instance, for CIS2010, covering the period 2008-2010, the one-year growth measures GDP growth between 2009 and 2010 whereas the two-year growth rate measures growth between 2008 and 2010. Using the one-year growth rate, we assign half of the sample to upturn phases, and roughly similar shares to the other three phases (see also Figure 3.1). Over 90% of the observation between 1998 and 2006 belong to upturn and boom phases. Until the year 2006 there were no observations assigned to a recession. A quite different picture emerges when we use two-year growth rates. We still observe a similar amount of observations belonging to a boom phase whereas the proportions of upturn and downturn are now similar at about 32%. Interestingly, most observations for CIS2010 (which includes the financial crisis of 2008-09) would be assigned to an upturn phase using the one-year growth rate. In contrast, the two-year GDP growth assigns the vast majority of observations to a recession.

**Figure 3.1: Distribution of CIS sample by sector and business cycle phases (in %)**




*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

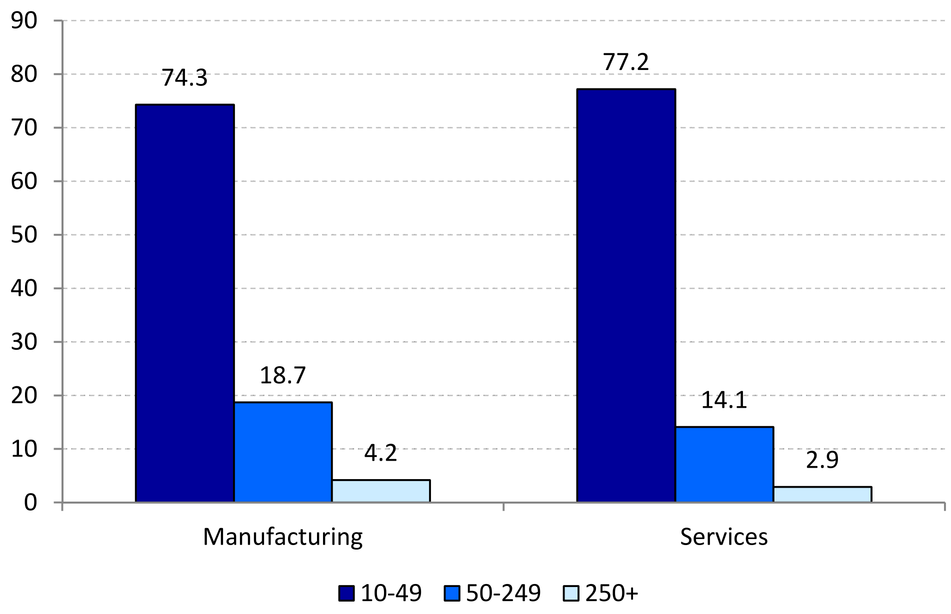
**Table 3.4: Distribution of the CIS sample by business cycle phases**

| Sample | Observation Period | Number of Observations by Business Cycle Phases Using One-Year GDP Growth Rates | | | | Number of Observations by Business Cycle Phases Using Two-Year GDP Growth Rates | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Upturn | Boom | Downturn | Recession | Upturn | Boom | Downturn | Recession |
| Total | 1998-2000 | 30,883 | 27,027 | 10,123 | 0 | 36,922 | 24642 | 6469 | 0 |
| | 2002-2004 | 61,414 | 14,910 | 2,765 | 0 | 76,324 | 1279 | 1386 | 0 |
| | 2004-2006 | 29,736 | 30,660 | 4,961 | 0 | 7,946 | 30660 | 26751 | 0 |
| | 2006-2008 | 10,391 | 0 | 54,329 | 34,936 | 0 | 732 | 98924 | 0 |
| | 2008-2010 | 71,476 | 0 | 0 | 30,863 | 3,536 | 0 | 0 | 98803 |
| | 1998-2010 | 203,900 | 72,597 | 72,178 | 65,799 | 124,728 | 57413 | 133530 | 98803 |
| | in % | 49 | 18 | 17 | 16 | 30 | 14 | 32 | 24 |
| Manufacturing | 1998-2000 | 19,452 | 18,375 | 5,813 | 0 | 23,756 | 16016 | 3868 | 0 |
| | 2002-2004 | 34,743 | 8,620 | 1,630 | 0 | 43,363 | 785 | 845 | 0 |
| | 2004-2006 | 16,702 | 17,917 | 2,860 | 0 | 4,399 | 17917 | 15163 | 0 |
| | 2006-2008 | 5,976 | 0 | 29,454 | 19,566 | 0 | 224 | 54772 | 0 |
| | 2008-2010 | 36,699 | 0 | 0 | 16,599 | 1,945 | 0 | 0 | 51353 |
| | 1998-2010 | 113,572 | 44,912 | 39,757 | 36,165 | 73,463 | 34942 | 74648 | 51353 |
| | in % | 48 | 19 | 17 | 15 | 31 | 15 | 32 | 22 |
| Services | 1998-2000 | 11,431 | 8,652 | 4,310 | 0 | 13,166 | 8626 | 2601 | 0 |
| | 2002-2004 | 26,671 | 6,290 | 1,135 | 0 | 32,961 | 494 | 541 | 0 |
| | 2004-2006 | 13,034 | 12,743 | 2,101 | 0 | 3,547 | 12743 | 11588 | 0 |
| | 2006-2008 | 4,415 | 0 | 24,875 | 15,370 | 0 | 508 | 44152 | 0 |
| | 2008-2010 | 34,777 | 0 | 0 | 14,264 | 1,591 | 0 | 0 | 47450 |
| | 1998-2010 | 90,328 | 27,685 | 32,421 | 29,634 | 51,265 | 22471 | 58882 | 47450 |
| | in % | 50 | 15 | 18 | 16 | 28 | 12 | 33 | 26 |

*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

Size is an important determinant of innovation activity. In order to test for firm size effects, the sample has been split into small (10-49 employees), medium (50-249 employees) and large (over 250 employees) firms. Figure 3.2 depicts the size distribution of the sample. With 74.3% and 77.2% both, in the manufacturing and the services sector, small firms are by far the largest group. The distribution within the sectors is about the same in manufacturing and services; however, in the manufacturing sector medium and large firms have a relatively higher share compared to the small firms than in the services sector.

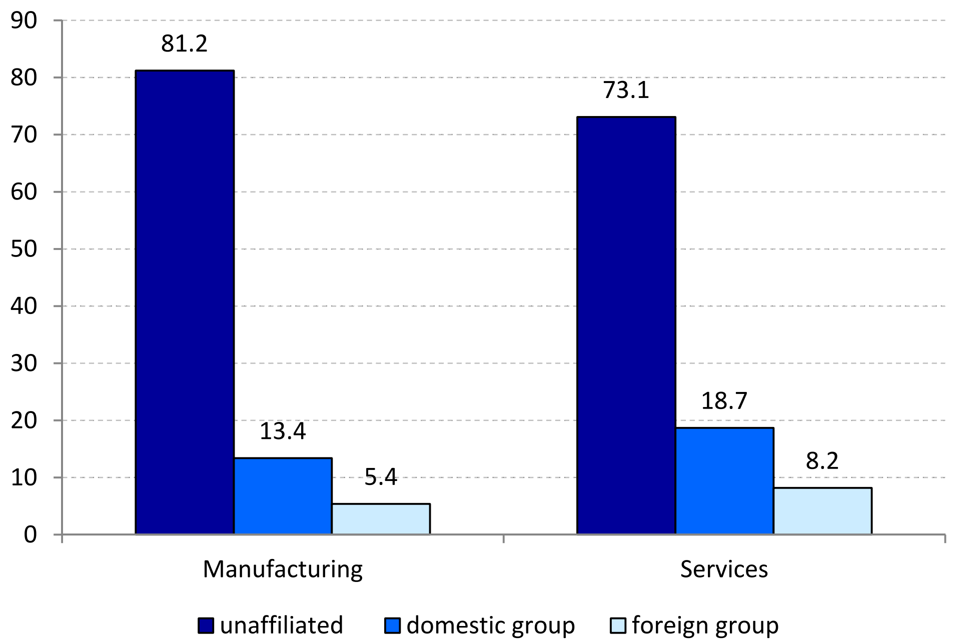
**Figure 3.2: Distribution of CIS sample by firm size**




*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

Furthermore, we split the sample according to the firm's affiliation to a domestic or foreign enterprise group. Foreign-owned and domestically-owned firms may differ in the extent of their employment growth due to price, demand and productivity effects. In both sectors, more firms belong to a domestic than to a foreign group. Nevertheless, the majority of the firms in the CIS sample is unaffiliated to a domestic or foreign group of enterprises.

**Figure 3.3: Distribution of CIS sample by ownership**




*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

### 3.3. MANNHEIM INNOVATION PANEL (MIP)

As a second main data source, we will exploit the German contribution to the CIS, the Mannheim Innovation Panel (MIP). It is conducted by the Centre of European Economic Research (ZEW), the Fraunhofer Institute for Systems and Innovation Research (ISI) and the Institute for Applied Social Sciences (infas) on behalf of the German Federal Ministry of Education and Research (BMBF). The MIP is based on a written survey and it likewise follows the definition of innovation and the recommendations on the survey methodology which are laid down in the Oslo manual. However, it deviates from the European CIS in three important aspects:

- First, the MIP is conducted annually. It started in 1993 in manufacturing and 1997 in services. Every second year (prior to 2005: every fourth year) the data set represents the German contribution to CIS. We will make us of the period 1993-2012. For comparability purposes we will also check results when we restrict the time period to 1998-2010 as in the cross-country analysis.
- Second, the main virtue of the German data is its panel design. That is the data set allows tracking firms over time. Hence, the models linking innovation to employment and productivity growth will be estimated using panel econometrics and thus controlling for firm fixed effects. It might also be used to identify dynamic aspects of the link between innovation and growth. The panel-data analysis for one country is seen as a complement to the findings of the European cross-country analysis.
- Third, the employment threshold in order to be included in the survey is smaller. That is, the MIP targets all legally independent enterprises with at least 5 employees.

# Chapter 4.
# INNOVATION ACTIVITIES OVER THE BUSINESS CYCLE IN EUROPE

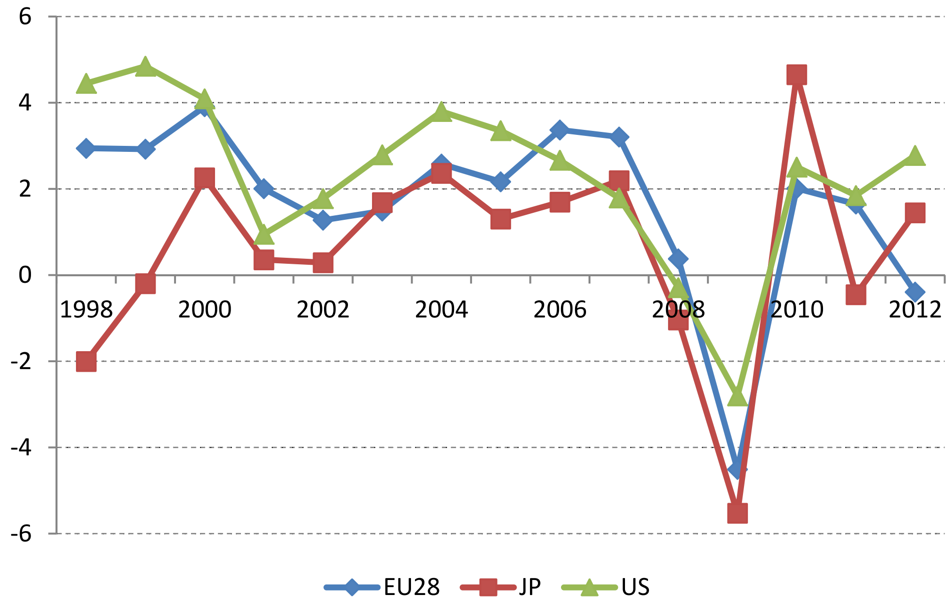
The aim of the study is to investigate the role innovation plays for firm growth over the business cycle. In the subsequent sections 5 to 10 we will explain how innovation affects changes in firms' productivity and employment in different phases of the business cycle based on multivariate estimation techniques. For a better comprehension of the estimation results, this section first provides some key figures on innovation activities and R&D investment over the course of the business cycle in Europe. We start by a brief description of the macroeconomic environment the firms were facing in terms of GDP development. In the following we show how R&D investment as a measure for the innovation input is related to GDP growth rates. Finally, we present some stylized facts about differences in innovation outcomes, measured by the share of innovators, over the course of the main business cycle phases.

## 4.1. THE DEVELOPMENT OF GDP

As explained in section 3.1 we base our business cycle indicators on country-level growth in GDP. We therefore start by presenting GDP growth rates for the period of 1998 to 2012. We focus on the period 1998-2012 since the CIS data that we use in the econometric analysis covers the years of 1998 to 2010. Since we want to show two more years of the post-crisis period of the recent financial crisis of 2008/2009, we have therefore included years 2011 and 2012 in the data presented in this and the next subsection.

Figure 4.1 presents the development of the annual real GDP growth rates of the world's main economic regions (in terms of GDP) between 1998 and 2012: an aggregate of the 28 countries of the European Union (EU-28), Japan (JP) and the United States (US). Although there are interregional differences in the levels of the growth rates, the overall growth trend is the same. The period between 1998 and 2000 has been a growth period. Remarkable is Japan's negative growth rate in 1998, which does not coincide with the positive rates of the US and the European Union's countries. This can be largely explained by the Asian financial crisis of 1997, which did not severely affect the US and Europe. All countries' relatively high growth rates around 1999/2000 had been primarily induced by a "dot-com hype" that transitioned into the so called "dot-com bubble". The burst of the bubble in the beginning of 2000 led to a period of strong economic downturn lasting two years until 2002, even though the annual GDP growth rates remained positive at that time. This downturn has been followed by a recovery period with a growth peak across the regions in 2004. Afterwards, the GDP growth cooled off again.

**Figure 4.1: Annual GDP growth of EU-28, Japan and the United States, 1998-2012 (in %)**

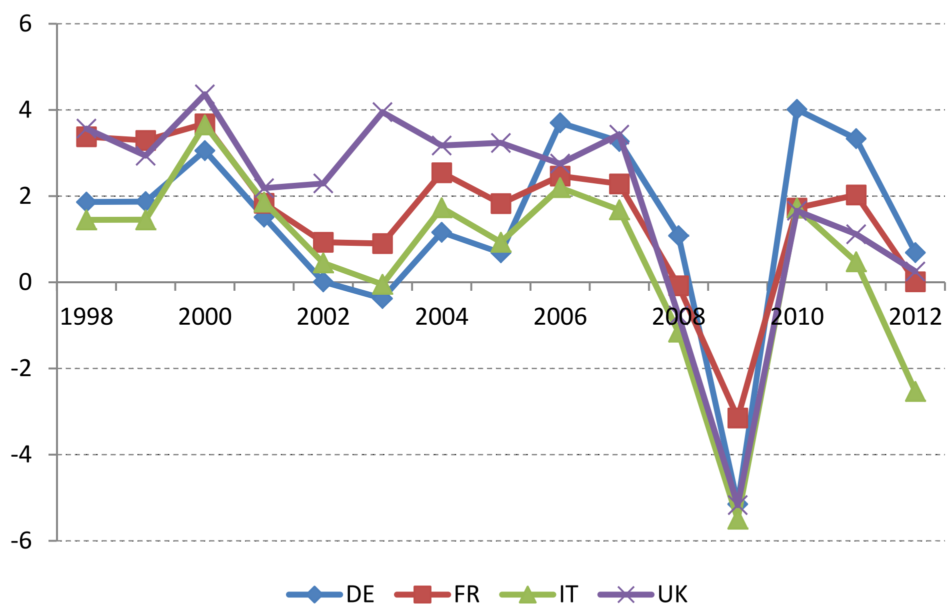



*Source: Eurostat (2014), own calculation.*

Note that while the US entered a period of continuous economic downturn from 2005 on until 2008, Japan's and Europe's growth rates started to rise again in 2006 (and in Japan also in 2007). The most recent financial crisis started to paralyze the economies of the US, Japan and Europe in 2008 and 2009. Europe and Japan have been severely affected by this crisis, witnessed by growth rates of -4.5% (EU-28) and -5.5% (Japan) in 2009, respectively. The US economy was hit a little less with a decrease in GDP by -2.8% in 2009. While all three regions have already recovered in 2010, only the US has managed to maintain the positive growth rates in the crisis' aftermath. Japan and Europe still seem to endure economic troubles.

Figure 4.2 additionally depicts GDP growth rates of EU-28's largest countries in terms of GDP: Germany, France, Italy and the United Kingdom. During the period of 1998 to 2012, the overall economic trend of these countries has been quite similar among each other as well as compared to EU-28, Japan and the US. A notable difference is the relatively stable and high growth rates of the UK after the burst of the dot-com bubble until the impact of the crisis of 2008/2009. When the most recent financial crisis started to shake the world's economies, not surprisingly, even Europe's strongest economies suffered from this crisis. However, compared to the relatively moderate decline of the French GDP growth rate (-3.1%) in 2009, Germany's, Italy's and the UK's growth rate dropped by even more than -5% in the same year.

**Figure 4.2: Annual GDP growth of selected EU-28 countries, 1998-2012 (in %)**




*Source: Eurostat (2014), own calculation.*

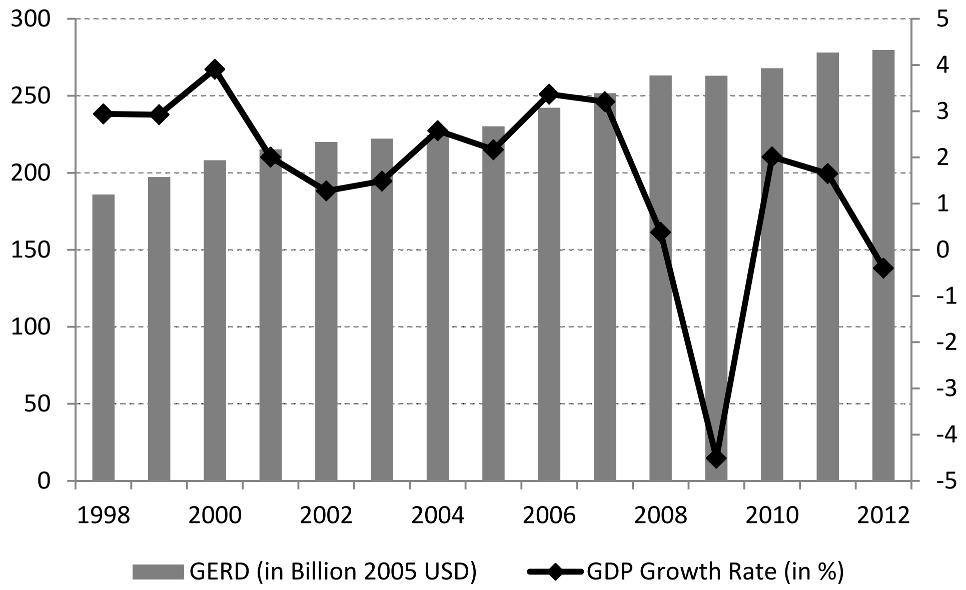
Although the four countries' GDP rates have started to grow again in 2010, all of them still seem to endure low or – in the Italian case – even negative growth rates. The post-crisis period of 2010-2012 remained as an unstable environment for firms. This indicates that not only resilience - the ability of countries to resist a crisis – is important for high levels of economic well-being, but also the ability to recover quick after a crisis, which is related to a high degree of flexibility in shifting resources between sectors.

## 4.2. GDP GROWTH AND R&D INVESTMENT

Demand fluctuations or – in terms of a longer term perspective –expectations of future demand as reflected by the firms' stock levels and business orders are important for firms to make a decision in favour of or against the conduction of specific R&D projects (see section 2.2). Hence firms' R&D and innovation activities are likely to be affected by a country's economic development. This section investigates to what extent R&D investment as an innovation input indicator is correlated with GDP growth.

The previous section has shown that the period 1998-2012 was characterized by a high volatility of GDP growth. Figure 4.3 compares EU-28's GDP growth rates (right axis) with the levels of gross domestic expenditure on R&D (GERD) (left axis) over time. In 1998, the level of GERD was about 186 billion USD (in constant prices, base year 2005). In 2012, 14 years later, this level amounts to almost 280 billion USD. This means that an overall increase in the gross domestic expenditure on R&D of about 50% has taken place. Moreover, this period has been characterized by constant annual increases in GERD, even though the increase in GERD was only modest during downturns. The only exception in which we observe a decrease in GERD is the year of 2009, which represents also the trough of the recent crisis. In sum, firms and governments taken together reduced their R&D expenditure in 2009. The last finding supports pro-cyclicality of R&D investment, as it has been largely found in the respective stream of literature. The pro-cyclicality becomes even more visible when we compare GDP growth rates with growth rates of R&D investment (see Figure 4.4).

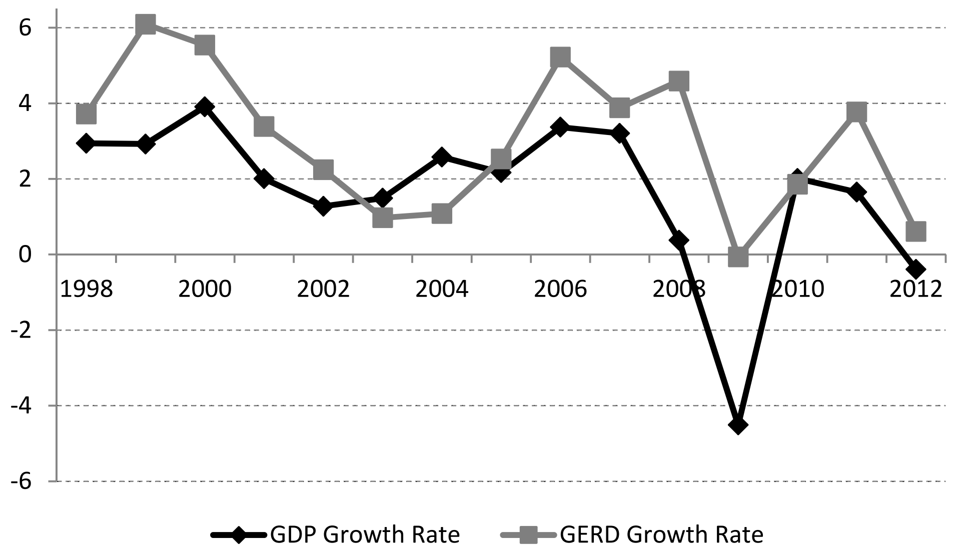
**Figure 4.3: GERD and annual GDP growth, EU-28, 1998-2012**




*Source: GERD data: OECD (2014); GDP data by Eurostat (2014), own calculation.*

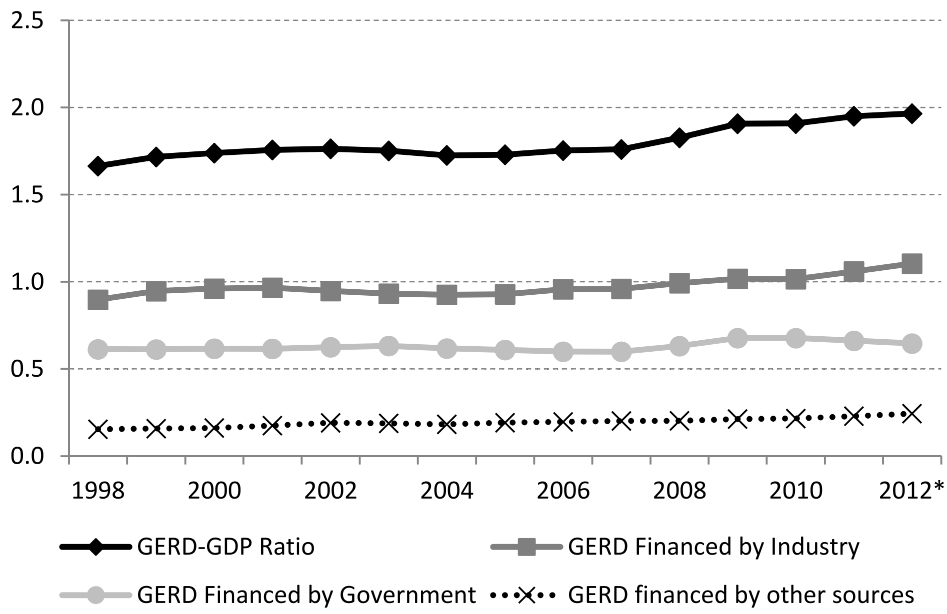
Figure 4.4 discloses a more unambiguous relationship between GDP growth and R&D investment during the observed period. The change of R&D investment largely co-evolves with the change of GDP. Higher (lower) growth rates of GDP are followed by higher (lower) growth rates of the overall R&D investment. The comparison of the R&D investment levels as well as the growth rates of the R&D investment with the growth rates of EU-28's GDP confirms a pro-cyclical R&D investment pattern of European firms.

**Figure 4.4: Annual growth of GERD and GDP, EU-28, 1998-2012 (in %)**




*Notes: GDP: gross domestic product; GERD: gross domestic expenditure on R&D; both measured in constant prices.*
*Source: GERD data: OECD (2014); GDP data: Eurostat (2014), own calculation.*

**Figure 4.5: GERD/GDP ratio by sources of finance, EU-28, 1998-2012 (in %)**




*Notes: Other sources include e.g. the university sector, private foundations and foreign countries. * Shares of the respective source of financing for 2012 are not yet available. In the figure, the 2012 shares are calculated based on the respective source of financing's growth rate of 2010 to 2011.*
*Source: OECD (2014), own calculation.*

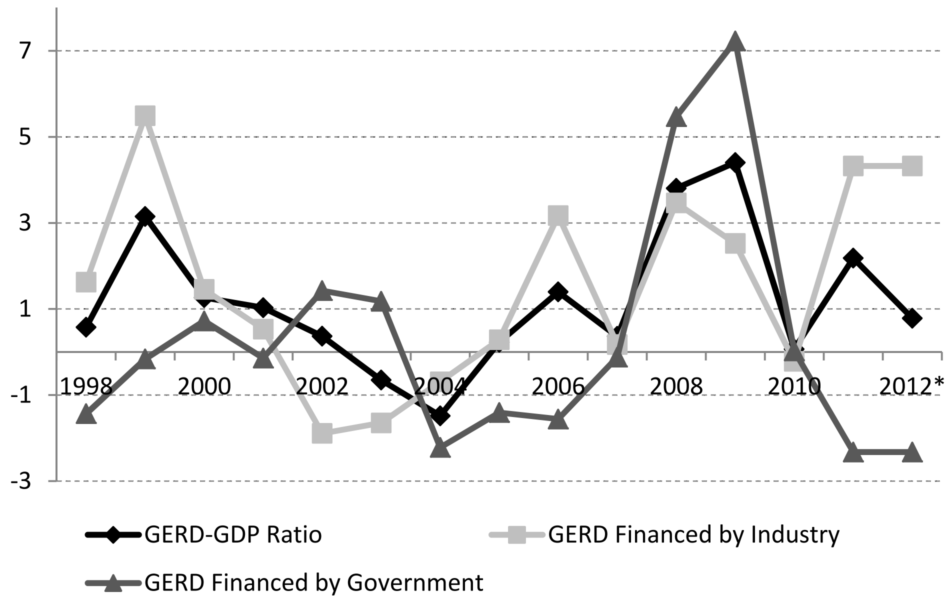
In most of the years, we observe a growth of GERD that is larger than the growth of GDP, the period 2003-2005 and the year 2010 being an exception. This in turn should have led to an increase in the GERD/GDP ratio over time, except for the aforementioned years. Figure 4.5 shows the development of the GERD/GDP ratio over time and confirms this finding. In 1998, the firms and governments of the European Union's countries in total spent about 1.66% of GDP for R&D investment. This ratio increased by almost 19% to 1.97% in 2012.[3] Maybe surprising at first glance is the increase in the GERD/GDP ratio during the deep crisis in 2009. It rose from 1.83% in 2008 to 1.91% in 2009. Though GERD contracted in 2009 as well, the decrease was much smaller than for GDP (see Figure 4.4) leading to a strong increase of the GERD/GDP ratio. The same argument holds in 2001 and 2002, the downturn period due to the burst of the dot-com bubble. Hence, whereas the gross expenditure on R&D (GERD) moves pro-cyclical, the ratio of GERD/GDP rather moves counter-cyclical.

In order to investigate whether the source of financing matters for the counter-cyclicality, Figure 4.5 additionally includes the development of EU-28's GERD/GDP ratio differentiated by the source of financing. The gross domestic expenditure on R&D that has been financed by the industry in relation to GDP ranges at about 1% during the period of 1998 and 2012. In 1998, the industry-financed GERD/GDP ratio was about 0.9% in EU 28. This ratio has increased by about 23% to 1.1% in 2012. This increase is relatively large compared to the development of other sources of finance during the same period. The government-financed GERD/GDP ratio has increased from 0.61% in 1998 to 0.65% in 2012, a rise of about 5.5%. The largest growth of GERD in relation to GDP during that period stemmed

[3] Eurostat (2014) reports a slightly higher GERD-GDP ratio of 2.07%.

from other financing sources. The ratio of GERD financed by other sources in relation to GDP mounted from 0.15% in 1998 to (provisional) 0.24% in 2012 – an increase of almost 59%.

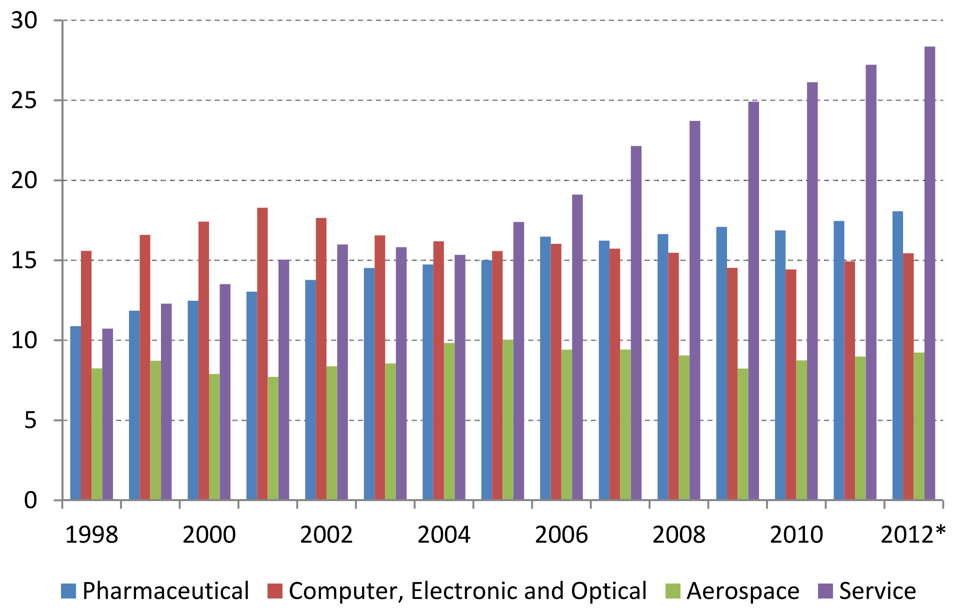
**Figure 4.6: Annual growth of GERD/GDP ratio, EU-28, 1998-2012 (in %)**




*Notes: The figure focusses on the main financing sources and leaves out other financing sources. *Only projections for 2012's government and industry rates are available, see note in Figure 4.5*
*Source: OECD (2014), own calculation.*

In addition to Figure 4.5, Figure 4.6 presents the annual growth rates of the respective GERD/GDP ratios, differentiated by the source of financing. The time series largely confirm the prior finding of counter-cyclicality in the GERD/GDP ratio. In particular, the government-financed GERD/GDP ratio has evolved counter-cyclical. From 1998 on, the government-financed GERD/GDP ratio has always increased when the economy has suffered from decreasing growth. On the contrary, the government-financed GERD/GDP ratio has declined when the economy has experienced increasing growth. Exceptions are the years of 2000 and 2001. While the government-financed GERD/GDP has evolved counter-cyclical according to Figure 4.6, the results are less stringent for industry-financed GERD/GDP ratio. The industry-financed GERD/GDP ratio strongly moved with the business cycle in the years of 1998, 2002, 2006, 2011 and 2012. In all other years, it evolved moderately counter-cyclical.

**Figure 4.7: BERD in selected high-tech industries in Europe, 1998-2012 (in billion 2005 USD)**

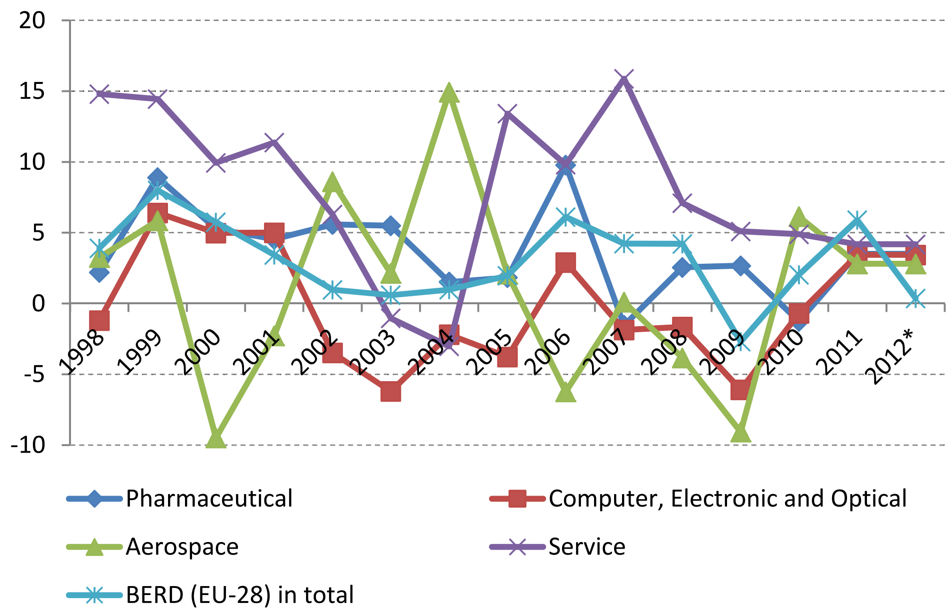



*Notes: Information on R&D expenditure in the four industries is not available for all EU-28 countries. The EU industry aggregate includes R&D expenditure of the following countries: Belgium, Czech Republic, France, Germany, Italy, Slovenia, Spain and The United Kingdom. * Data for 2012 not yet available. 2012 values have been calculated based on industry-wide BERD growth rates between 2010 and 2011.*
*Source: OECD (2014), own calculation.*

An interesting question is whether the development of R&D expenditure is similar in all industries. Time series are not available for all industries in all EU 28 countries. Hence, Figure 4.7 highlights the development of R&D expenditure done in the business sector (BERD) for some selected high-tech industries, i.e. pharmaceutical industry, the computer, electronic and optical industry, the aerospace industry and service industry. In addition, Figure 4.8 depicts the annual growth rates of BERD in the selected high-tech industries. The service industry, in particular IT services, has experienced a steady increase in R&D expenditure. Its level mounted from almost 11 billion 2005 USD in 1998 to about 28 billion 2005 USD in 2012. That is a growth by about 164%.[4] By 2012 it has become the most important industry among the different high-tech industries in terms of BERD. Overall, the growth rates of R&D expenditure moves pro-cyclical in the service industry, with exceptions being the years of 2001-2004 (see Figure 4.8). Among the four industries, R&D expenditures are smallest in aerospace. In this industry, R&D expenditures have grown from more than 8 billion 2005 USD to more than 9 billion 2005 USD (+12%) but R&D exhibits a pro-cyclical pattern over the period (except for the period 2002-2002). A pro-cyclical pattern of R&D expenditure is also observed for the computer, electronic and optical industry. Interestingly, we observe a decline trend of R&D expenditure over time in this industry with a decrease of R&D expenditure between 1998 and 2012 of about 1%. In pharmaceuticals R&D expenditures have steadily grown from 1998 to 2006. Since then R&D expenditures have remained rather constant.

[4] Part of this increase might be artificial due to an increased effort to cover service firms in R&D surveys.

**Figure 4.8: Annual BERD growth rates in selected high-tech industries in Europe, 1998-2012 (%)**




*Notes: See Figure 4.7*
*Source: OECD (2014), own calculation.*

## 4.3. INNOVATOR SHARES OVER THE BUSINESS CYCLE

So far, we have described the very basic macroeconomic environment of the observed period. Additionally, we have linked it to the development of the R&D investment as an indicator for innovation input, measured as gross domestic expenditure on R&D. The comparison of GDP growth rates with growth rates of GERD supports evidence for pro-cyclicality.

This subsection presents evidence on innovation activity indicators over the business cycle. We investigate the shares of different kinds of innovators over the main phases of a business cycle: recession, upturn, boom and downturn. In the following we use the two-year GDP growth to define these business cycle stages. According to this indicator, the EU-28 region has suffered from a recession in the years of 2009 and 2010. An upturn has taken place in 1998 and 1999 as well as between 2004 and 2006 and finally in the year of 2011. The years of 2000 and 2007 are identified as boom phases. A downturn has been observed between 2001 and 2003 as well as in 2008 and in 2012.

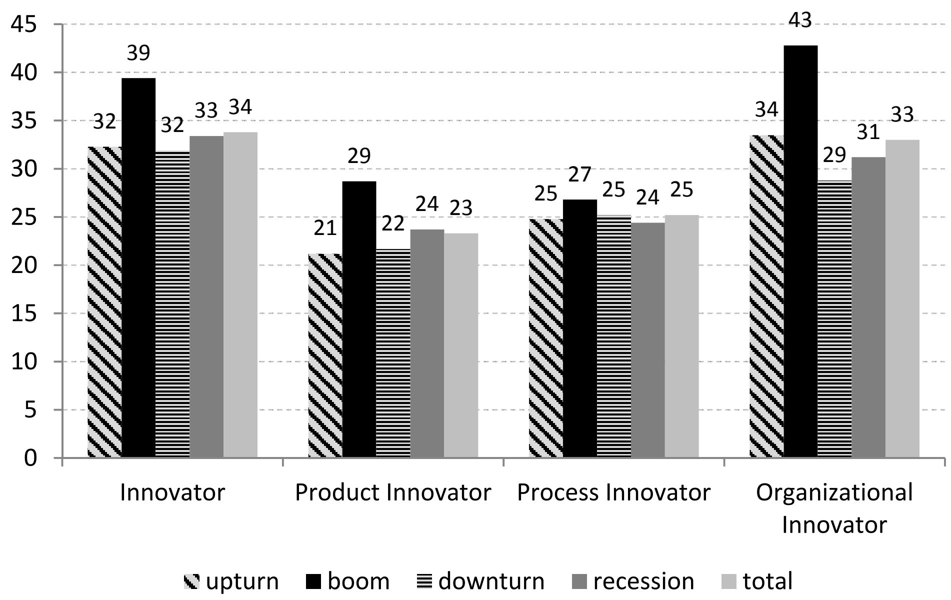
Figure 4.9 compares the shares of different kinds of innovators over the particular business cycle phases. Note that in Figure 4.9 and in all following figures weighted shares are reported.[5] 34% of all observed firms (across all observed countries) introduced at least one product or process innovation over the sample period of 1998 to 2010, 33% of the firms introduced at least one organizational innovation while 23% (25%) introduced at least one

[5] Eurostat provides weights for each firm which extrapolate to the number of firms in the population in each strata in the respective country. Industry and size classes serve as stratification characteristics.

product (process) innovation.[6] This means that there have been almost as many technological innovators as non-technological innovators.

As one would expect from the literature, the share of innovators is highest in a boom phase. This may be explained by higher growth expectations in boom phases, more favourable opportunities to finance innovations, and a more optimistic business environment in general. While 29% of the firms embraced the opportunity to introduce at least one new product in a boom phase of their home country, 27% decided to implement at least one process innovation and even 43% have carried out new changes in their organizational processes. There are two really unexpected outcomes. On the one hand, there have been almost as many overall technological innovators during a downturn period (31.9%) than during an upturn period (32.3%). On the other hand – and that is more surprising – there have been even slightly more overall technological innovators during the recession periods (33.4%) than during the downturn and upturn periods. These two unexpected outcomes are more pronounced in the case of product innovators. Accordingly, there have been more product innovators during downturns (21.7%) than during upturns (21.2%). Moreover, 23.7% of the companies whose home country was stuck in a recession implemented their innovations at that time. We would rather expect a firm to innovate during a period of relatively stable and positive demand, not during a period of increasing uncertainty, lower demand and potentially diminishing expectation of future demand growth. The process innovators provide larger expected outcomes although the innovator shares do not differ much.

**Figure 4.9: Innovator shares over the business cycle (in %)**

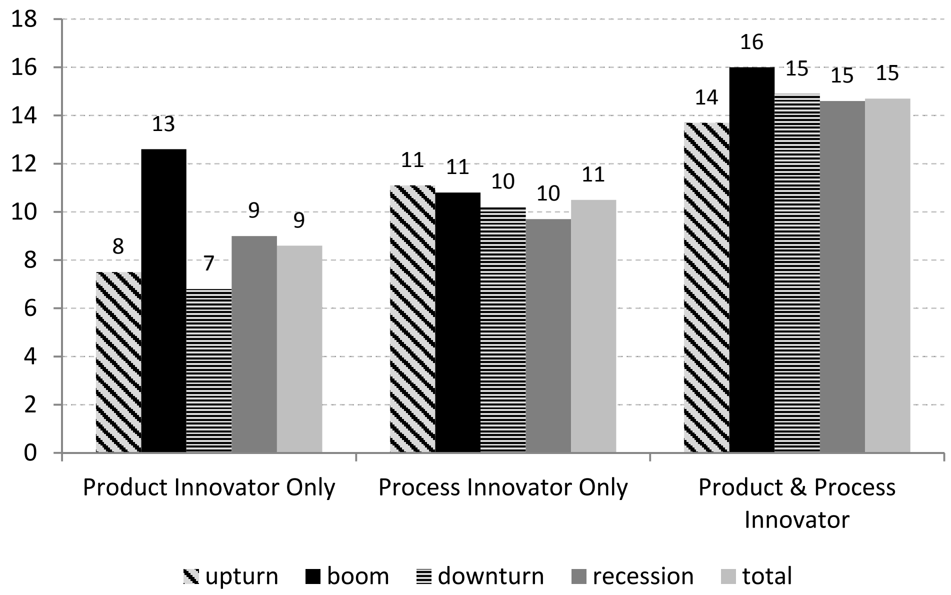



*Notes: Innovator shares are weighted. Weights are provided by Eurostat.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

[6] Product and process innovators are considered as technological innovators while organizational innovators are considered non-technological innovators. The term "Innovator" refers to companies who have implemented at least one product and/or at least one process innovation. They are considered overall technological innovators.

The share of firms that implemented at least one process innovation while the economy was in the middle of a downturn period (25.2%) slightly exceeds the process innovator share during an upturn period (24.8%). Both shares are greater than the process innovator rate during a recession (24.4%). Ultimately, process innovations seem to be not as business cycle dependent as product innovations. Obviously there is no optimal period to improve efficiency as opposed to introduce new products. The shares in Figure 4.9 can be a bit misleading in the sense that the denoted product and process innovators are not pure product and process innovators. Accordingly, a firm that implemented a product innovation in a given period also could have implemented a process innovation. Figure 4.10 highlights differences in product and process innovation strategies among European firms over the business cycle.

**Figure 4.10: Product and process innovation strategies over the business cycle (in %)**

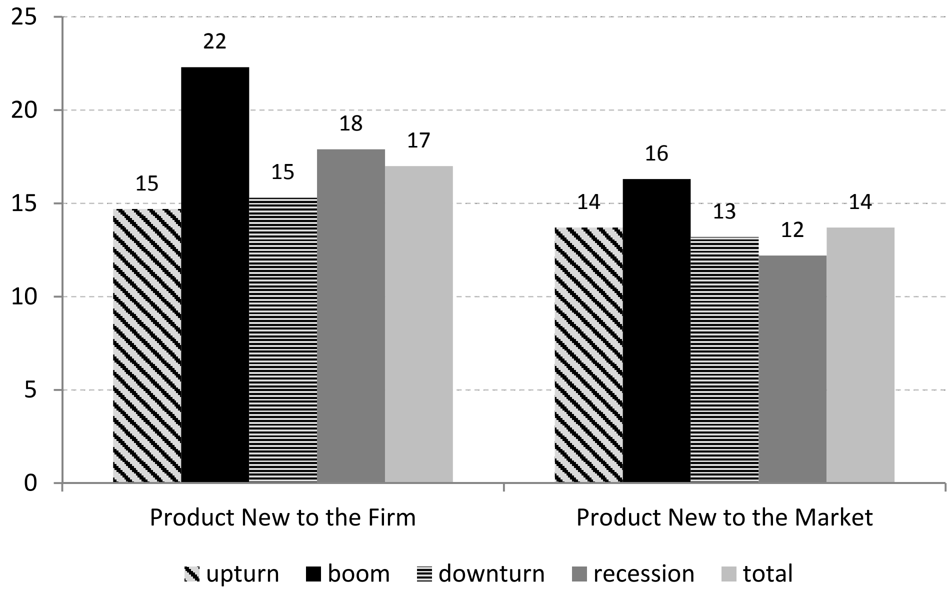



*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

A pure product innovator implemented at least one product innovation between 1998 and 2010 and did not simultaneously implement any process innovation. Even during recession times, firms have been more inclined to introduce only product innovations (9%) than during upswing periods (7.5%). However, there have been more pure product innovators during upturns (7.5%) than during downturns (6.8%). Contrary to pure product innovations, the relationship between the business cycle and the implementation of pure process innovations seems to be more pro-cyclical. Companies who have only implemented new processes prefer upturns (11.1%) over booms (10.8%). Downturn (10.2%) and recession (9.7%) periods have been chosen less frequently. Thus, firms who are inclined to implement only new processes show evidence for deciding about the implementation in favour of growth periods. In contrast, firms who have introduced at least one product and one process innovation (Product & Process Innovators) in a given period have preferred boom phases (16%), followed by downturns (14.9%), recessions (14.6%) and upturns (13.7%). However, there is not much variation between the phases.

A better understanding of the greater shares of (pure) product innovators during recession periods compared to upturn and downturn periods requires knowledge of the degree of the product innovations. A product innovating firm can basically decide on whether to offer a new product that is already offered by a rival – a product new to the firm (product imitation) – or whether to introduce a product that is new to the market (market novelty). A firm's trade-off is then to choose between a product that has not been offered on the market before and a product that in a similar manner that has already been existent on the market for some time, which embodies a more calculable risk. Thus, it is a trade-off on uncertainty of the market demand.

**Figure 4.11: Product innovators distinguished by the degree of innovation over the business cycle (in %)**




*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

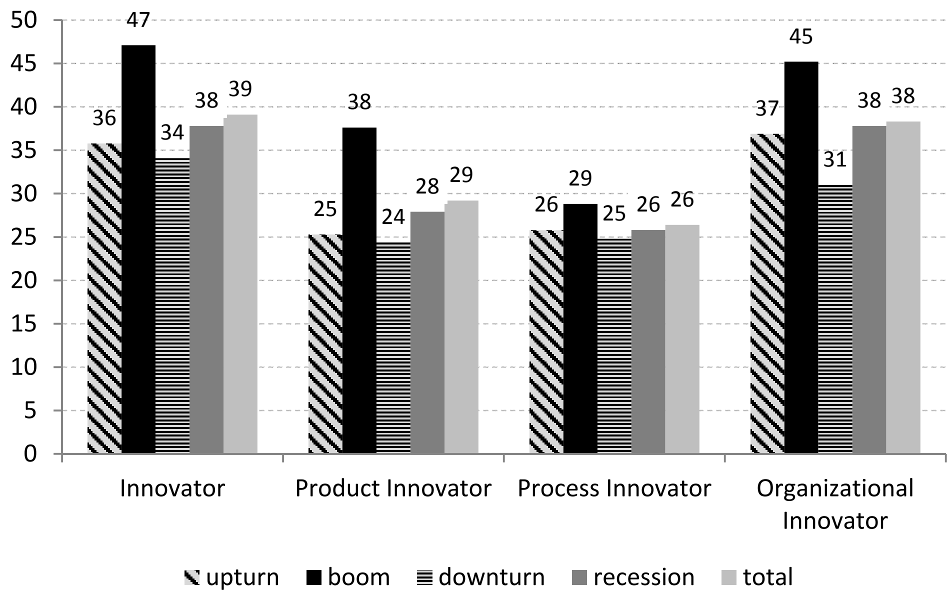
According to Figure 4.11, the share of innovators for both types of product innovation is highest during a boom period; 22.3% and 16.3% for firm and market novelties, respectively. Interestingly and in contrast to firm novelties, we observe a clear pro-cyclical pattern for market novelties. That is, firms are more inclined to introduce market novelties during flourishing market conditions (boom and upturns) than during downturns and recessions in particular. As expected, the more uncertain the product innovation success, the more of a stable and calculable market environment is required. On the contrary, however, we do not observe the same pattern for firm novelties. That is, we likewise observe the highest engagement during boom periods, but followed by recession and downturn periods. The finding of a more pronounced imitation strategy during downswings and recessions supports the view that the lack of demand and intensified competition encourages firms to adopt new products that have already been (successfully) introduced by competitors.

We conclude this section by investigating whether differences in innovation strategies over the business cycle exist between firms from different regions. We broadly distinguish between two regions: Firms located in North-west Europe, which includes Belgium, Germany, Denmark, France, Finland, Ireland, Luxemburg, the Netherlands, Sweden, Iceland, Norway, and firms located in South-east Europe.[7] South-eastern European countries comprise Bulgaria, Cyprus, Czech Republik, Estonia, Greece, Croatia, Hungary, Italy, Latvia, Lithuania, Malta, Poland, Portugal, Romania, Slovakia, Slovenia and Spain. On average,

[7] Austria, Poland and the UK have not sent CIS micro data to Eurostat.

firms in North-west Europe are larger, more concentrated in high-technology industries and more competitive. Figure 4.12 presents the innovator shares for North-western European countries. It turns out that the distributions of technological and non-technological innovators are quite similar.

**Figure 4.12: Share of innovators over the business cycle in North-western European countries (in %)**




*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

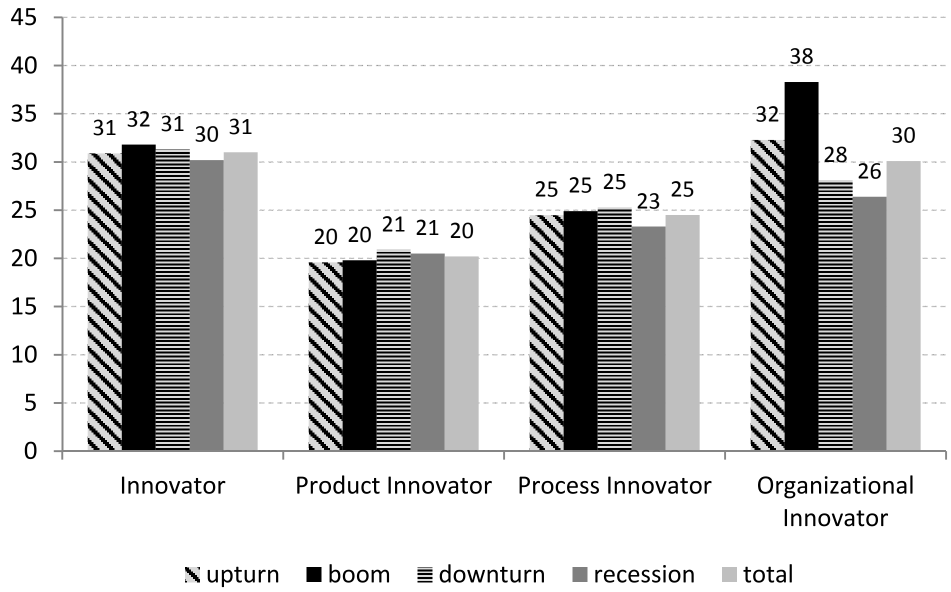
We find a similar pattern than or Europe as a whole. In particular, firms that have implemented a technological innovation have most frequently chosen boom phases (47.1%), followed by recessions (37.8%), upturns (35.8%) and finally downturns (34.1%) as the introduction period. In contrast to the overall shares inFigure 4.9, it turns out that both product and process innovators are more frequent in recession periods than in downturn phases. Moreover, there have been more product (25.3%) and process (25.8%) innovators during upturn periods than during downturn periods (24.4% and 24.8%, respectively) in North-western European countries.

As expected, North-western European firms have been more innovative than the South-eastern European firms. Compared to firms from North-west Europe, firms from South-east Europe were less likely to implement at least one product or process innovation between 1998 and 2010 (39.1% compared to 31.0%). A similar gap is observed for organizational innovation between North-west and South-east Europe (38.1% compared to 30.1%).

A surprising result, however, is the apparent business cycle independence among firms from South-east Europe, see Figure 4.13. The maximum and the minimum shares within the group of product and process innovators and thus also for overall technological innovators do not differ by more than 2%-points. The respective innovator shares across the business cycle phases range from 30.2% to 31.8% (overall technological innovators), from 19.6% to 20.9% (product innovators) and from 23.3% to 25.3% (process innovators). Thus, no clear pattern among the technological innovators is disclosed. In contrast, non-technological innovators have an innovator share distribution that is similar to the distributions of the North-western European countries.

This section has shown that firms tend to use recession times more frequently to implement innovations as we would have expected. It therefore underlines the finding that a considerable heterogeneity of pro- and counter-cyclical strategies exists in the business sector. Moreover, firms do not really seem to prefer an upturn period over a downturn period for implementing an innovation, though there is a small difference in the propensity. Unambiguously, firms choose boom phases for the implementation of technological as well as non-technological innovations. Due to the counter-cyclical tendency arising from the considerably strong relationship between innovating and recession times, the results so far do not really show a convincing pro-cyclical innovation pattern.

**Figure 4.13: Share of innovators over the business cycle in South and East Europe (in %)**



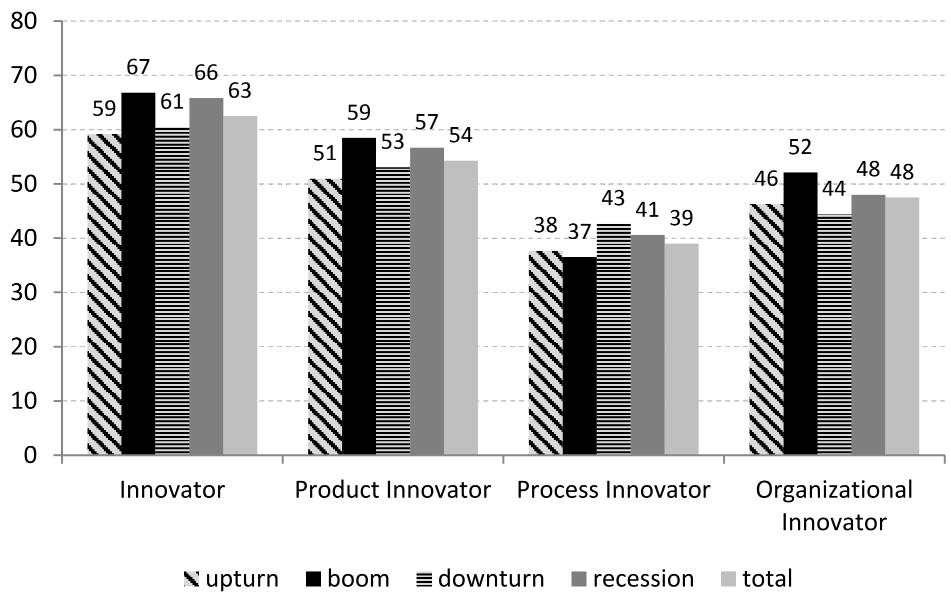

*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

## 4.4. INNOVATOR SHARES AND THE BUSINESS CYCLE ACROSS DIFFERENT SECTORS

Firms that are active in high-technology sectors are considered to be more innovative in terms of R&D intensity. In order to compete successfully, such firms have to keep pace with the state-of-the-art technology. That is only possible by conducting (own) R&D on a continuous base or at the very least on an occasional base. Hence, the lower the technology sector class a firm is part of the lower should be the share of innovators, on average. In the following we make use of a Eurostat classification categorizing sectors based on their technology intensity. In manufacturing, we distinguish between high-technology, medium-technology and low-technology sectors and in services between knowledge-intensive and less knowledge-intensive services; for a definition see Table 11.1 in the Table Appendix.

The first hint for this conjecture to be true is given by Figure 4.14. 62.5% (47.5%) of the companies of the high-technology sector have implemented at least one technological (non-technological) innovation. In fact, this sector is really an innovative one. Most of the firms (66.8%) chose to implement their innovations (66.8%) while having been in a boom phase but the percentage of firms that innovated while the home country was suffering from a recession is almost as high (65.8%). High-technology sector companies thus seem to prefer (or to wait for) business cycle extremes to make their implementation decision.

**Figure 4.14: Share of innovators in high-tech sectors over the business cycle (in %)**



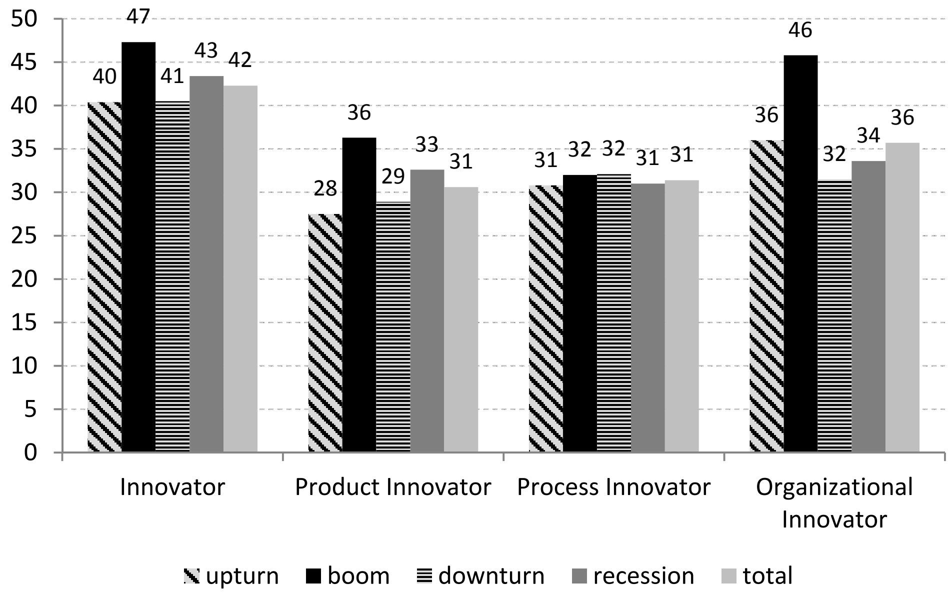

*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

The difference between the implementation during an upturn (59.2%) or during a downturn (60.5%) is only a slight one, again. In that case, however, firms were more inclined to implement the innovation during an economic downturn. The distribution of the innovator shares related to product innovators is similar to the distribution related to the overall technological innovators, even though the levels are lower. In contrast, the innovator share distribution of the process innovators differs. Accordingly, 42.7% of the firms implemented at least one new process while undergoing a downturn period. Even the respective share of firms who were in the middle of a recession (40.6%) exceeds the share of firms having been in a boom (36.5%) and an upturn phase (37.7%), respectively. Thus, for process innovations in the high-tech sector it seems to be most convenient to be implemented during economically difficult times. Organizational innovators, however, are more likely to innovate during an economic boom (52.1%) than during a recession (48%).

Companies that are part of a lower technology – the medium-technology – sector are not as likely to be an innovator as are firms of the high-technology sector (Figure 4.15). 42.3% of the medium-tech firms introduced technological innovations during the sample period while the equivalent share of high-tech firms is 62.5%.

The innovator share distributions of medium-tech firms largely correspond to the distributions of high-tech firms, at least among the group of the overall technological innovators and product innovators. Process innovating medium-tech firms seem to be business cycle independent regarding their implementation decision, with the shares ranging from 31% (recession) to 32% (boom), unlike organizational innovators. In contrast to high-tech organizational innovators, the medium-tech equivalents were more likely to implement their innovations during boom phases (45.8%), followed by upturn periods (36%). The relationship is more pro-cyclically shaped.

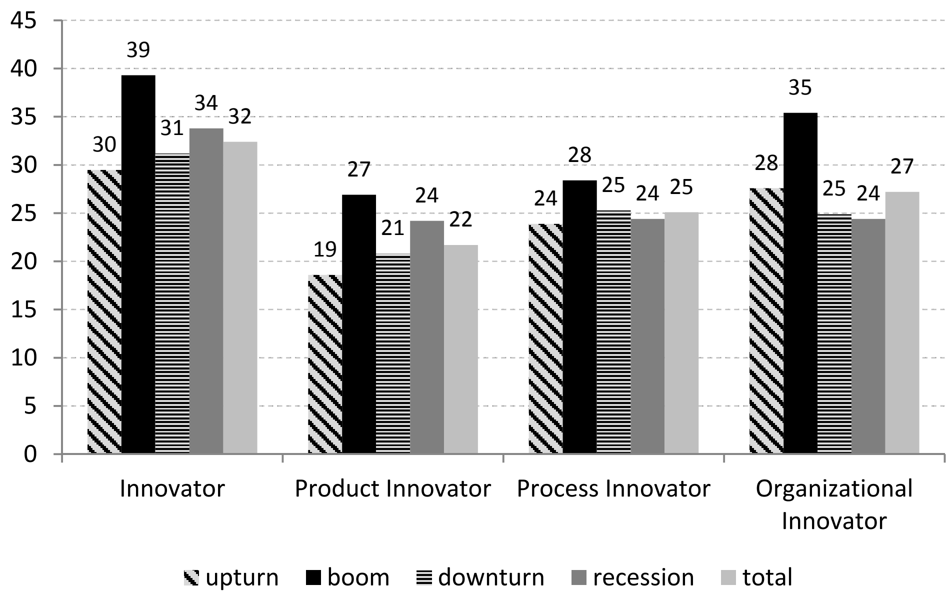
**Figure 4.15: Share of innovators in medium-tech sectors over the business cycle (in %)**




*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

Figure 4.16 presents the innovator shares of low-technology firms over the business cycle phases. The overall technological (non-technological) innovator share is 32.4% (27.2%). That means, low-technology firms are the least innovative among the firms of the different technology sector classes. Unlike the organizational and process innovators, product innovators as well as the group of the overall technology innovators have the same preference order regarding their implementation decision. While experiencing an economic boom, 39.3% of the firms decided to implement at least one technological innovation and 26.9% of the firms decided to introduce new products. The propensity to innovate is at lowest during an economic upturn – 29.5% (18.6%) for technological (product) innovators. The difference between the shares of the process innovators is relatively small. They range from 23.9% (upturn) to 28.4 (downturn). Contrary to the other types of innovators, organizational innovators seem not only to prefer boom phases (35.4%) but also upturn periods (27.6%) as the period of introduction.

**Figure 4.16: Share of innovators in low-tech sectors over the business cycle (in %)**

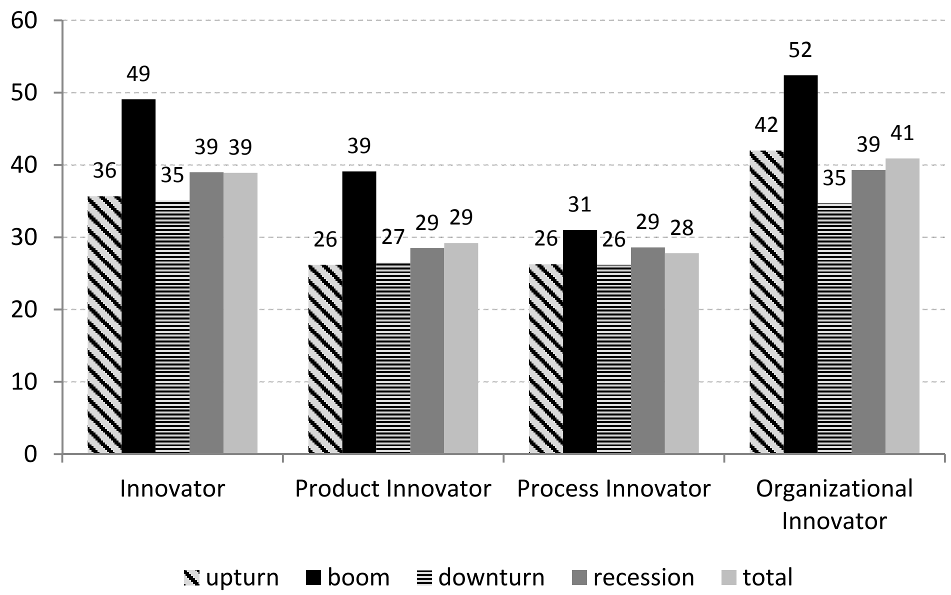



*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

Apart from the strong propensity of firms to innovate during traditional periods of high demand (booms), high-tech, medium-tech and low-tech firms seem to be more inclined to implement their technological innovations during economically difficult times. They do show some evidence for counter-cyclicality. Organizational innovators, however, chose growth periods for the implementation.

Since the classification of high-tech, medium-tech and low-tech only applies to firms of the manufacturing sector we also want to describe the innovator shares of the service sector. For that reason, we add two more figures, distinguished by knowledge-intensive and less knowledge-intensive firms.

**Figure 4.17: Share of innovators in knowledge-intensive service sectors over the business cycle (in %)**



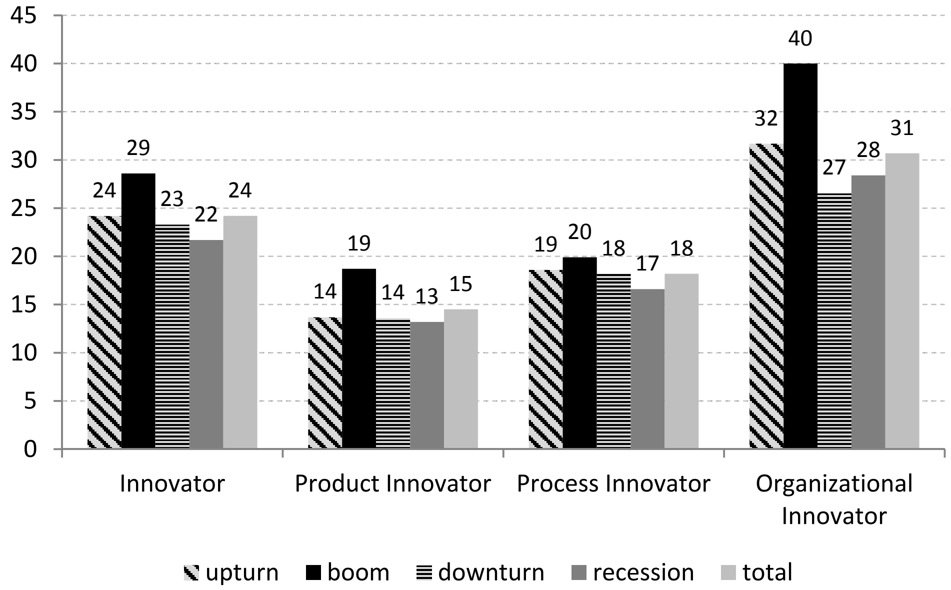

*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

Figure 4.17 presents the innovator shares of firms who have been part of the knowledge-intensive service sector. In effect, there is not a big difference of the innovator shares compared to the ones of the manufacturing sector's technology classes. A notable difference, however, is that the downturns do not seem to be a better opportunity for the introduction of technological innovations compared to upswing periods. That is a hint for more of a pro-cyclical behaviour. While this upswing share is slightly larger for the overall innovators – 35.7% (upswing) compared to 35.1% (downturn) – the respective shares for product (process) innovators have become more balanced, ranging from 26.2% (26.3%) for upswing periods compared to 26.5% (26.2%) for downturn periods. Nevertheless, the share of firms who have implemented technological innovations during recession is larger than the respective share for downturn and upturn periods. Despite that, some evidence for pro-cyclicality remains.

This pro-cyclicality is more pronounced for firms of the less knowledge-intensive services, see Figure 4.18. As in previous figures, most of the companies who were inclined to innovate implemented their innovations during boom phases. Moreover, not only product and process innovators have been more likely to implement their innovations during upturns (13.7% and 18.6%) than during downturns (13.6% and 18.2%). In the case of the less knowledge-intensive firms, even recession periods (13.2% and 16.6%) seem to have been much less of an implementation option.

The current section discloses two results. First, the stronger the technology focus of manufacturing firms and the stronger the knowledge requirements for services firms the more likely is a firm to innovate. Thus, there is a positive correlation between the probability of being a technological or non-technological innovator and the degree of sophistication on the goods/services market. Second, services firms reveal a stronger pro-cyclical innovation behaviour than manufacturing firms.

**Figure 4.18: Share of innovators in less knowledge-intensive service sectors over the business cycle (in %)**




*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

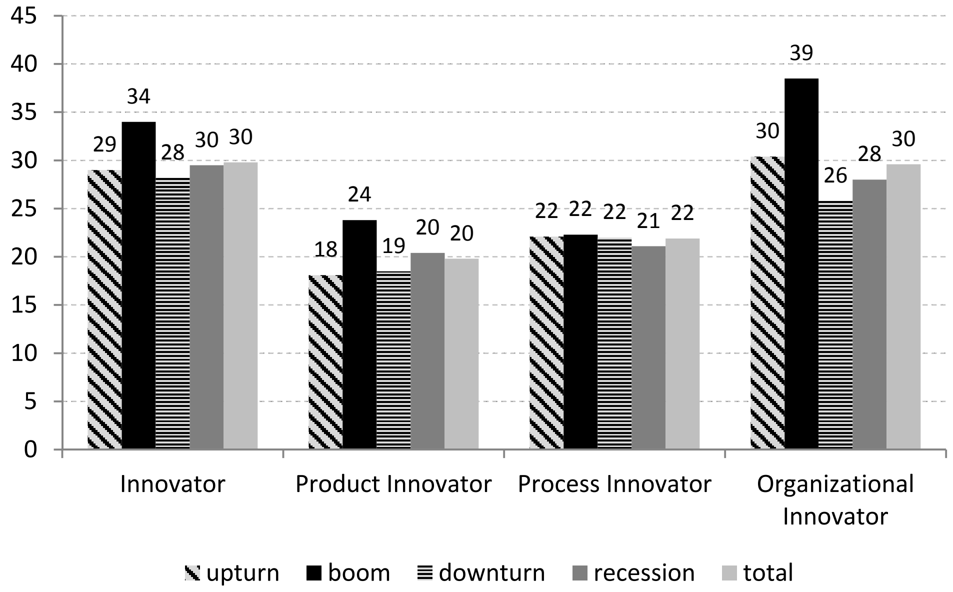
## 4.5. INNOVATOR SHARES ACROSS DIFFERENT SIZE CLASSES

One of the key determinants of innovation activity is firm size, e.g. measured by the number of employees. Larger firms are usually facing more competition as they tend to participate in more than a few goods/services markets. The (optimal) provision of innovation activities requires firms to have sufficient financing resources. The problem is information asymmetries and high sunk costs related to innovation activities. Indeed, a larger employment stock does not alleviate the problem of sunk costs but it contributes to the reduction of existing informational asymmetries. Moreover, larger firms tend to have more collaterals, which improve a firm's credit rating. Thus, the number of employees should be positively correlated with innovation activities.

We start by presenting the innovator shares of small firms having 10-49 employees in Figure 4.19. Overall, 30% of small firms in Europe have implemented at least one technological innovation. Non-technological innovations are equally present among small firms.

As before, economic boom phases have been unambiguously the most frequent periods for the introduction of new products (19.8%), processes (21.9%) and organizational methods (29.6%). Process innovators, however, do not show such unambiguity as do the other types of innovators. The likelihood of an innovation implementation is rather equally distributed. For process innovators the phase of the business cycle has not been pivotal for their decision, they seem to be generally engaged in process innovating activities. Their innovator shares range from 21.1% (recession) to 22.3% (boom). Apart from the boom phase, firms who have implemented product innovations preferred recession periods (20.4%) over downturns (18.5%) and upturns (18.1%), respectively. Firms who have implemented new organization methods preferred upturns (30.4%) over recessions (28%) and downturns (25.8%), respectively. Apart from the relatively strong propensity to innovate during boom phases, only organizational innovators reveal a rather pro-cyclical innovation pattern. While process innovators seem to be indifferent, product innovators' shares show small indication for counter-cyclical behaviour.

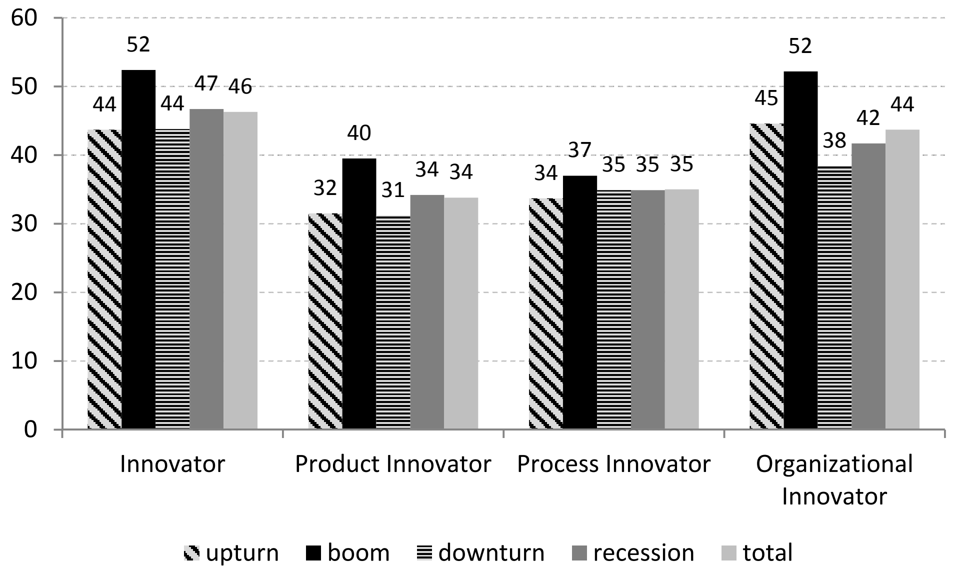
**Figure 4.19: Innovator shares of small enterprises over the business cycle (in %)**




*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

Figure 4.20 shows the innovator shares of firms with more than 49 and less than 250 employees. The distributions of the innovator shares are very similar to the ones from Figure 4.19. Nevertheless, there is one notable, expected difference. There have been more firms innovating during 1998 and 2010 than smaller firms. While 46.3% of the firms introduced at least one overall technological innovation, 33.8% and 35% (43.7%) introduced a new product and a new process (organizational method).

**Figure 4.20: Innovator shares of medium enterprises over the business cycle (in %)**

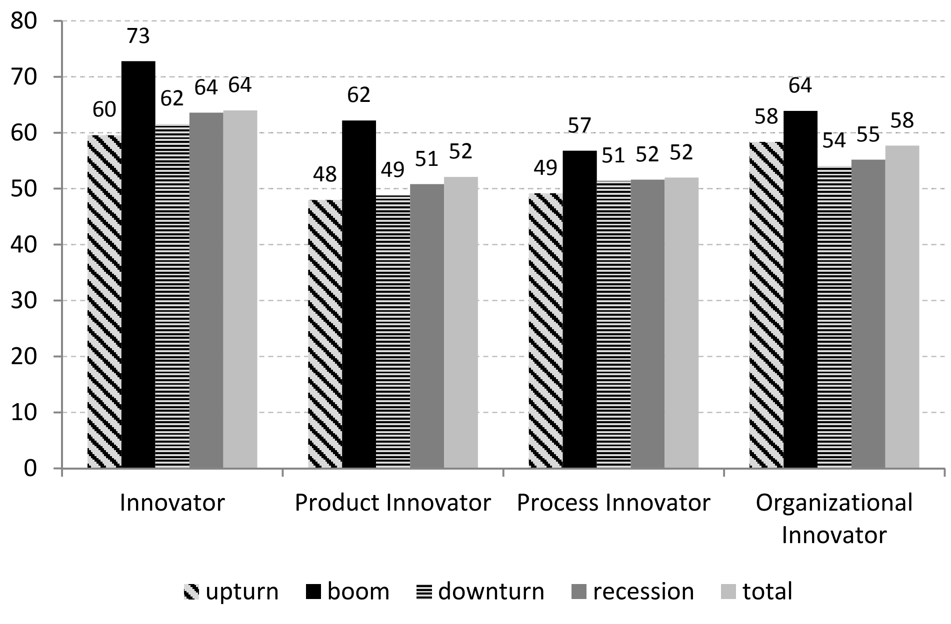



*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

Figure 4.21 presents the share of large enterprises with 250 and more employees who have implemented innovations during the sample period. These large firms' shares indicate a strong propensity to innovate. Almost two out of three firms (64%) have implemented a technological innovation, more than every second firm (57.7%) has implemented organizational innovations. Every second firm has been a product innovator (51.1%) or a process innovator (51%). Large firms seem to generally require more new products/processes/organizational methods than firms with less than 250 employees.

Thus, the necessity to compete successfully requires firms to constantly update their innovation portfolios. The innovator share distributions reveal one clear pattern for technological innovators. As expected, most of the firms whose home country has been in an economic boom implemented at least one product or process innovation (72.8%), at least one new product (62.2%) or at least one new process (56.8%) in the same phase of the business cycle. Recession periods have been the second most important phase for the introduction of technological innovations. These shares amount to 63.6% (overall technological innovator), 50.8% (product innovator) and 51.6% (process innovator). There have been 51.6% (61.6%) of the firms who implemented at least one technological innovation while they were in an upturn (downturn). The respective shares are 48% (48.8%) for product innovators and 49.2% (51.4%) for process innovators. These distributions show counter-cyclical tendencies, when disregarding the shares of the boom phases. Non-technological innovators seem to be more pro-cyclically oriented. Their preferred periods are boom phases (63.9%) as well as upturns (58.4%) followed by recessions (55.2%) and downturns (54.1%).

**Figure 4.21: Innovator shares of large enterprises over the business cycle (in %)**




*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

This section closes with the findings that the more employees a firm has the more frequently it implements technological as well as non-technological innovations. Non-technological innovators show a pro-cyclical pattern. When disregarding economic booms, technological innovators show some evidence for counter-cyclicality.

## 4.6. SUMMARY

This section has given an overview on innovation activities and the business cycle. For R&D expenditures we mainly find a pro-cyclical pattern so that higher (lower) growth rates of gross domestic product (GDP) are accompanied by higher (lower) growth rates of overall R&D investment. While the level of R&D expenditures moves pro-cyclical, the GERD/GDP ratio rather follows a counter-cyclical pattern. This is particularly driven by government-financed GERD since the government-financed GERD/GDP ratio has always increased when the economy has suffered from decreasing growth and vice versa. Results are somewhat more mixed for innovation activities. Table 4.1 summarizes the findings with respect to pro- and counter-cyclicality of innovation activities. The following conclusions can be drawn. First, boom phases have been by far the most frequent periods for the implementation of technological as well as non-technological innovations. That is, we observe a pro-cyclical behaviour in boom periods. This result almost holds across different sectors, sizes and regions. Second, while product and organizational innovators react pro-cyclical in boom phases, they behave counter-cyclical in recession periods. That is in most of the cases, we observe an increase in the respective proportion of innovators compared to a downswing and often the proportion is even higher than in upturns. Third, for product innovators this counter-cyclicality in recession periods is driven by new products that are new to the firm only. This may be a hint that firms are more eager to copy (successful) product innovations of rivals under bad economic circumstances. In contrast, the share of firms which introduce new products which are new to the market and hence involve a higher risk declines in recession periods. That is there is evidence that firms postpone the introduction of market novelties to phases of higher demand. Fourth, the preference for innovation during upturn and downturn periods has been quite balanced. Fifth, the fluctuation over the business cycle is strongest for organizational innovations. And sixth,, the decision to introduce new production processes is less dependent on the business cycle as it is for product and organizational innovations. In particular, we find mixed evidence how firms process innovation activities react in recession periods.

**Table 4.1: Summary: Pro- and counter-cyclicality of innovation activities**

| | PD | | PC | | Orga | | MN | | FN | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Boom | Reces. | Boom | Reces. | Boom | Reces. | Boom | Reces. | Boom | Reces. |
| Total | pro | counter | pro | pro | pro | counter | pro | pro | pro | counter |
| North-West | pro | counter | pro | counter | pro | counter | | | | |
| South-East | - | - | - | pro | pro | pro | | | | |
| HT | pro | counter | counter | counter | pro | counter | | | | |
| MT | pro | counter | - | - | pro | counter | | | | |
| LT | pro | counter | pro | pro | pro | pro | | | | |
| KIS | pro | counter | pro | counter | pro | counter | | | | |
| LKIS | pro | pro | pro | pro | pro | counter | | | | |
| Small | pro | counter | - | - | pro | counter | | | | |
| Medium | pro | counter | pro | - | pro | counter | | | | |
| Large | pro | counter | pro | counter | pro | - | | | | |

*Notes: Pro in boom (recession) phases denotes an increase (decrease) in the respective proportion of innovators. Counter in boom (recession) periods indicate a decrease (increase) in the respective proportion of innovators. PD,PC and Orga denote product, process and organisational innovation. MN and FN is the share of firms that have introduced new or significantly improved products to the market and to the firm only. "-" indicates that there is (almost) no change in the proportion of innovators.*

*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

One limitation of our analysis is the fact that the sample composition varies across different CIS sample. The fact that the composition of firms varies within a given country over time has been addressed by using weighting factors. However, the fact that also the sampled countries differ across waves could not be addressed.

# Chapter 5.
# INNOVATION AND EMPLOYMENT GROWTH OVER THE BUSINESS CYCLE

This chapter investigates the micro-dynamics of innovation and firm growth in Europe in terms of employment growth. In particular, we are interested in analysing the contribution of different types of innovation to employment growth in European firms over the course of the business cycle. In the last two decades services have gained great importance and much of the employment creation in recent years has been in services. We therefore present evidence separately for manufacturing and the service sectors in this sector. We will go beyond this simple split and we will shed further light on the question whether and to what extent the micro-dynamics of innovation and employment growth depend on industry characteristics in chapter 6, firm characteristics such as firm size or ownership in chapter 7 and regional characteristics in chapter 8.

Based on the economic theory and empirical findings discussed in the literature review, we will first set forth the empirical model that we use for estimating the relationship of innovation on employment growth in section 5.1, followed by its empirical implementation in section 5.2. The estimation approach is explored in section 5.3. In section 5.4 we provide descriptive evidence on the growth performance of innovators and non-innovators over the business cycle, followed by the econometric analysis in section 5.5. Section 5.6 complements this section by using an alternative indicator for the size of economic growth.

## 5.1. EMPIRICAL MODEL

We adopt the approach developed by Harrison et al. (2014) to investigate the impact of innovation on employment growth. It establishes a theoretical relationship between employment growth and different kinds of innovation output at the firm level. It is tailor-made for answering the question how product and process innovation translate into employment growth using information that is provided by CIS data. In particular, a main virtue of the model is that it leans on innovation output indicators and thus also corporates the demand situation which is an important factor for firms' employment decisions. Originally, the model was used to identify the effects of product and process on employment growth in a cross-section covering three years. In its original form it has been used to study employment effects for four European countries, the UK, Spain, France and Germany (Harrison et al 2014), Italy (Hall et al. 2008), Chile (Benavente and Lauterbach 2007), China (Mairesse et al. 2011 and Mairesse and Wu 2014) and Latin America (Crespi and Zuniga 2012, Crespi and Tacsir 2013). Peters (2008) used the model to study different types of product innovation, Peters et al. (2013) incorporated organizational innovation and Licht and Peters (2013, 2014) extended the model to investigate employment effects of environmental and non-environmental product and process innovation. Recently, Rojas Pizarro (2013) employ the model to study employment effects of product and process innovation in Spain using data for four waves of CIS-like data. However, though using a panel set, Rojas Pizarro (2013) does not explicitly study the effect of the business cycle on the innovation-employment nexus. We will extend the model to investigate whether and to what extent employment effects of product and process innovation differ in different phases of the business cycle. We briefly explain the model in what follows; for more details, we refer to Harrison et al. (2014).

The basic idea of the theoretical model is as follows: The framework is a simple multi-product model. That is, it is assumed that a firm can produce different products.[8] Furthermore, we observe a firm in two points in time t (= 1, 2). At the beginning in t=1, the firm produces a set of products which are aggregated to one product and which are labelled as the "old product" or "existing product". Between t=1 and t=2, the reference period, the firm can decide to introduce one or more new or significantly improved products. The new product can (partially or totally) replace the old one if they are substitutes or enhance the demand of the old product in case of complementarity. That is, at the end of the reference period, the firm will produce either only old products, only new products or both types of both products.

In order to produce the different outputs, we assume the following production function for product *i* in time *t*:

(5.1) $$Y_{it} = \theta_{it} F\left(C_{it}, L_{it}, M_{it}\right) e^{\eta + \omega_{it}} \quad i = 1,2;\ t = 1,2$$

The conventional production function F is linear homogeneous in the conventional inputs labour L, capital C and material M. Moreover, the output depends on specific efficiencies for the production process of both goods at each point of time $\theta_{it}$. It is driven by the knowledge capital of the firm which is assumed to be a non-rival input.

A firm can increase its efficiency in the production of the old product $\theta_{it}$ for instance by investing in process innovation or organizational innovation, better human capital endowment or training. In addition, within-firm learning effects, spillover effects, mergers and acquisitions or selling unprofitable business units might also drive efficiency gains. Since the increase in efficiency is likely to differ for non-process innovators and process innovators, Harrison et al. (2014) suggested separating the effect of process innovation from the other sources of efficiency improvements. Peters et al. (2013) further separate organizational innovation.

Based on these assumptions, Harrison et al. (2014) derive the conditional labour demand functions for each product for each point in time and, as a result, the overall employment growth rate:

(5.2) $$l = \alpha_0 + \alpha_1 pc + \alpha_2 orga + y_1 + \beta y_2 + u$$

A main virtue of the model is that we can disentangle some of the theoretical employment effects explained in section 2. Equation (5.2) shows that employment growth $l$ stems from three different sources in the model.

- The first source captures efficiency increases in the production of the old product, which negatively affect labour demand. This effect is separated into three components: efficiency gains that are related to process innovation ($\alpha_1$), organizational innovation ($\alpha_2$) and other non-innovation related types of efficiency gains ($\alpha$ ). Note, in the estimation the latter effect will be country-, industry-, size- and ownership specific.

[8] In the following the term product always comprises both goods and/or services unless stated otherwise.

- The second source of employment growth stems from the rate of change in the real output of the old product ( $y_1$ ). This change in the output production of old products might be provoked by the firm's own new product, the induced change being negative for substitutes (cannibalization effect) and positive for complements. But it also accounts for demand shifts for old products due to new products introduced by rivals (business stealing), price reductions following own process innovations (compensation effects of process innovation), general business cycle effects (as long as we do not separately control for them), changes in consumer preferences or new products in upstream or in downstream firms.[9] The existence of additional demand would allow us to separate the compensation effect of process innovation and the demand effect of product innovation on old products which are both captured by $y_1$. However, with the data at hand we are unable to do it.
- Finally, changes in employment growth may result from starting the production of the new product (positive sign). The employment effect of the latter depends on the efficiency ratio between both production technologies ( $\beta = \theta_{11} / \theta_{22}$ ) and the real output growth due to new products ( $y_2$ ). A value of $\beta < 1$ indicates that new products are produced with higher efficiency and thus less labour than the old product.

However, we cannot estimate equation (5.2) since we usually do not observe real output growth rates in the data. Instead we substitute unobserved real output growth rates by observed nominal output growth rates. This leads us to the following estimation equation (5.3) which describes the relationship between employment growth, efficiency gains process and organizational innovation and the sales growth due to new products:

$$(5.3) \qquad l-\left(g_1-\tilde{\pi}_1\right)=\alpha_0+\alpha_1 pc+\alpha_2 orga+\beta g_2+v$$

$g_1$ and $g_2$ denote the nominal output growth (sales growth) due to old and new products, respectively, with $g_1 = y_1 + \pi_1$ and $g_2 = y_2 + \pi_2 y_2$. Since the coefficient of the real output growth $y_1$ is equal to one, it can be subtracted from *l*. As explained $y_1$ is not observed in the data but proxied by $g_1 - \pi_1$. The variable $g_2$ can be calculated using CIS data. $g_1$ can be calculated by the total sales growth rate minus the sales growth rate due to new products. $\pi_1$ measures the (unobserved) price growth rate of old products at the firm level. Since data sets usually do not include information on firm-level price changes, $\pi_1$ is proxied by $\tilde{\pi}_1$ which is the price growth rate of old products at the industry level. If we do not properly account for firm-level price changes, we cannot identify the displacement effect of process innovation. $\pi_2$ denotes the price difference between the new and the old product in relation to the price of the old product at the firm level. The new error term $v$ is

[9] In addition to employment effects that we observe in the innovating firm, additional employment effects of innovations may occur in rival firms or upstream and downstream firms. If, e.g., the innovative firm is able to increase its output, its suppliers also benefit and they 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. With the exception of firm exiting the market due to own unsuccessful innovation or rivals' innovation and innovative firms entering the market, our estimation accounts for these effects. However, due to data constraints, we cannot further disentangle these effects.

$$v = -E\left(\pi_1 - \tilde{\pi}_1\right) - \beta\pi_2 y_2 + u \ .$$

One problem that arises in this model is the fact that the sales growth rate from new products is correlated with the error term $v$. An appropriate econometric method to deal with such an endogeneity problem is to use instrumental variable techniques. The instruments should be correlated with the sales growth due to new products (i.e. innovation success), but not correlated with the error term. In particular it has to be uncorrelated with the relative price difference of new to old products. We explain in the next section in more detail how we empirically address this problem by using an instrumental variable estimation approach.

In order to investigate whether the business cycle matters for the relationship between innovation and employment growth we could either introduce interaction terms between business cycle indicators and the innovation measures or, allowing more flexibility, we can estimate the model separately for firms in different phases of the business cycle. We mainly follow the second approach.

## 5.2. EMPIRICAL IMPLEMENTATION

In section 3.1 we have already explained how we measure different phases of the business cycle that we will employ for splitting the sample. In this section we explore how we specify the variables used in the econometric estimation and explain the estimation method.

### 5.2.1. Dependent Variable

Our dependent variable is EMP. Following the theoretical model EMP is defined as $l-\left(g_1-\tilde{\pi}_1\right)$:

In the data *l* is measured using EMPGR which denotes the employment growth rate in head counts over a three-year period, that is it measures employment changes between year *t-2* and *t*. In each wave, CIS requests information on current employment but also asked retrospectively for employment numbers for year *t-2*. Hence information for both years always comes from the same CIS survey. The real output growth due to old products $\left(g_1-\tilde{\pi}_1\right)$ is subtracted from the employment growth rate *l* since the coefficient is supposed to be one. Specifying *l* as dependent variable and $\left(g_1-\tilde{\pi}_1\right)$ as additional explanatory variable where the coefficient is restricted to be 1 leads to the same result. Hence, we can still interpret our econometric results in terms of employment growth when we use EMP as dependent variable.

1. The real output growth due to old products $\left(g_1-\tilde{\pi}_1\right)$ is calculated as the difference between
   - the nominal sales growth rate with old products ( $g_1$ / SGR_OLDPD) and
   - the growth rate of prices for old products at the industry level ( $\tilde{\pi}_1$ / PRICEGR).

Both growth rates also refer to the period *t-2* to *t*. $g_1$ can be calculated from the data as total sales growth rate (*g* / SGR) minus the sales growth rate that is due to new products $g_2$ (SGR_NEWPD, see below).

As already explained, we do not observe firm-level price changes and use price deflators at the industry level instead. We used producer price indices at the country-industry level (2-digit NACE rev. 1.1 for CIS 3, CIS4 and CIS2006 and NACE rev. 2 for CIS2008 and CIS2010) as published by Eurostat.[10]

### 5.2.2. Innovation Indicators

We aim at elucidating how innovation shapes employment growth. In particular, we interested in whether there are any differences between different types of innovation and whether we can identify that the link between different types of innovation and growth varies across the business cycle. In our empirical analysis we distinguish between three types of innovation:

1. *Product innovation*. A product innovation is a product (incl. services) whose components or basic characteristics (technical features, components, integrated software, applications, user friendliness, availability) are either new or significantly improved. A product innovation must be new to the enterprise, but it does not need to be new to the market. A firm is called a product innovator if it has introduced at least one product innovation in the period *t-2* to *t* (PD). The empirical model relates employment growth not to the introduction of new products but to its innovation success measured by the sales growth rate due to new products. In the empirical model, however, we do not use a product innovation dummy but the *sales growth rate due to new products* ( $g_2$ or SGR_NEWPD). This quantitative measure for innovation success can be calculated from the data as year *t*'s share of sales with new products that have been introduced in the three-year period *t-2* to *t* times the ratio of sales in year *t* to sales in year *t-2*. In order to investigate whether the type of product innovation matters for employment growth, we further calculate the sales growth rate due to new products that are new to the firm only (firm novelties; SGR_FN) and that are new to the market (market novelties; SGR_MN).

**Box 5-1: Examples of product innovation**

Innovations may not be instantly recognized by the respondents of the CIS questionnaire. To facilitate filling out the questionnaire, Eurostat (2013) proposed some examples for each category of innovation. Examples for product innovations include:

- Replacing existing materials with materials with improved characteristics, e.g. breathable textiles, light but strong composites, environmentally-friendly plastics, etc.
- Introducing new or improved components in existing product lines, e.g. cameras in mobile telephones, fastening systems in clothing, etc.
- Equipment that incorporate software that improves user friendliness or convenience, such as toasters that automatically shut off when the bread is toasted or GPS systems that identify the location of specific types of shops or services.
- Adding new functions: double sided printing, bicycle lights that can be recharged through a UBS port, rubbish bins that signal when they are full, products that can fold for easy storage, etc.
- Improving customers' access, such as a home pick-up and drop-off service for rental cars.
- First time introduction of internet services such as banking, bill-payment systems, electronic purchase and ticketing of travel and theatre tickets, social networking sites, etc.
- New forms of warranty, e.g. an extended warranty on new or used goods, bundling warran-

[10] In services, information on producer prices is not available for all industries over the whole period. If producer price deflators are unavailable, we have used the harmonized consumer price index instead country level.

ties with other services, such as with credit cards, bank accounts, or customer loyalty cards.

- Installing video on demand screens in the back of airline, bus or train seats.

2. *Process innovation.* The CIS defines a process innovation as the implementation of a new or significantly improved production process, distribution method, or support activity for goods or services within the three-year period *t-2* to *t* (PC). This includes significant changes in techniques, equipment and/or software used to produce goods or services. Process innovations can be intended to decrease unit costs of production or delivery, to increase quality, or it can be a by-product of the introduction of new products. The latter reason provokes an important empirical problem in accurately disentangling the employment effects of product and process innovation since many firms report both kinds of activities simultaneously. This leads to a situation in which we do not know whether for process innovators (i) all process innovations are aimed at improving the efficiency of the old products, (ii) all process innovations take place in order to produce the new product(s) or (iii) a mixture of both is true. We follow previous work, and define a dummy variable that takes the value 1 if the firm has introduced only process innovations but no product innovations (PCONLY). This definition ensures that we identify the efficiency improvements in the production of old products since for non-product innovators all process innovations must be related to old products. For firms that do both, the effect of process innovations with respect to an increase in efficiency in the production of old products cannot be identified with CIS data, and it is in fact captured by the sales growth due to new products.[11] We also experimented with an additional dummy variable that is 1 if firms do both product and process innovation (PCAPD). However, in most specifications it turns out to be insignificant. It is likely that this effect was in fact captured by the sales growth due to new products variable which as a quantitative variable had a much stronger explanatory power.

**Box 5-2: Examples of process innovation**

- Installation of new or improved manufacturing technology, such as automation equipment or real-time sensors that can adjust processes.
- New equipment required for new or improved products.
- Computer-assisted product development or other technology to improve research capabilities, such as bio-imaging equipment.
- More efficient processing that reduces material or energy requirements per unit of output.
- Introduction of bar-coding or passive radio frequency identification (RFID) chips to track materials through the supply chain.
- GPS tracking systems for transport equipment.
- Automated feed-back to suppliers using electronic data exchange.
- Introduction of software to identify optimal delivery routes.
- New or improved software or routines for purchasing, accounting or maintenance systems.

3. *Organizational innovation*. Besides technological innovations (product and process), CIS data also provides information on whether firms have introduced non-technological innovations such as organizational innovation (ORGA). Organizational

[11] Licht and Peters (2013) exploited a specificity of the German CIS2008 which allowed them to define process innovation related to old products. The overall finding of only a small impact of process innovation on employment growth was confirmed using the preferred measurement of process innovation.

innovation encompasses the occurrence of at least one of the following events in the three-year period:

i. The introduction of a new organizational method in a firm's enterprise business processes. This includes for instance changes in knowledge management, supply chain management, business re-engineering, lean production or quality management.

ii. The introduction of a new workplace organization. It captures new methods of how firms organize work responsibilities and decision making, it can take place for instance through team work, decentralization, integration or de-integration of departments, job rotation, etc.

iii. The implementation of new external relations that has not been previously used in the enterprise or new methods of organizing external relations with other firms or public institutions. This includes first use of alliances, partnerships, outsourcing or sub-contacting. One drawback is that the way the question on organizational innovation was posed slightly differs across the first and later CIS waves.[12] However, we compared the share of firms with organizational innovation in different waves and believe that they are by and large comparable across waves.

**Box 5-3: Examples of organisational innovation**

- Establishment of formal or informal work teams to improve the access and sharing of knowledge from different departments, such as marketing, research, production, etc.
- Introduction of quality control standards for suppliers and subcontractors.
- Supply management systems to optimize the allocation of resources from sourcing inputs to the final delivery of products.
- First introduction of group or individual performance incentives.
- First introduction of teleworking or a "paperless" office.
- Reduction or increase in the hierarchical structure for decision making.
- Change in responsibilities, such as giving substantially more control and responsibility over work processes to production, distribution or sales staff.
- Introduction of a High Performance Work System (HPWS) characterised by a holistic organisation featuring flat hierarchical structures, job rotation, self-responsible teams, multi-tasking, a greater involvement of lower-level employees in decision making and the replacement of vertical by horizontal communication channels.
- New training or education systems, such as regular videos on each employee's work station that describe on-going challenges for the enterprise or provide skill upgrading, with the goal of improving the ability of employees to recognize problems and take responsibility.
- Creation of a new division, for example by splitting the management of marketing and production into two divisions, or alternatively a change to integrate divisions.
- First use of outsourcing of research or production if it requires a change in how work flows are organised within the enterprise.
- First use of alliances that require staff to work closely with staff from another organisation, including temporary staff exchanges.

[12] In CIS3 organizational innovation is measured as the introduction of new or significantly changed organizational structures and the introduction of progressive management technologies/concepts in the enterprise.

### 5.2.3. Business Cycle Variables

In order to investigate how business cycle effects change the relationship between innovation and employment we follow two strategies. First, we estimate a pooled model in which we additionally include information about country-level real GDP growth rates between year *t-2* and *t* (GDPGR) and interaction terms of GDPGR with innovation variables. However, the growth rate of GDP, let's say 0.5%, does not say whether the economy is an upturn or downturn phase. Our second and main strategy is therefore to estimate equation (5.3) for different phases *j* of the business cycle with *j*=(upturn, boom, downturn, recession). Splitting the sample according to the business cycle phase on the other hand would actually ignore the information about the strength of GDP growth. Hence, we additionally include information about country-level real GDP growth rates between year *t-2* and *t* (GDPGR) in some specifications. This captures general demand effects. But note that firm-specific demand effects should already be captured by $g_1$ and $g_2$.

Note that we will assume in the empirical analysis that the business cycle is exogenous to firms' innovation behaviour and employment decisions. Since we follow a strict firm-level approach, this assumption seems reasonable. One might doubt the assumption of business cycle causality and instead prefer the notion of business cycle correlation. Correlation might occur because in addition to the fact that the business cycle impacts the relationship between innovation and employment, there might be a reverse causality effect. That is, the fact that innovation affects employment growth has itself an impact on the business cycle. This argument might be reasonable to assume at the macro or industry level. However, at the firm-level is reasonable to assume the business cycle is exogenous to the firms. This is underpinned by findings of Geroski and Walters (1995) who showed that economic growth granger causes innovation.

### 5.2.4. Control Variables

Employment growth is likely to be influenced by many other economic factors as well. Hence, the econometric approach additionally controls for the impact of a number of other variables. Besides innovation, wages, investment in physical capital or labour supply factors like preferences for leisure or the qualification level of the labour supply may also affect employment growth. Since we do not observe firm-level changes in wages, investment or labour supply, we therefore assume that they follow the development of wages at the industry and country level and can thus be captured by industry and country dummies. Hence, we include a set of industry and country dummies which have been both defined in section 3.3. In addition, we control for firm size by adding two size dummies variables which indicates firms with 50-249 (MEDIUM) and 250 and more employees (LARGE) at the beginning of the reference period in *t-2*, respectively. Firms with 10-49 employees (SMALL) build the reference category. The role of firm size for employment growth has been controversially discussed in the literature. While Robert Gibrat postulated in the 1930s that firms grow proportionally and independently of firm size, Jovanovic (1982) took the view that surviving young and small firms growth fast than older and larger ones for instance because of managerial efficiency and learning by doing. Recent studies have furthermore found that employment grows less (Dachs and Peters 2014) and is also more volatile in foreign-owned companies (Scheve and Slaughter 2004; Buch and Lipponer 2010). In order to control for ownership effects, we incorporate two dummy variables indicating that in year *t* a firm belongs to a company group which has a domestic (DGP) and foreign headquarter (FGP), respectively. Note that a group which has a domestic headquarter can be a multinational or purely domestic group. Domestic unaffiliated firms serve as reference category (DUF) reference group.

Since employment dynamics have been quite different in manufacturing and services in the last decade, we estimate equation (5.3) separately for manufacturing and services.

The following Table 5.1 summarizes the variables used in the econometric analysis.

**Table 5.1: Variable definitions**

| Variables | Theoretical model | Description |
|---|---|---|
| ***Dependent variable*** | | |
| EMP | $l-(g_1-\tilde{\pi}_1)$ | According to the theoretical model, EMP is defined as follows: |
| EMPGR | $l$ | Employment growth rate in head counts between *t* and *t-2*. Information for both years comes from the same CIS survey. |
| SGR_OLDPD | $g_1$ | Sales growth rate due to old products between t and t-2. It can be calculated as total sales growth rate *g* between *t* and *t-2* minus the sales growth rate due to new products $g_2$ (see below). |
| PRICEGR | $\tilde{\pi}_1$ | Price growth rate for existing products between *t* and *t-2*. Price growth is measured using producer price indices at the country-industry level (2-digit NACE rev. 1.1 for CIS 3, CIS4 and CIS2006 and NACE rev. 2 for CIS2008 and CIS2010). In services, information on producer prices is not available for all industries over the whole period. If producer price deflators are unavailable, we have used the harmonized consumer price index instead country level. |
| ***Explanatory variables*** | | |
| SGR_NEWPD | $g_2$ | Sales growth rate between *t* and *t-2* due to new products. It has been calculated by multiplying the share of sales in *t* due to new products introduced between *t* and *t-2* with the ratio of sales in *t* and *t-2*.<br>Note: A new product (product innovation) is a product (incl. services) whose components or basic characteristics (technical features, components, integrated software, applications, user friendliness, availability) are either new or significantly improved. A product innovation must be new to the enterprise, but it does not need to be new to the market. A firm is called a product innovator if it has introduced at least one product innovation in the period *t-2* to *t* (PD). |
| PCONLY | $pc$ | Dummy variable = 1 if a firm has introduced at least one process innovation but no product innovation in the period *t-2* to *t* and zero otherwise.<br>Note: A process innovation is the implementation of a new or significantly improved production process, distribution method, or support activity for goods or services within the three-year period *t-2* to *t* (PC). This includes significant changes in techniques, equipment and/or software used to produce goods or services. Process innovations can be intended to decrease unit costs of production or delivery, to increase quality, or it can be a by-product of the introduction of new products. |
| PCAPD | | Dummy variable = 1 if a firm has introduced at least one process innovation and one product innovation in the period *t-2* to *t* and zero otherwise (only used for robustness checks). |
| ORGA | $orga$ | Dummy variable = 1 if a firm has undertaken at least one |

| | |
|---|---|
| | organizational innovation in the period *t-2* to *t* and zero otherwise.<br>Note: Organizational innovation encompasses the occurrence of at least one of the following events in the three-year period: the introduction of a new organizational method in a firm's enterprise business processes, the introduction of a new workplace organization or the implementation of new external relations that has not been previously used in the enterprise or new methods of organizing external relations with other firms or public institutions. |
| DUF / DGP / FGP | A set of dummy variables for ownership in year *t*. We distinguish between unaffiliated firms (DUF; reference) and firms that belong to a company group which has a domestic (DGP) and foreign headquarter (FGP), respectively. |
| SMALL / MEDIUM / LARGE | A set of dummy variables for each size class in year t-2. We distinguish between firms with 10-49 (SMALL; reference), 50-249 (MEDIUM) and 250 and more employees (LARGE). |
| GDPGR | Country-level real GDP growth rates between year *t-2* and *t*. |
| COUNTRY | A set of dummy variables for each country in the sample (see Table 3.2). |
| INDUSTRY | A set of dummy variables for each industry (see Table 3.3). |
| ***Instrumental variables*** | |
| RANGE | Variable that indicates whether the product innovation was aimed at increasing the product range (0/1) in the period *t-2* to *t*. |
| RD | Dummy variable = 1 if the firm carries out R&D continuously in the period *t-2* to *t*. |
| COOP | Dummy variable = 1 if the firm has cooperated in innovation projects with other agents in the period *t-2* to *t*. |
| CLIENT | Dummy variable that equals 1 if clients have been a high-to-medium important information source for innovation in the period *t-2* to *t* (not available in CIS 2010 and therefore only used for a few some sub-samples if one of the other instruments turned out to be invalid). |

## 5.3. ESTIMATION APPROACH

We employ an instrumental variable approach to estimate equation (5.3). The IV strategy is a solution to the problem that our key variables, the sales growth rate due to new products should be endogenous due to a measurement error. Variables that qualify as instruments should be correlated with the sales growth due to new products (i.e. innovation success), but should be uncorrelated with the error term. That means in particular that the instrument has to be uncorrelated with the relative price difference of new to old products. As we have five waves, one might think of lagged values of $g_2$ that could serve as instruments. However, since firm identifiers are not available at Eurostat's Safecenter, we cannot trace firms over time and cannot employ this instrument. Instead we use three variables as instruments that have been found to be important in explaining innovation success but that are presumably uncorrelated with the relative price difference of new to old products. The first instrument that we use is RANGE, a variable that measures whether the product innovation was aimed at increasing the product range (0/1). It is likely that RANGE is correlated with the expectations of new products sales and thus innovation success but enlarging the range of products doesn't imply any particular direction of the changes in prices. It is also unlikely that it is correlated with unanticipated productivity shocks (Harrison et al. 2014). The second and third instrument that we use are two dummy variables that indicate whether the firm carries out R&D continuously (RD) and whether firms have cooperated in innovation projects with other agents (COOP). RANGE and RD have been used as instruments in prior work (see Harrison et al. 2014, Peters 2008, Hall et al. 2009, Dachs and Peters 2014, Peters et al. 2013). Instead of COOP many of these studies used an information whether clients have been used as information source as an additional instrument. However, this information was not available in CIS2010. Similarly to RANGE, we argue that firms that have cooperated in innovation projects demonstrate higher innovation success. But cooperating doesn't imply any particular direction of the changes in prices.

The consistency of our results depends on the validity of instruments. We have therefore tested the validity of the instruments using a Sargan-Hansen J test on overidentifying restrictions for overall instrument validity and the difference-in-Sargan-Hansen C statistic to test for exogeneity of a single instrument.[13] It turned out that in the pooled model, when we do not split the sample by business cycle phases, all three instruments were valid both in manufacturing and services and each of the single instruments passes the test on exogeneity. When we split the sample, however, it turns out in some cases RD violates the assumption of a valid instrument in manufacturing. In services, we are confronted with a similar finding for RANGE. When we use sample splits, we therefore left out RD and RANGE as instruments in manufacturing and services, respectively.

In addition to instrument validity we check for non-weakness of the instruments. Weak instruments can lead to a large relative finite-sample bias of IV compared to the bias of OLS in case of endogenous variables. All first stage regression results demonstrated that RANGE and COOP in manufacturing and RD and COOP in services are highly correlated with the endogenous variable sales growth due to new products (SGR_NEWPD) in the first stage regression. Furthermore, the F-test of excluded instruments always yields a statistic that is clearly larger than 10. In addition to this rule of thumb for non-weak instruments, the tables display the Kleibergen-Paap LM test on underidentification. The null hypothesis of underidentification is always rejected which likewise confirms that the excluded instruments are correlated with the endogenous regressor(s). Alternatively, we test for the absence of weak instruments using the F tests proposed by Cragg and Donald (1993) and Kleibergen and Paap (2006). If we have weak instruments, a Wald test for our endogenous variable SGR_NEWPD would reject the null hypothesis of no impact too often and thus falsely indicate a significant effect of SGR_NEWPD. The test statistic is based on the rejection rate $r$ (10%, 20%, etc.) that the researcher is willing to tolerate if the true rejection rate should be the standard 5%. Weak instruments are defined as instruments that will lead to a rejection rate of at least $r$ when the true rejection rate is 5% (Baum et al. 2007). The difference between the two test statistics is that the Cragg-Donald test assumes i.i.d. errors while the Kleibergen-Paap test is robust to heteroskedasticity. The null hypothesis of weak instruments is always rejected. Thus, we conclude that our instruments are valid and non-weak.

[13] More precisely, we use the Hansen statistic instead of the Sargan statistic since we estimate clustered-robust errors. In contrast to the Hansen statistic, the Sargan statistic is not consistent if heteroskedasticity is present.

## 5.4. DESCRIPTIVE EVIDENCE ON GROWTH EFFECTS OF INNOVATION OVER THE BUSINESS CYCLE

In the following, we present descriptive evidence on the linkage between innovation and employment growth as well as productivity and sales growth in different phases of the business cycle. We provide separate results for the manufacturing and the services sector. For a more detailed analysis, we report employment growth for innovators, product innovators, pure process innovators, organizational innovators, and non-innovators. Furthermore, sales growth effects due to old and new products for process and product innovators are evaluated.

### 5.4.1. Employment Growth in Different Phases of the Business Cycle

In Figure 5.1, for each sector – manufacturing and services – the mean employment growth with their respective median in the four phases of the business cycle is displayed for the period of 1998-2010. Like one would expect, mean employment growth is highest in phases of economic boom as well as in phases of upswing in both, manufacturing and in services. Notably, the mean value of economic growth in a recession is clearly negative for the manufacturing sector whereas, it is still positive for firms in services sector. This could indicate that the service sector has been less affected by the crisis but it could also be a sign of higher rigidity of employment in services compared to manufacturing. Additionally, the growth rates are overall higher in the services sector than in manufacturing.

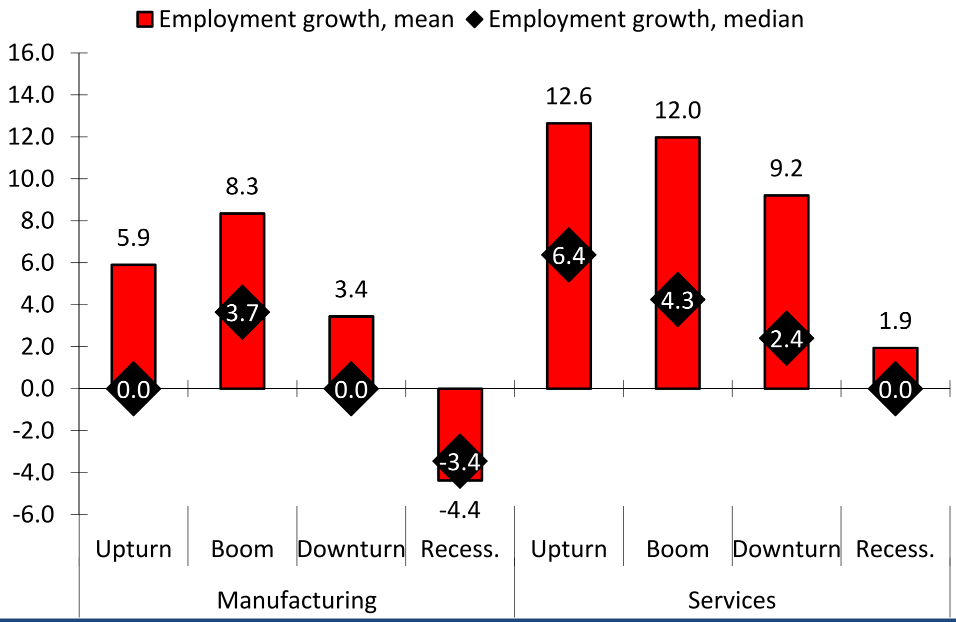
In the phases of economic upturn, boom, and downturn, the median values are considerably lower than the mean values. This leads to the conclusion that the mean employment growth is attained through the contribution of a few firms, which perform above-average relating to employment growth. This relationship is less distinct in phases of recession.

To obtain insight into the composition of the employment growth for different types of innovators, we separate the sample into innovators, product innovators, pure process innovators, organizational innovators, and non-innovators. The mean two-year employment growth (over the period 1998-2010) in the manufacturing sector is illustrated in Figure 5.2 (see Figure 5.3 for the services sector).

Across the different phases of the business cycle, an almost identical pro-cyclical distribution pattern (on the same level) is observable for all types of innovators. All groups exhibit a clear negative employment growth in the recession phases, whereas, the highest values of growth are noticeable again in the boom and upturn phases of the business cycle. It is striking that the levels of employment growth in boom and upturns are almost identical for all types of innovators in the manufacturing sector. One exception is the group of product innovators in the recession period. In the economic crisis, we also observe a shrinking employment (-2.2%) but the decrease is less pronounced than in firms that have focused on process (-3.2%) and organizational innovation (-3.3%).

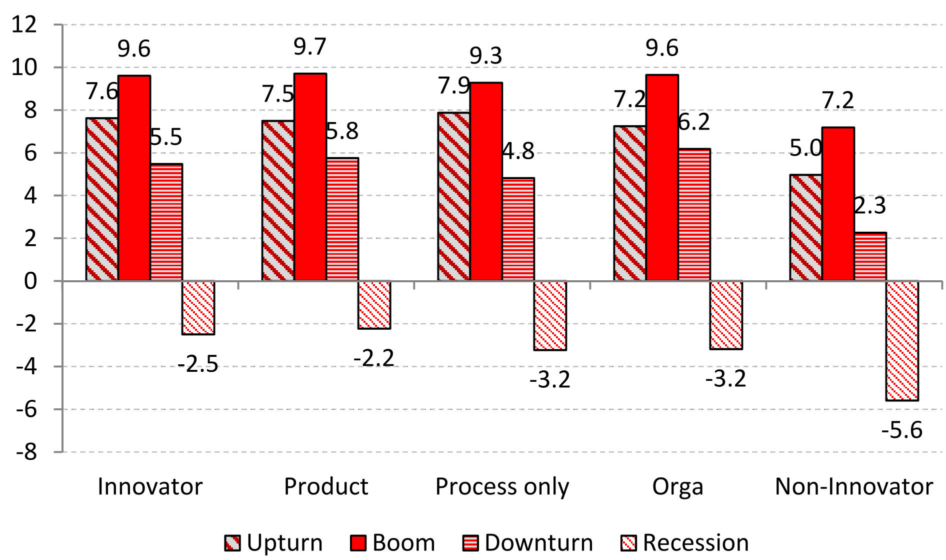
In contrast to innovating firms, non-innovators demonstrate a significantly lower employment growth. This pattern can be observed in all phases of the business cycle but it is particularly pronounced in downturn and recession periods where the gap to innovators is about 3.5 percentage points. In upturn and boom periods innovators grow on average 2.5 percentage points more than non-innovators.

**Figure 5.1: Employment growth in European firms in different phases of the business cycle, 1998-2010**




*Notes: Weighted figures. Depicted are average two-year employment growth rates. Accordingly, the business cycle is defined using two-year GDP growth rates.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

**Figure 5.2: Employment growth in different phases of the business cycle by innovation status, manufacturing, 1998-2010**



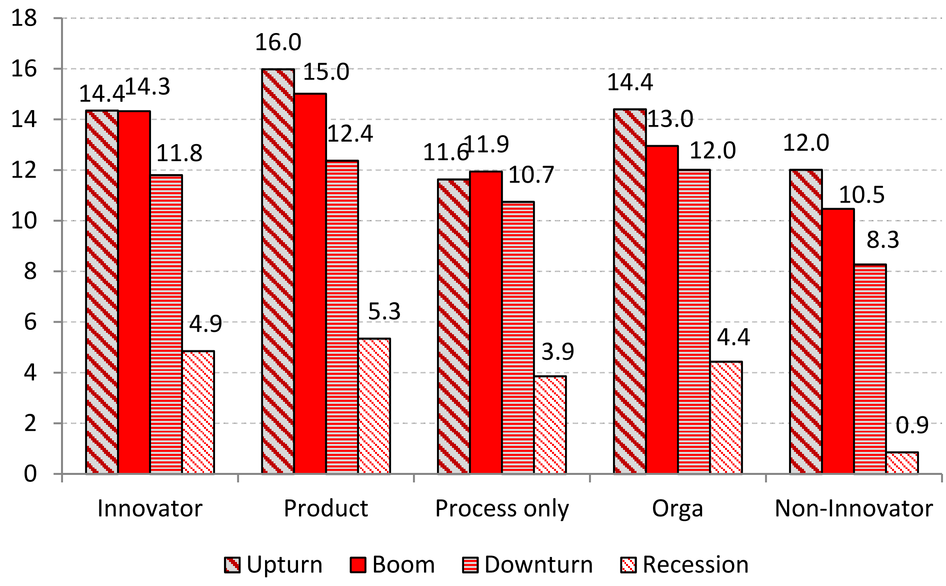

*Notes: Weighted figures. Depicted are average two-year employment growth rates. Accordingly, the business cycle phases are defined using two-year GDP growth rates.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

Services differ from manufacturing in overall employment growth rates, which are higher for both, innovators and non-innovators than in manufacturing (see Figure 5.3). This is in line with the macroeconomic evidence which indicates that since the 1980s, employment in

Europe grew mainly in service industries (Rubalcaba et al. 2008). Higher employment growth of services compared to manufacturing has been explained by various factors (Maroto-Sánchez 2009): First, researchers have attributed higher income elasticities to services such as education, health, or leisure, culture etc., so that final demand for these services increases disproportional with rising economic wealth. Second, productivity in a number of services grows slower than in manufacturing, so that employment shifts from manufacturing to services because of lower price elasticity of demand in services compared manufacturing (Baumol's cost desease, see Baumol 1967). Finally, the faster growth of services has been explained by the usage of services as intermediate goods in the production in manufacturing and service industries (Peneder et al. 2003). This trend seems most relevant for knowledge-based services, and is also related to outsourcing and offshoring of service activities.

Comparing different types of innovators, it turns out that service firms that engage in product innovation exhibit the highest employment growth rates in all business cycles whereas firms that only conduct process innovation have the lowest rates among innovative firms. But process innovators still create more employment than non-innovators in all phases of the business cycle except for upturn periods in which both groups show more or less the same employment dynamic.

**Figure 5.3: Employment growth in different phases of the business cycle by innovation status, services, 1998-2010**




*Notes: Weighted figures. Depicted are average two-year employment growth rates. Accordingly, the business cycle phases are defined using two-year GDP growth rates.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

The group of product innovators and organizational innovators deviate in one interesting aspect. They show the highest employment growth in phases of economic upturn, not during the boom (see also Figure 5.1).

Like in manufacturing innovators outperform non-innovating service firms in all phases of the business cycle. Compared to product innovators, non-innovators demonstrate an employment growth that is about 4 percentage points smaller in all phases. Performance differences are generally smaller when non-innovators are compared with organizational or process innovators. But we find the same finding as for manufacturing that the gap is largest in periods of an economic crisis. This finding underpins the importance of innovation as a mean to improve competitiveness and preserve jobs particularly in recession periods.

### 5.4.2. Productivity Growth in Different Stages of the Business Cycle

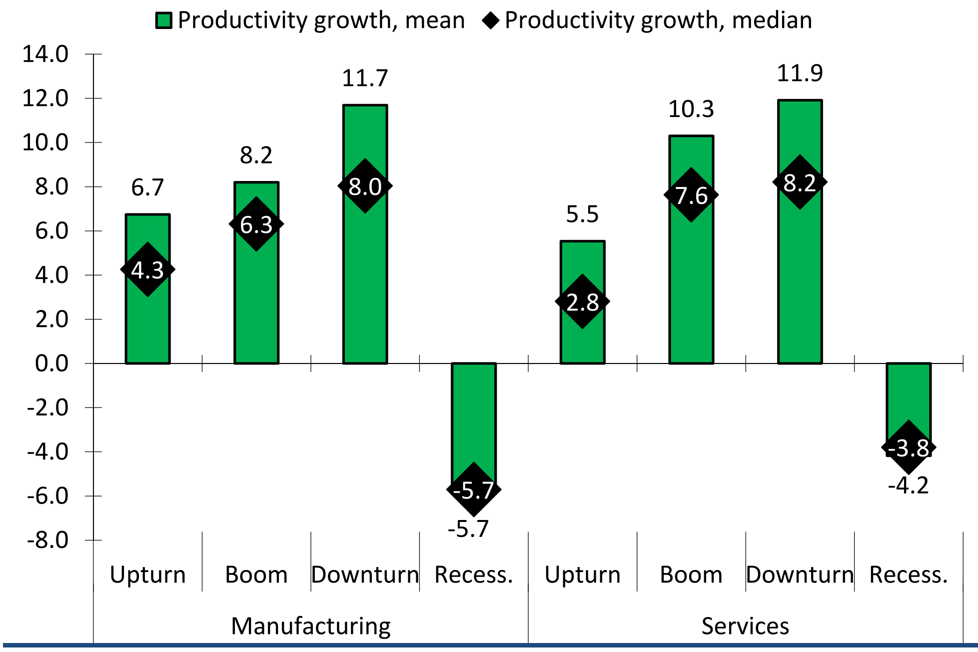
We have already seen from the theoretical model that employment growth is related to productivity growth. In this section, we additionally present some empirical evidence on productivity growth in different stages of the business cycle. Productivity growth is measured as growth in labour productivity (ratio of sales to employment). Since CIS data does not include information on capital, we cannot calculate total factor productivity.

In the literature different arguments have been put forward explaining pro- or counter-cyclicality of productivity. One argument for higher productivity growth in downswings and thus counter- cyclicality is the fact that it is likely that in deteriorating economic circumstances less productive firms exit the market leading to an increase of average productivity among surviving firms (Aghion and Saint-Paul 1998). The opportunity cost and intertemporal substitution is another argument that supports this finding (Aghion and Saint-Paul 1998). Productivity-improving activities such as process innovation, reorganizations or training often take place at the expense of directly productive activities (manufacturing); since the return to the latter is lower in downturns and recessions due to lower demand for the manufactured good, the opportunity cost in terms of foregone profits of “reorganizations” activities will be lower in deteriorating economic circumstances than in expansion. This leads to more productivity-improving activities such as reorganizations in downturns. Finally, the finding of higher productivity growth in downswings might also result from time lags in innovations that have been introduced during earlier stages of the business cycle. On the other hand, firms might hoard labour during times of economic downturn and as a consequence accept productivity losses in favour of a reduction of redundancies. This argument speaks in favour of pro-cyclicality of the evolution of productivity.

Interestingly, and in contrast to employment growth, we do not find average nominal productivity growth to be pro-cyclical in a sense that phases of boom show the highest growth values (see Figure 5.4). Instead, economic downswings are characterized by the highest nominal growth rates in both manufacturing and services, followed by those in phases of boom and upturn. This pattern is not caused by some high-growing firms in the downturn but we find this pattern to hold also for median productivity growth rates.

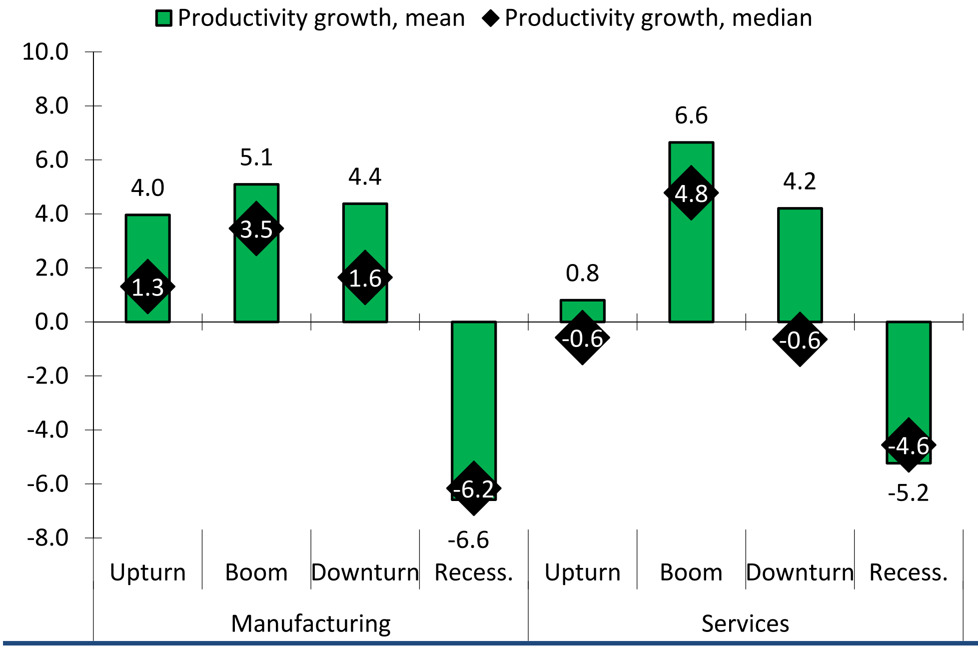
However, when we account for price changes and look at real productivity growth rates we do confirm a clear pro-cyclical evolution of productivity (see Figure 5.5). The latter finding supports the hypothesis of labour hoarding during times of economic downturn, where a productivity loss is accepted in favour of a reduction of redundancies.

**Figure 5.4: Nominal productivity growth in European firms in different phases of the business cycle**




*Notes: Weighted figures. Depicted are average two-year nominal productivity growth rates. Accordingly, the business cycle phases are defined using two-year GDP growth rates.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

**Figure 5.5: Real productivity growth in European firms in different phases of the business cycle**




*Notes: Weighted figures. Depicted are average two-year real productivity growth rates. Accordingly, the business cycle phases are defined using two-year GDP growth rates.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

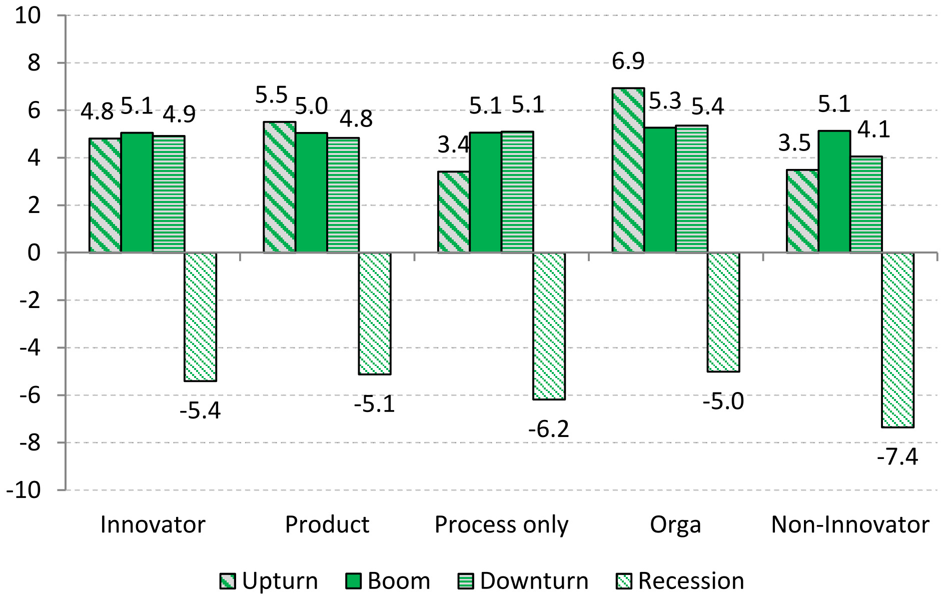
Figure 5.5 further demonstrates that mean and median productivity growth is the very similar for European manufacturing and services over most stages of the business cycle, except for upturn phases. This finding contradicts theoretical arguments that services are laggards in terms of productivity growth, as well as it contradicts empirical evidence that points to a faster productivity growth in manufacturing compared to services (Rincon-Aznar 2009). However, as pointed out in Box 1, the data presented in this report refer to the firm level, and, for some reasons explained in Box 1, do not resemble data at the aggregate level.

Furthermore, productivity losses during a recession are smaller in the services sector than in manufacturing; this is also the case for the phase of economic upturn. Similar to the employment growth (see Figure 5.1), the median values of productivity growth in the business cycle phases are again lower than the mean values, which indicates that some firms have a productivity growth higher than most of the other firms in the sample. Notably, in the case of the recession phase in the manufacturing sector, the median equals the mean value.

The distinction of productivity growth by different types of innovators (see Figure 5.6) reveals some interesting insights in manufacturing. Innovators reveal a higher productivity growth in all stages of the business cycle compared to non-innovators. Interestingly, however, the smallest differences in productivity growth between innovators and non-innovators in manufacturing are found in an economic boom. This may indicate that innovators do not utilize all opportunities for productivity growth in this stage of the business cycle due to the favourable economic climate.

Compared across the innovation statuses, the growth rates are almost on the same level in booms and downturns. In upturns, however, we observe more productivity variation among firms with different innovation strategies. That is, product innovators experience higher productivity growth rates in upturns than firms that focus solely on process innovations. In fact, across all business cycles it turns out that productivity growth among product innovators is highest in upturns where they particularly benefit from product innovations. Productivity gains in upturns are even higher for firms that perform organizational innovation. One argument could be that organizational innovations also capture new business models or new external relationships and that these are particularly worthy in flourishing economic conditions. Like for employment growth, we find productivity growth to be lower for non-innovators during all business cycle phases from 1998-2010. Compared to innovators, the productivity gap of non-innovators is particularly large in a recession (-2.2 percentage points) and around 1 percentage points in up- and downturns. Interestingly, however, in booms we hardly see any differences in productivity growth among innovators and non-innovators in manufacturing. Another exception is the upturn phase in which non-innovators have experienced similar productivity gains than process innovators but performed worse than product or organizational innovators.

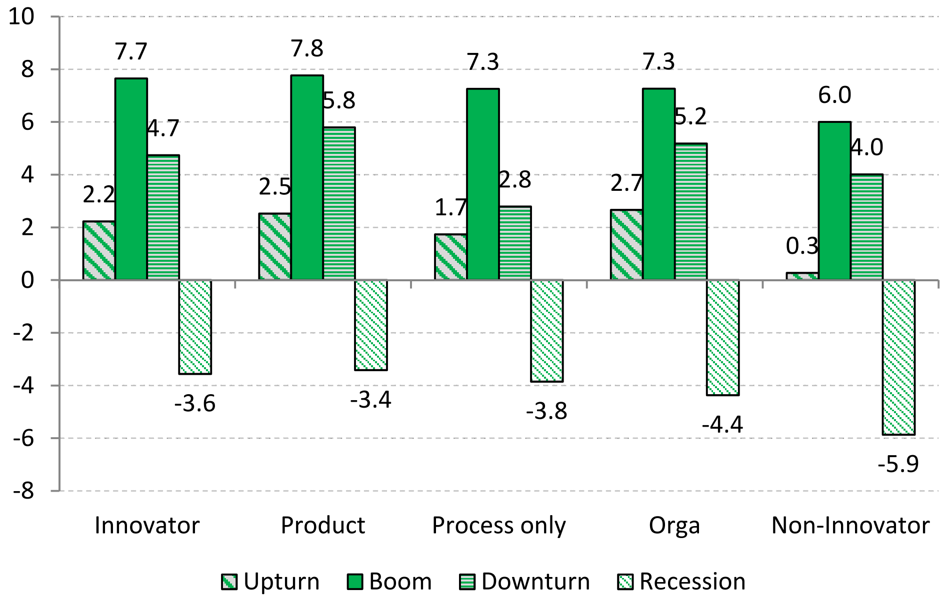
**Figure 5.6: Real productivity growth in different phases of the business cycle, manufacturing, 1998-2010**




*Notes: Weighted figures. Depicted are average two-year real productivity growth rates. Accordingly, the business cycle phases are defined using two-year GDP growth rates.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

Figure 5.7 shows the same distribution of productivity growth across different stages of the business cycle for various types of innovators and non-innovators in services. From that figures we can conclude the following. First, boom periods exhibit the highest productivity growth across all innovations statuses, followed by downturn phases. Furthermore, the productivity gap between boom and downturn phases are much larger than in manufacturing. Second, the main finding from the manufacturing sector that non-innovators demonstrate much lower productivity growth than innovators in confirmed for the service sectors. In the recession and downturn periods, the productivity gap is of similar magnitude as in manufacturing (-2.1 and -1 percentage points in recession and downturns respectively). In upturns (-1.9 percentage points) and booms (-1.7 percentage points), however, the productivity gap is larger for non-innovators in services than in manufacturing. Third, among innovators, firms which are only process innovators, have the lowest overall productivity growth, whereas the highest rates are observable in the group of product innovators.

**Figure 5.7: Real productivity growth in different phases of the business cycle, services, 1998-2010**



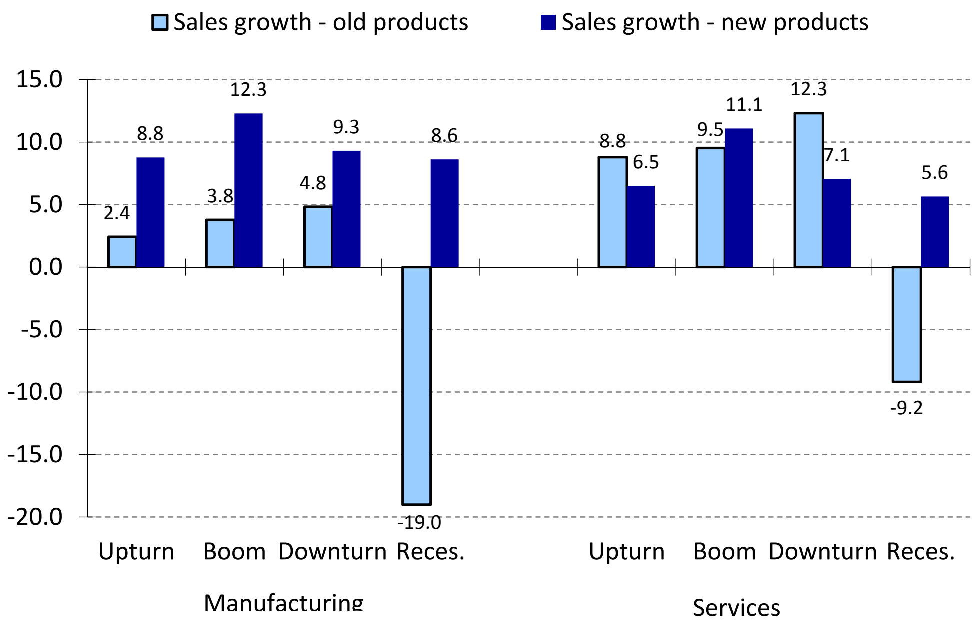

*Notes: Weighted figures. Depicted are average two-year real productivity growth rates. Accordingly, the business cycle phases are defined using two-year GDP growth rates.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

### 5.4.3. Innovation Performance in Different Stages of the Business Cycle

We now turn to the effects of business cycle fluctuations on the innovation performance of firms as measured by sales growth from new and old products. Both are key variables in the empirical model relating innovation to employment growth. Average nominal sales growth due to sales new and old products for all four phases of the business cycle is displayed in Figure 5.8.

The manufacturing sector and the services sector differ considerably with respect to the effects of the business cycle on their sales growth due to old and new products. Whereas in manufacturing the increase in sales is significantly larger for new than for old products in all phases of the business cycle, the sales growth of old products dominates over sales growth of new products in the services sector, at least in phases of economic upturn, boom, and downturn. It is only in an economic boom where the sales growth due to new products exceeds the growth due to old products in services. Highly striking is the strong decline of sales growth due to old products during recessions, in manufacturing as well as in services. This is probably a combination of two effects; a sharp decline in the demand for old products and (as a consequence) firms that thin out their product range during a recession. Taken as a whole, and not surprising, firm-level sales growth due to old as well as due to new products clearly follows a pro-cyclical path, with a peak in phases of boom. But, the sales growth due to new products is much less affected by the business cycle. In manufacturing it is never lower than 8%. In services the lower threshold for sales growth due to new products is about 5.6%. We will see later that this robustness of sales growth due to new products is a main reason why innovating firms perform better during recessions than non-innovators.

**Figure 5.8: Sales growth due to new and old products in European firms in different phases of the business cycle**

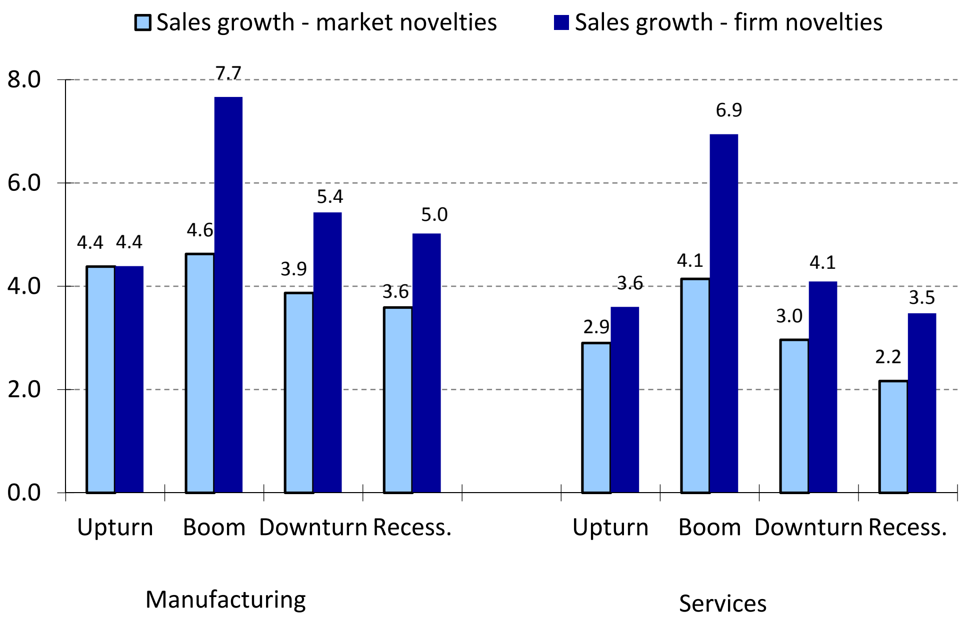



*Notes: Weighted figures. Depicted are average two-year nominal sales growth rates due to new and old products, respectively. Accordingly, the business cycle phases are defined using two-year GDP growth rates.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

New products do not necessarily be products or services new to the market. In fact, most of the sales growth from new products comes from products that someone else have already introduced to the market (see Figure 5.9). This result points to the importance of technology diffusion and the economic benefits of the application, rather than the invention of a new product or technology.

Market novelties and firm novelties both contribute positively to sales growth in all phases of the business cycle. In the services sector, sales growth exhibits pro-cyclicality due to market novelties as well as due to firm novelties. However, this is only partly true for the manufacturing sector, where the share of market novelties in sales growth is the highest during upturn phases, followed by boom periods. But all in all, sales growth due to market novelties in the manufacturing sector seem to be rather unaffected by the business cycle, ranging between 4.4% in upturns and 3.6% in the recession periods.

**Figure 5.9: Sales growth due to market and firm novelties in European firms in different phases of the business cycle**

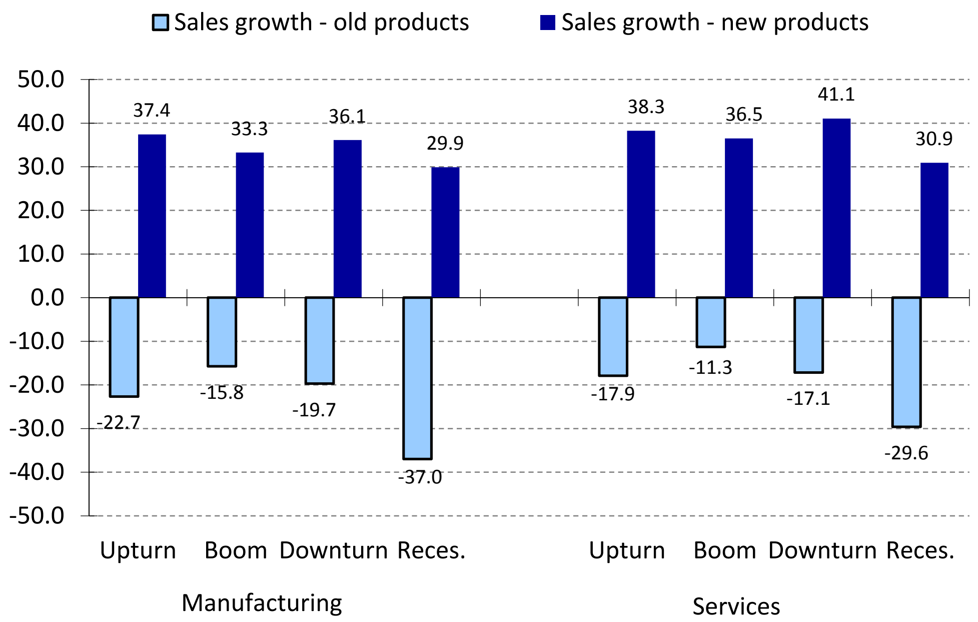



*Notes: Weighted figures. Depicted are average two-year nominal sales growth rates due to market and firm novelties, respectively. Accordingly, the business cycle phases are defined using two-year GDP growth rates.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

Whereas Figure 5.8 has depicted average sales growth rates due to new and old products for all firms, Figure 5.10 shows results sales growth rates due to new and old products for product innovators. This allows assessing the importance of cannibalization of old products sales due to new products sales. As mentioned in section 5.1, the change in sales due to old products can be attributed to at least three sources: introduction of firm's own product innovations (cannibalization), foregone sales stolen by rivals' product innovation (business stealing) or autonomous change in demand. Due to data constraints, we cannot disentangle the three effects. However, for product innovators it is likely to assume that cannibalization makes up the largest proportion.[14] The figures point towards cannibalization since we observe continuous negative growth rates due to old products over all phases of the business cycle (see Figure 5.10). Nevertheless, a pro-cyclical pattern is observable in a sense that the decline in old products sales in largest in recessions and smallest in boom periods. In contrast, the sales growth of new products remains almost the same over upturns, booms and downturns. In the recession periods, sales growth due to new products fall for product innovators by roughly 6 percentage points as well but still remain high with about 30%. Overall, the sales growth due to new products compensates the loss due to old products in all phases of the business cycle in services. In manufacturing, this holds in economic upturn, boom and downturn, but not during recession.

[14] Under additional assumptions, Harrison et al. (2014) estimated the effects of business stealing to account for less than one third of the employment creation of new products.

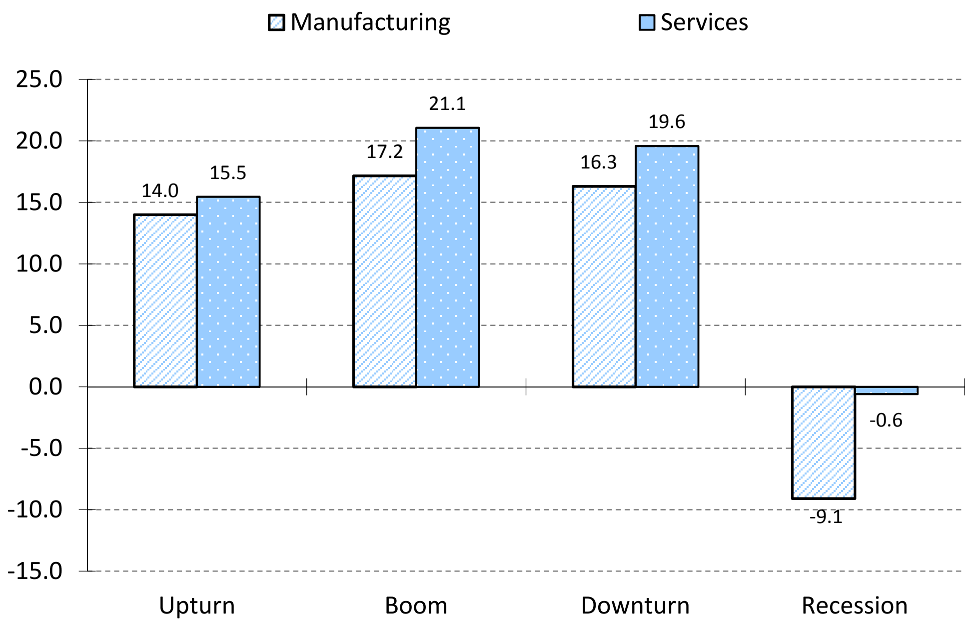
**Figure 5.10: Sales growth due to new and old products for product innovators in different phases of the business cycle, 1998-2010**




*Notes: Weighted figures. Depicted are average two-year nominal sales growth rates due to new and old products, respectively. Accordingly, the business cycle phases are defined using two-year GDP growth rates.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

Figure 5.11 illustrates the changes in sales growth due to old products for process innovators. A change in sales with old products for process innovators can also be traced back to three main sources: An increase in demand due to price reductions following enabled by cost savings, an autonomous change in demand, and business stealing due to rivals' product or process innovation. In the manufacturing and the services sector, the highest sales growth is achieved in phases of boom with decreasing values in economic downswing and finally, negative growth in times of recession. In all phases of the business cycle, sales in the services sector exceed the growth in the manufacturing sector – especially during phases of recession. While process innovators in services have experienced only a slight decrease in sales with old products, process innovators in manufacturing suffered by a decline in sale with old products of about 9.2% on average.

**Figure 5.11: Sales growth due to old products for process innovators in different phases of the business cycle, 1998-2010**




*Notes: Weighted figures. Depicted are average two-year nominal sales growth rates due to old products for firms that have introduced only process innovations. Accordingly, the business cycle phases are defined using two-year GDP growth rates.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

## 5.5. ECONOMETRIC EVIDENCE ON EMPLOYMENT EFFECTS OF INNOVATION OVER THE BUSINESS CYCLE

Descriptive evidence provided in the previous section suggests that the employment growth of innovators is higher than that of non-innovators in all phases of the business cycle. This section analyses the relationship between employment and innovation in more depth with the employment growth model introduced in section 5.2. We will first describe the effect of innovation on employment where we distinguish only between economic upturn and downturn phases.[15] In a second step, we will enlarge the model to four phases of the business cycle. In a third step, we will apply an alternative measure of business cycles in section 5.6.

A first set of econometric estimations of the employment growth model is shown in Table 5.2 for the estimates split by business cycle phases. The regressions provide estimates of the coefficients for the three innovation variables (SGR_NEWPD, PCONLY, ORGA), GDP growth at the country level (GDPGR), firm size dummies (LARGE, MEDIUM), and ownership dummies (DGP, FGP). A full description of the independent variables is provided in section 5.2.4.

[15] We additionally estimated the model using the pooled sample for the period 1998-2010. Results are available upon request.

We estimated two specifications of the model for manufacturing and services, one without interaction terms (specifications 1, 2, 5 and 6 in Table 5.2) and one in which we interact GDP growth with the three innovation variables (specifications 3, 4, 7 and 8 in Table 5.2).

The coefficient of the sales growth rate due to new products (SGR_NEWPD) is central in our assumptions on the relationship between employment growth and innovation. The coefficient reveals the average change in employment growth as a reaction to a growth in the firm's sales caused by new products. The first important finding is that in both manufacturing and services higher sales growth rates due to new products are associated with significantly higher employment growth in economic upturns as well as downturns. We can thus conclude that successful product innovation significantly spurs employment growth in manufacturing and service firms in both phases of the business cycle.

In the structural model approach, the coefficient of the sales growth due to new products variable measures efficiency differences in the production of old and new products. A value of less than one implies that new products are produced with higher efficiency and thus less labour input than old products. A value of one indicates the same efficiency of old and new products and thus no additional productivity effects and labour savings due to the introduction of new products. In both manufacturing and services, the coefficient is slightly below 1 in upturn phases. The coefficient turns out to be slightly higher in downturns. But altogether, the coefficients of SGR_NEWPD tend to be quite similar in an upturn and in a downturn. And indeed, the t-test does not reject the null hypothesis that the coefficient is one in both industries and both phases of the business cycle.[16] Thus an increase in sales growth due to new products of 1% leads to an increase in gross employment by 1% in all for samples. As was shown in section 5.4.3, product innovations simultaneously replace existing products to a considerable extent which is captured by $g_1$ in the structural model and which might lead to labour displacement. An estimate of the net employment effect of product innovation is given below in the decomposition analysis. The fact that we find no significant differences in the productivity effect of product innovation between manufacturing and services, does not support Baumol's (1967) observation of a cost disease in services.

The coefficient of organisational innovation (ORGA) is negative in all estimates. However, it is only significant in manufacturing and in upturn phases for service firms. This result indicates that firms with at least one organisational innovation on average experienced a lower employment growth than firms with no organisational innovation. This effect is stronger in upswings than in downturns, which suggests that firms try harder to increase productivity with organisational innovation in times of economic prosperity. This fits to the observation that productivity growth is pro-cyclical.

The coefficient of process innovation (PCONLY) is likewise significantly negative in manufacturing and productivity gains due to process innovation are of similar magnitude than of organizational innovations in upturns and even somewhat higher in downturns. In services, however, process innovations do not matter for employment growth in both phases of the business cycle. Readers, however, should consider that PCONLY only captures the productivity effects of process innovation in firms without product innovation. For product innovators, as explained in section 5.2.2, productivity effects of process innovation are difficult to distinguish, so both effects are captured by the coefficient of SGR_NEWPD.

Employment growth in all firms - innovative or not - benefits from demand growth as measured by real GDP growth at country level (GDPGR) in an upturn. This can be seen from the positive coefficients of GDPGR in an upturn. Somewhat puzzling, however, is the

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16 In manufacturing, a one-sided t-test would reject the null hypothesis that the coefficient is equal or larger than 1 at the 10% level, thus indicating that new products are produced with a higher productivity and need less labour input than old products.

negative coefficient in a downturn. But the reader should keep in mind that GDP growth measures general demand factors while we have already accounted for firm-specific changes in demand for existing and new products which are highly significant. The demand effect is furthermore not symmetric since the coefficients in upturns are much larger than in downturns.

**Table 5.2: Impact of innovation on employment growth in economic downturns and upturns, manufacturing, 1998-2010**

| | Manufacturing | | | | Services | | | |
|---|---|---|---|---|---|---|---|---|
| **Dep var:** | **Upturn** | **Downturn** | **Upturn** | **Downturn** | **Upturn** | **Downturn** | **Upturn** | **Downturn** |
| $EMP = l - (g_i - \hat{\pi}_i)$ | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** | **(7)** | **(8)** |
| SGR_NEWPD | 0.966*** | 0.987*** | 1.045*** | 0.993*** | 0.937*** | 1.034*** | 0.931*** | 1.041*** |
| | (0.021) | (0.022) | (0.041) | (0.022) | (0.049) | (0.031) | (0.088) | (0.032) |
| PCONLY | -1.558** | -1.295* | 0.399 | -1.070 | -1.095 | 0.288 | -0.436 | 0.264 |
| | (0.724) | (0.746) | (1.309) | (0.733) | (1.481) | (0.824) | (2.365) | (0.807) |
| ORGA | -1.669*** | -0.835** | -5.069*** | -0.800** | -0.789 | -0.263 | -3.344** | -0.220 |
| | (0.460) | (0.401) | (0.772) | (0.397) | (0.765) | (0.451) | (1.401) | (0.453) |
| GDPGR | 3.673*** | -0.598*** | 3.609*** | -0.549*** | 1.897 | -1.092*** | 1.722 | -1.064*** |
| | (0.562) | (0.138) | (0.571) | (0.143) | (1.831) | (0.150) | (1.877) | (0.151) |
| SGR_NEWPD | | | -0.013*** | -0.005* | | | 0.001 | -0.006 |
| x GDPGR | | | (0.005) | (0.003) | | | (0.010) | (0.005) |
| PCONLY | | | -0.363** | -0.269** | | | -0.115 | -0.001 |
| x GDPGR | | | (0.179) | (0.137) | | | (0.282) | (0.124) |
| ORGA | | | 0.606*** | -0.002 | | | 0.439** | 0.006 |
| x GDPGR | | | (0.115) | (0.067) | | | (0.178) | (0.087) |
| MEDIUM | -1.867*** | -1.535*** | -1.884*** | -1.547*** | -3.223*** | -3.960*** | -3.248*** | -3.948*** |
| | (0.451) | (0.438) | (0.449) | (0.436) | (0.883) | (0.431) | (0.888) | (0.430) |
| LARGE | -3.939*** | -2.420*** | -4.023*** | -2.394*** | -4.418*** | -5.494*** | -4.433*** | -5.490*** |
| | (0.637) | (0.543) | (0.638) | (0.534) | (1.063) | (0.725) | (1.066) | (0.720) |
| DGP | 0.549 | 0.950* | 0.502 | 0.949* | -0.377 | 0.363 | -0.378 | 0.365 |
| | (0.722) | (0.509) | (0.736) | (0.506) | (0.852) | (0.453) | (0.853) | (0.453) |
| FGP | -0.123 | -0.728 | -0.173 | -0.724 | -3.771*** | 0.714 | -3.816*** | 0.693 |
| | (0.662) | (0.501) | (0.659) | (0.497) | (1.184) | (0.538) | (1.187) | (0.542) |
| Constant | -63.590*** | -11.981*** | -63.084*** | -11.946*** | -32.560 | 1.944 | -31.246 | 1.941 |
| | (7.397) | (2.414) | (7.440) | (2.397) | (23.997) | (2.917) | (24.225) | (2.938) |
| Obs | 85,718 | 118,395 | 85,718 | 118,395 | 56,964 | 100,788 | 56,964 | 100,788 |

*Notes: Method: Instrumental variables estimation. Weighted regression. ***, ** and * indicate significance at the 1%, 5% and 10% level. Reported are only the main variables of interest. The full results including first stage results and specification tests are provided in the Table Appendix Table 11.2 and Table 11.3.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

Interaction variables between GDPGR and the innovation variables are only significant in manufacturing. Most notable is that the effect from GDP growth is significant if GDPGR interacts with PCONLY; a higher growth rate seems to be an incentive for process innovators to increase productivity in the production of their old products.

The coefficients of the size dummies (MEDIUM, LARGE) are negative in economic upturns and downturns. This finding indicates that small firms have a faster and higher employment growth than medium-sized and large firms over all phases of the business cycle. This effect can be observed in services and in manufacturing. Ownership dummies, in contrast, are not significant in most cases, which means that the fact that a firm is domestically owned or foreign-owned has no relevance for its employment growth. An exception is foreign ownership in services. For foreign-owned firms we find a significantly lower employment growth in prospering market conditions.

We complement the econometric analysis with a decomposition analysis. The decomposition allows quantifying the absolute *contribution* of different *sources to employment growth* for *different types of firms*. In particular, we are able to disentangle the employment effects of product, process and organizational innovation from effects originating from general demand and productivity trends.

We follow the decomposition of employment growth proposed by Harrison et al. (2014) and Peters et al. (2013):

$$
\begin{aligned}
(5.4) \qquad l = \underbrace{\hat{\alpha}_0}_{1} + \underbrace{\hat{\alpha}_1\, pc}_{2} + \underbrace{\hat{\alpha}_2\, orga}_{3} + \underbrace{\left[1 - I\left(g_2 > 0\right)\right]\left(g_1 - \tilde{\pi}_1\right)}_{4} \\
+ \underbrace{I\left(g_2 > 0\right)\left(g_1 - \tilde{\pi}_1\right)}_{5a} + \underbrace{I\left(g_2 > 0\right)\hat{\beta}\, g_2}_{5b} + \hat{v}
\end{aligned}
$$

The first term $\hat{\alpha}_{0,}$, measures the contribution of the *general trend in productivity* in the production of *old products* to employment growth. It accounts for all changes in efficiency and in turn in employment that are not attributable to firm's own process, product or organizational innovation. That is, it captures employment effects of training, improvements in the human capital endowment, corporate restructuring, acquisitions of firms, productivity effects from spillovers, wages, business cycle effects etc. The general productivity trend $\hat{\alpha}_0$ is calculated in a way that it is industry-, country-, time-, size- and ownership specific since it captures not only the effect of the constant but also of the corresponding dummy variables and of changes in GDP growth. It is measured as the average effect across innovators and non-innovators.

Term 2 captures changes in employment due to additional changes in efficiency that result from the introduction of *process innovation* applied in the production of *old* products. That is, term 2 measure the displacement effect (gross effect) of process innovation related to old products. Term 3 presents the contribution of organizational innovations to employment growth.

In equation (5.4) $I(.)$ denotes the indicator function. It is 1 if the condition in brackets is fulfilled and 0 otherwise. $1 - I\left(g_2 > 0\right)$ therefore indicates non-product innovators. This implies that the fourth component captures shifts in employment which originate from the real *growth of output in old products* for firms that do *not* introduce any new products. Changes in output for old products might occur because of autonomous changes in demand for the firm's old product, consumers' preferences, price reductions but also because of rivals' product innovations. This term therefore also comprises the (positive or negative) externalities that arise from product innovation of other firms. The occurrence of negative externalities is known as 'business stealing' effect. Substitution between sales from old and from new products within the same firm, however, is included in terms 5a.

Components 5a and 5b summarize for product innovators the *net* contribution of *product innovation* to employment growth. The net effect of product innovation results from

i. increases in the demand for new products $I\left(g_2 > 0\right)\hat{\beta}\, g_2$, and

ii. possible (positive or negative) shifts in demand for the old product $\left(I\left(g_2 > 0\right)\left(g_1 - \tilde{\pi}_1\right)\right)$.

Note that the employment effect that stems from an increase in demand for new products ( $I\left(g_2 > 0\right)\hat{\beta}\, g_2$ ) depends on three factors, i.e.

- the share of firms engaged in innovation ( $I\left(g_2 > 0\right)$ ),
- the innovation success measured as sales growth due to new products $\left(g_2\right)$, and
- the way how innovation success is translated into employment growth. This means whether there is a potential productivity effect associated with new products $\left(\hat{\beta}\right)$.

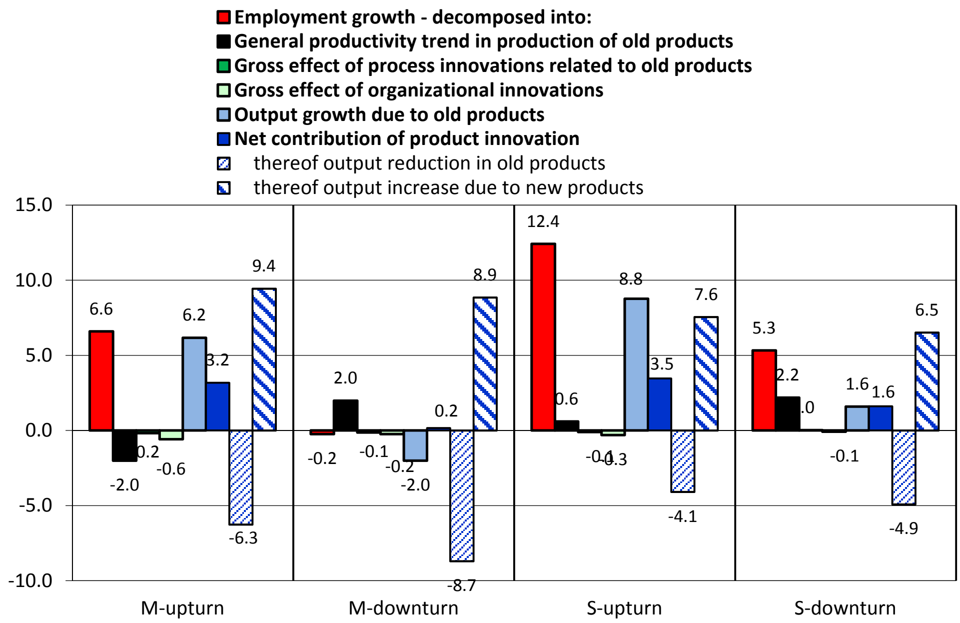
We can obtain an estimate of the decomposition of the average employment growth by inserting into the equation the

- estimated coefficients $\hat{\alpha}_{0,}, \hat{\alpha}_1, \hat{\alpha}_2,$ and $\hat{\beta}$ (we use the preferred specification without interaction terms between innovation variables and GDP of Table 5.2),
- average shares of non-innovators, process, organizational and product innovators and
- employment, price and sales growth rates (either total or for the corresponding group of firms).

The residual is zero by definition.

Figure 5.12 provides a graphical illustration of the decomposition, while the full results are found in Table 5.4. The figure shows the decomposition of employment growth for manufacturing and services in upturns and downturns. The five sources general productivity trend in production of old products (black bar), displacement effect of process innovation (light green bar) and organizational innovation (dark green bar), output growth due to old products (light blue bar) and net contribution of product innovation (dark blue bar) sum up to total employment growth (red bar). The graph further splits the net contribution of product innovation in the increase in demand for new products and (positive or negative) shifts in demand for the old product (both blue stripes).

**Figure 5.12: Contribution of innovation to employment growth in economic up- and downturns, 1998-2010**




*Notes: M denotes manufacturing and S services. Decomposition is based on regressions (1), (2), (5) and (6) of Table 5.2.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

The figure reveals that the net contribution of product innovation to employment growth is positive in both economic upturns and downturns. Most interesting in Figure 5.12 is the reaction of the output of new products to different phases of the business cycle. In an upturn, product innovation creates much more new sales due to the direct demand effect than it destroys due to the productivity effect and substitution effects between old and new products such as 'cannibalization'. This in isolation has led to an increase in employment by 3.2% in manufacturing and 3.5% in services in upturn periods. In a downturn, this margin between the gains from new and losses from old products shrinks, but is still positive with +0.2% in manufacturing and 1.6% in services. The main reason is a relatively stable engagement in product innovation and innovation success over the business cycle whereas the estimates haven't pointed towards major productivity effects and thus labour savings associates with product innovations over the business cycle.

But Figure 5.12 also shows that in an upturn the main sources of employment growth are not product innovations but output growth due to old products of non-product-innovators (light blue bar). This holds in both manufacturing and services. Whereas sales of old products by non-product innovators are the main contributor to employment growth in upturns, they are also the main source of employment losses in downturns. Thus, it is the ability of product innovators to substitute losses due to old products by gains due to new products that keeps employment losses limited in a recession or even allow slight employment growth.

Another factor that softens employment fluctuations over the business cycle is the general productivity trend in the production of old products. In manufacturing, its contribution to employment growth is negative in an upturn, and positive in a downturn, which means that falling productivity increases employment in a downturn, while rising productivity decreases employment in an upturn. An explanation for this finding is labour hoarding, a tendency of firms to reduce their labour force much slower than their sales or output fall in an economic downturn; employees merely reduce their efforts as sales or output shrinks. In economic upturns, productivity rises because employees increase their efforts.

The displacement effects of process and organizational innovations negatively contribute to employment growth. Similar to the general productivity trend, the process and organizational innovation-related productivity increases and thus labour savings are stronger in upturns and in manufacturing. Whereas it is close to zero in downturns. All in all, compared to the other sources displacement effects of process innovation are of minor importance for employment growth.

In the remaining parts of this section, we will enlarge the 2-phase indicator for the business cycle by a more sophisticated approach that distinguishes between four phases of the business cycle (see section 3.1). Table 5.3 reports results similar to Table 5.2 but distinguishing between four phases. Figure 5.13, Figure 5.14 and Table 5.4 complement the analysis with the decomposition.

The results of Table 5.3 largely confirm the findings of the 2-phase indicator. We see only little variation in the size of the coefficient on SGR_NEWPD. The coefficients of SGR_NEWPD tend to be smaller in upturn and boom periods than in downturn and recession periods and the differences between the phases of the business cycle are more pronounced in services. However, t-tests cannot confirm that they are significantly different. This indicates a stable relationship between innovation output measured by sales growth due to new products and employment growth through all states of the business cycle.

In manufacturing process innovations lead to labour downsizing in upturns and downturns, but not in booms or recessions. Thus, the productivity effect of process innovation on employment growth is most pronounced in these two phases of the business cycle. This applies also to organizational innovations. How can we explain these findings? One reason could be different motives for process innovations in these phases. In boom periods, when utilization of production capacities is high, process innovations are likely to be a mean to organize production processes more efficiently in order to meet high demand but not to dismiss employees. In economic downturns, when demand cools down, firms seem to use process innovations in order to increase productivity and save labour which has reached high levels during the boom period. In the recession, however, they have already reached a relatively low level of employment and do not further cut labour.

An interesting side result is that affiliates of foreign multinational firms (FGP) in manufacturing lose more employment in a recession than domestically owned firms. An explanation is that foreign-owned firms are more exposed to world markets via exporting, and exports suffered more than domestic demand during the last recession which is covered by the data. However, this result may also indicate that multinational firms rather prefer to cut jobs abroad than at home in a recession. A similar effect cannot be observed in services, where foreign ownership exerts a negative effect during upturns.

While a firm's own demand is highly significant for its employment growth, mixed results are again found for variations in general demand conditions, which are proxied by the coefficient of GDPGR. In manufacturing, the size of GDP growth seems to stimulate employment growth only in upturns. The coefficient is considerably smaller and negative in downturns, and not significant in booms and recessions. This indicates the importance of positive expectations of future demand for employment growth in manufacturing firms. Surprisingly, the same coefficient is not significant in services which may be a sign that demand expectations are less important for employment growth of service firms.

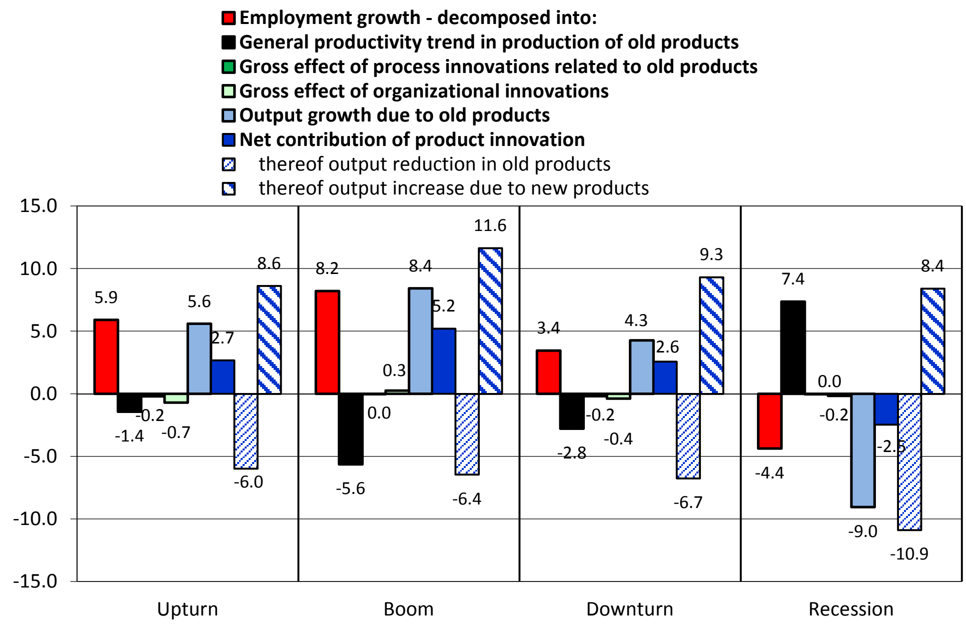
**Table 5.3: Impact of innovation on employment growth in different phases of the business cycle, 1998-2010**

| | Manufacturing | | | | Services | | | |
|---|---|---|---|---|---|---|---|---|
| | **Upturn** | **Boom** | **Downturn** | **Recession** | **Upturn** | **Boom** | **Downturn** | **Recession** |
| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** | **(7)** | **(8)** |
| SGR_NEWPD | 0.984*** | 0.965*** | 1.002*** | 0.976*** | 0.988*** | 0.845*** | 1.036*** | 1.026*** |
| | (0.024) | (0.029) | (0.025) | (0.026) | (0.051) | (0.119) | (0.046) | (0.036) |
| PCONLY | -1.747** | -0.268 | -1.835* | -0.367 | -0.524 | -1.831 | 1.224 | -0.255 |
| | (0.853) | (1.391) | (0.941) | (1.027) | (1.463) | (4.295) | (1.097) | (0.882) |
| ORGA | -2.207*** | 0.601 | -1.373** | -0.567 | -2.034** | 1.501 | -1.390* | 0.338 |
| | (0.467) | (0.738) | (0.617) | (0.490) | (0.793) | (1.970) | (0.825) | (0.565) |
| GDPGR | 3.641*** | 2.816 | -0.600*** | -0.017 | 1.694 | -3.500* | -0.631*** | 0.846*** |
| | (0.556) | (1.811) | (0.175) | (0.278) | (2.084) | (2.008) | (0.220) | (0.256) |
| MEDIUM | -3.080*** | -0.006 | -1.255** | -2.019*** | -4.640*** | -1.045 | -3.376*** | -4.197*** |
| | (0.460) | (0.865) | (0.596) | (0.496) | (0.942) | (1.720) | (0.646) | (0.581) |
| LARGE | -4.718*** | -3.542*** | -1.351* | -3.979*** | -4.890*** | -4.085** | -5.868*** | -4.922*** |
| | (0.609) | (1.284) | (0.787) | (0.659) | (1.531) | (1.914) | (1.174) | (1.058) |
| DGP | -1.472* | 3.213*** | 0.567 | 1.290* | -1.169 | 0.346 | 0.119 | 0.380 |
| | (0.791) | (1.163) | (0.648) | (0.661) | (1.094) | (1.578) | (0.631) | (0.609) |
| FGP | -1.130 | 1.034 | 0.124 | -1.805*** | -5.169*** | -1.844 | 0.118 | 0.462 |
| | (0.804) | (1.147) | (0.659) | (0.631) | (1.359) | (2.202) | (0.801) | (0.830) |
| Constant | -67.186*** | -33.372** | -15.091*** | 3.049* | -32.862 | 18.939 | -6.139* | 15.404*** |
| | (7.291) | (15.808) | (2.647) | (1.654) | (25.674) | (17.056) | (3.585) | (1.221) |

*Notes: Weighted regression. ***, ** and * indicate significance at the 1%, 5% and 10% level. This table reports only the results of the main variables of interest. The full set of results can be found in the Table appendix, Table 11.4 and Table 11.5.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

Figure 5.13 and Table 5.4 give a more refined illustration of the contributions of different types of innovations to employment growth over the business cycle. Even more pronounced than before, we see the pro-cyclicality of the general productivity trend leading to a counter-cyclical effect on employment in manufacturing. That is, the increase in the general productivity in isolation would have led to a loss of employment which is the largest in the boom period. In the recession, we again see the dampening effects of labour hoarding in the contribution of general productivity trends in the production of old products. Old products contribute considerably to employment growth in upturns, booms and downturns. In all three phases of the business cycle, their contribution is larger than the contribution of product innovation. However, old products are the largest burden for employment growth in a recession, where sales of old products fall much more than sales of new products.

**Figure 5.13: Contribution of innovation to employment growth over four phases of the business cycle, manufacturing, 1998-2010**




*Notes: Decomposition is based on regressions (1) to (4) of Table 5.3.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

Again, most interesting is the contribution of new products in different phases of the business cycle. In an upturn, product innovation tends to create much more employment due to the demand effect than it destroys due to the productivity effect and substitution effects between old and new products (+2.7%). This effect is even stronger in an economic boom (+5.2%). In downturns, absolute employment creation effects of product innovation shrink but less than those of old products. They remain positive and of similar size than in upturns. This implies that compared to old products product innovations are becoming relatively more important for employment growth in downturns and this is even more so in recession periods. Why? Indeed the contribution of product innovation has become negative in the recession period because output from new products does not grow fast enough to compensate losses in old products. Here, innovation has lost the race between jobs creation by new products and jobs destruction by shifting demand patterns for old products.[17] However, the loss in demand and as a result in employment (-2.5%) was much smaller than for non-product innovators (-9%). In a Schumpetarian view recessions provide a cleansing mechanism for correcting organizational inefficiencies and for encouraging firms to reorganize, innovate or relocate to new markets. In this sense recessions are means to reconstruct the economic system on a more efficient plan (see Aghion et al 2012). The results points toward the functioning of this mechanism. Firms that have introduced product innovation during recessions experience larger efficiency gains and higher employment growth than non-product innovators.

Thus, employment fluctuations over the business cycle are mainly related to changes in demand for old products of non-product innovators and the contribution of product innovation to employment growth. The results confirm our assumption that market acceptance for new products and the potential for demand expansion and extra-normal profits is higher during upswings and booms of the business cycle, leading to a stronger *demand effect* and larger employment creation from product innovation during upswings and booms than during downswing or recession. Our assumption that the within-firm business stealing effect (cannibalization effect) is smaller in a growing than in a stagnant market is only partly confirmed. Output reduction in old products is considerably higher only in recessions.

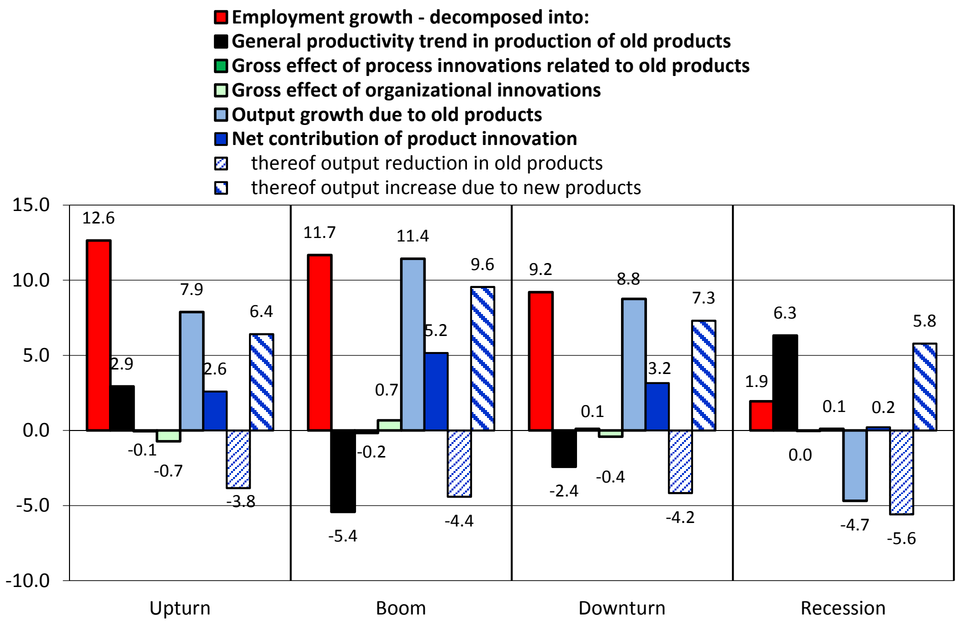
We also assumed that the lack of demand dynamics in economic downswings or recessions may hamper the employment-creating demand effect of product innovation. This is only partly true; new products also find customers also in recessions.

The productivity effect of process innovation on employment, in contrast, is much smaller than expected. This may be due to identification problems which has led us to consider only effects of non-product innovators. Moreover, there seems to be no variation in the size of the productivity effect of process innovation over the business cycle.

Figure 5.14 depicts the decomposition for service industries. The results are more or less the same, despite that employment growth and the contributions of different forms of innovation are higher in services in all phases of the business cycle.

[17] The observation period mainly covers the deep recession caused by the financial crisis in 2008. Whether the contribution of product innovation is also negative in other recession periods remain for further investigation.

**Figure 5.14: Contribution of innovation to employment growth over four phases of the business cycle, services, 1998-2010**




*Notes: Decomposition is based on regressions (5) to (8) of Table 5.3.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

**Table 5.4: Contribution of innovation to employment growth over the business cycle, 1998-2010**

| | 2-phase BC indicator | | | | 4-phase BC indicator | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Manufacturing** | | **Services** | | **Manufacturing** | | | | **Services** | | | |
| | Down-turn | Upturn | Down-turn | Upturn | Upturn | Boom | Down-turn | Reces-sion | Upturn | Boom | Down-turn | Reces-sion |
| Employment growth | -0.2 | 6.6 | 5.3 | 12.4 | 5.9 | 8.2 | 3.4 | -4.4 | 12.6 | 11.7 | 9.2 | 1.9 |
| Decomposed into | | | | | | | | | | | | |
| (1) General productivity trend in production of old products | 2.0 | -2.0 | 2.2 | 0.6 | -1.4 | -5.6 | -2.8 | 7.4 | 2.9 | -5.4 | -2.4 | 6.3 |
| (2) Gross effect of process innovations related to old products | -0.1 | -0.2 | 0.0 | -0.1 | -0.2 | 0.0 | -0.2 | 0.0 | -0.1 | -0.2 | 0.1 | 0.0 |
| (3) Gross effect of organizational innovation | -0.2 | -0.6 | -0.1 | -0.3 | -0.7 | 0.3 | -0.4 | -0.2 | -0.7 | 0.7 | -0.4 | 0.1 |
| (4) Output growth of old products for non-product innovators | -2.0 | 6.2 | 1.6 | 8.8 | 5.6 | 8.4 | 4.3 | -9.0 | 7.9 | 10.5 | 8.8 | -4.7 |
| (4a) Thereof for non-innovators | -2.1 | 4.9 | 1.1 | 7.5 | 4.3 | 6.8 | 3.3 | -8.0 | 6.7 | 9.7 | 7.7 | -4.6 |
| (4b) Thereof for process innovators | 0.0 | 1.3 | 0.4 | 1.3 | 1.2 | 1.6 | 1.0 | -1.0 | 1.1 | 1.7 | 1.1 | -0.1 |
| (5) Net contribution of product innovations | 0.2 | 3.2 | 1.6 | 3.5 | 2.7 | 5.2 | 2.6 | -2.5 | 2.6 | 5.2 | 3.2 | 0.2 |
| (5a) Thereof output reduction in old products | -8.7 | -6.3 | -4.9 | -4.1 | -6.0 | -6.4 | -6.7 | -10.9 | -3.8 | -4.4 | -4.2 | -5.6 |
| (5b) Thereof output increase in new products | 8.9 | 9.4 | 6.5 | 7.6 | 8.6 | 11.6 | 9.3 | 8.4 | 6.4 | 9.6 | 7.3 | 5.8 |

*Notes: Decomposition based on regressions (1), (2), (5) and (6) of Table 5.2 and Table 5.3.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

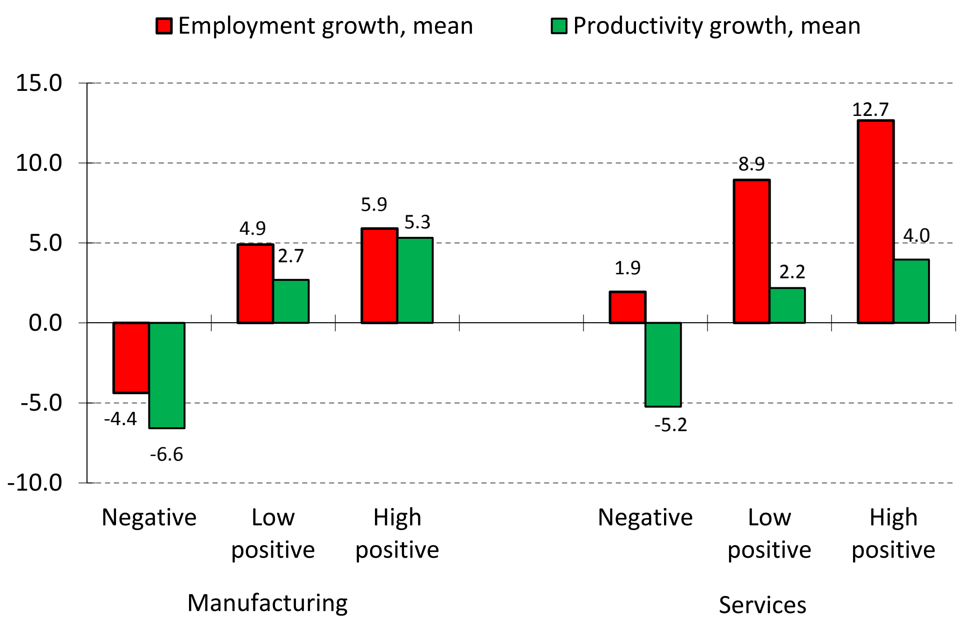
## 5.6. EMPLOYMENT EFFECTS OF INNOVATION DEPENDING ON THE LEVEL OF ECONOMIC GROWTH

The definition of different phases of the business cycles employed in the previous section does not fully consider the strength of GDP growth in a particular period. As an alternative, we further investigate the relationship between innovation and employment growth of firms depending on the level of real GDP growth. Within the EU-28, the average annual real GDP growth was about 2% over the period 1998-2020 and the average two-year GDP growth was close to 4%. For each country, we define three phases of economic growth:

- *Negative growth*: defines a period in which the two-year GDP growth of country *j* was negative.
- *Low growth*: defines a period in which the two-year real GDP growth of country *j* was positive but below 4%.
- *High growth*: defines a period in which the two-year real GDP growth country *j* was above 4%.

A comparison of employment growth and productivity growth for the defined three phases of economic growth (i.e. negative, low positive and high positive economic growth) is given in Figure 5.15. Periods with negative growth are by definition recession periods. Hence, we will mainly focus our discussion on results about phases of low and high positive economic growth.

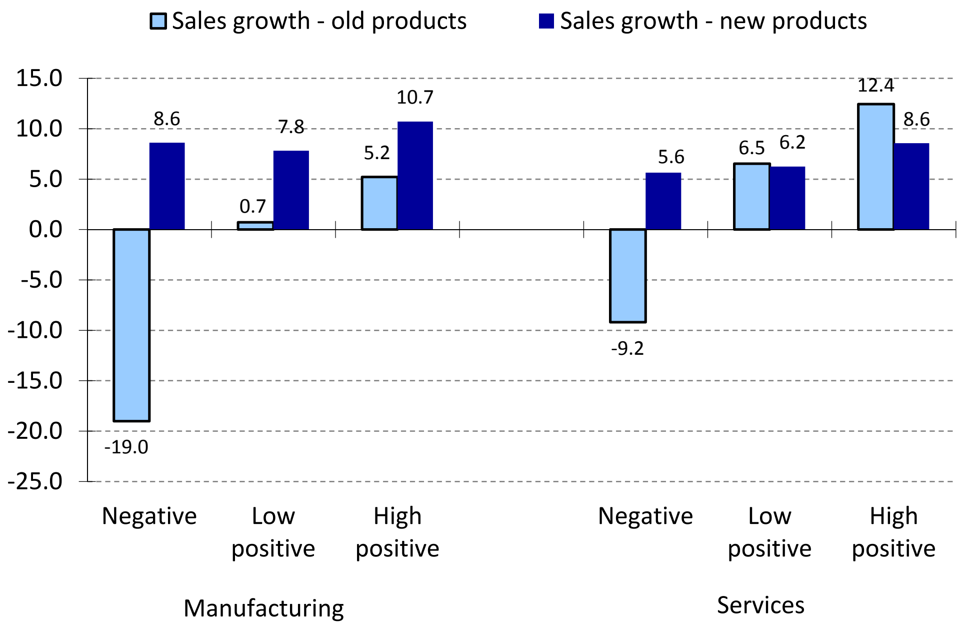
**Figure 5.15: Employment and productivity growth by strength of economic growth, 1998-2010**




*Notes: Weighted figures. Depicted are two-year employment and real productivity growth rates, respectively.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

Not surprisingly, we find that firm-level employment growth as well as productivity growth correlates positively with GDP growth, since for both, manufacturing and services, low rates of GDP growth coincide with low rates of employment and productivity growth and vice versa. It stands out that in services average employment growth exceeds productivity growth in all phases of the business cycle. The phase of negative economic growth is characterized by a negative productivity growth, whereas employment growth is positive. This finding points to lower technological opportunities in many service industries.

**Figure 5.16: Sales growth due to new and old products by strength of economic growth, 1998-2010**




*Notes: Weighted figures. Depicted are average two-year nominal sales growth rates due to new and old products, respectively. Accordingly, the business cycle phases are defined using two-year GDP growth rates.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

Regarding the phases of economic growth and the sales growth due to new and old products (see Figure 5.16), it is noticeable that sales growth due to old products sharply rises with increasing economic growth, whereas the innovation success measured in terms of sales growth due to new products remains relatively stable across different phases of GDP growth. That is, sales growth due to new products seems to be relatively independent of the level of economic growth. Nonetheless, the highest values are identifiable in periods of high positive economic growth. Whereas, new products are predominant for (positive) sales growth in manufacturing, old products are predominant in services. Strong negative sales growth due to old products is observable in manufacturing as well as in services during phases of negative economic growth; however the negative impact is by far stronger in manufacturing sectors.

Econometric evidence of the impact of innovation on employment with respect to the level of economic growth in Table 5.5 in general confirms the econometric findings from the previous section 5.5.

**Table 5.5: Impact of innovation on employment growth in phases of negative, low and high economic growth, 1998-2010**

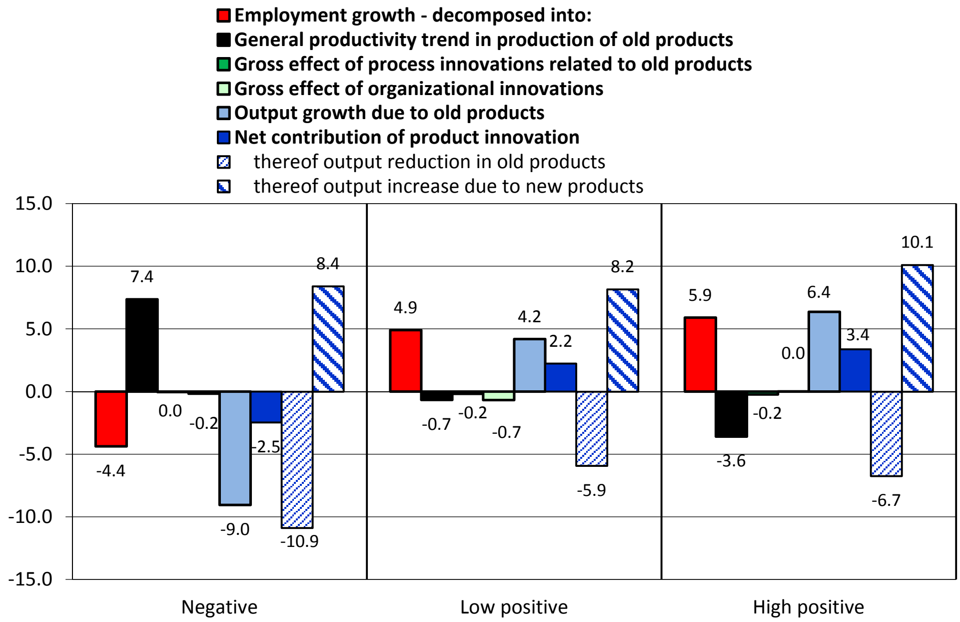
| | Manufacturing | | | Services | | |
|---|---|---|---|---|---|---|
| | **Negative** | **Low pos.** | **High pos.** | **Negative** | **Low pos.** | **High pos.** |
| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** |
| SGR | 0.976*** | 1.042*** | 0.943*** | 1.026*** | 0.986*** | 0.965*** |
| _NEWPD | (0.026) | (0.031) | (0.016) | (0.036) | (0.053) | (0.047) |
| PCONLY | -0.367 | -1.386* | -2.230*** | -0.255 | -0.089 | -1.011 |
| | (1.027) | (0.777) | (0.715) | (0.882) | (1.269) | (1.436) |
| ORGA | -0.567 | -2.112*** | 0.011 | 0.338 | -1.408 | -0.263 |
| | (0.490) | (0.598) | (0.422) | (0.565) | (0.938) | (0.816) |
| GDPGR | -0.017 | 1.391*** | -0.379 | 0.846*** | 3.031*** | -0.721** |
| | (0.278) | (0.509) | (0.237) | (0.256) | (0.655) | (0.315) |
| MEDIUM | -2.019*** | -3.989*** | -0.764 | -4.197*** | -5.612*** | -2.283*** |
| | (0.496) | (0.613) | (0.488) | (0.581) | (0.865) | (0.804) |
| LARGE | -3.979*** | -4.859*** | -2.592*** | -4.922*** | -6.930*** | -3.902*** |
| | (0.659) | (0.843) | (0.709) | (1.058) | (1.809) | (1.020) |
| DGP | 1.290* | -0.750 | 1.469** | 0.380 | -0.657 | 0.685 |
| | (0.661) | (0.845) | (0.647) | (0.609) | (0.942) | (0.754) |
| FGP | -1.805*** | -0.270 | -0.071 | 0.462 | -1.847 | -2.443** |
| | (0.631) | (0.814) | (0.600) | (0.830) | (1.534) | (1.059) |
| Constant | 3.049* | -15.214*** | -14.253*** | 15.404*** | -13.285*** | 1.108 |
| | (1.654) | (2.929) | (3.764) | (1.221) | (2.653) | (5.219) |

*Notes: Weighted IV regression. This table reports only the results of the main variables of interest. The full set of results can be found in the Table appendix, Table 11.6.*

Product innovation spurs employment growth. The coefficients in all periods lie close to one, in manufacturing and in services. In manufacturing, however, we find significant productivity effects associated with the introduction of product innovation in phases of high economic growth. Under these circumstances, firms produce their new products with less employees than they did before with their old products, dampening positive employment effects from product innovation. The impact of process innovation on employment growth is negative in all cases, however, it is only highly (weakly) significant in periods of high (low) positive economic growth in manufacturing. These findings suggest that particularly in manufacturing in phases with positive economic growth, process innovation decreases employment growth.

The illustration of the decomposition of employment growth for negative, low positive and high positive economic growth is given in Figure 5.17 (for manufacturing; for services see Figure 5.18). Employment growth is found to be negative in periods of negative economic growth (-4.4 percentage points), while it is positive in phases of positive (low and high) growth. Therefore, the decomposition of the employment growth differs strongly between periods of negative economic growth and those with positive economic growth. In the case of negative economic growth, i.e. recession period, the output growth due to old products would have led to a decrease in employment growth by -9%. A negative net contribution of product innovation accounts for a further reduction in employment by -2.5 percentage points. It is the labour hoarding effect and an associated increase in the general productivity trend in production of old products that dampens this effect by 7.4 percentage points. In the case of positive economic growth (low and high), the general productivity trend in production of old products has a negative impact on the employment growth – in contrast to the period of negative economic growth. Also, the output growth due to old products and the net contribution of product innovation are positive.

**Figure 5.17: Contribution of innovation to employment growth in phases of negative, low and high economic growth, manufacturing, 1998-2010**

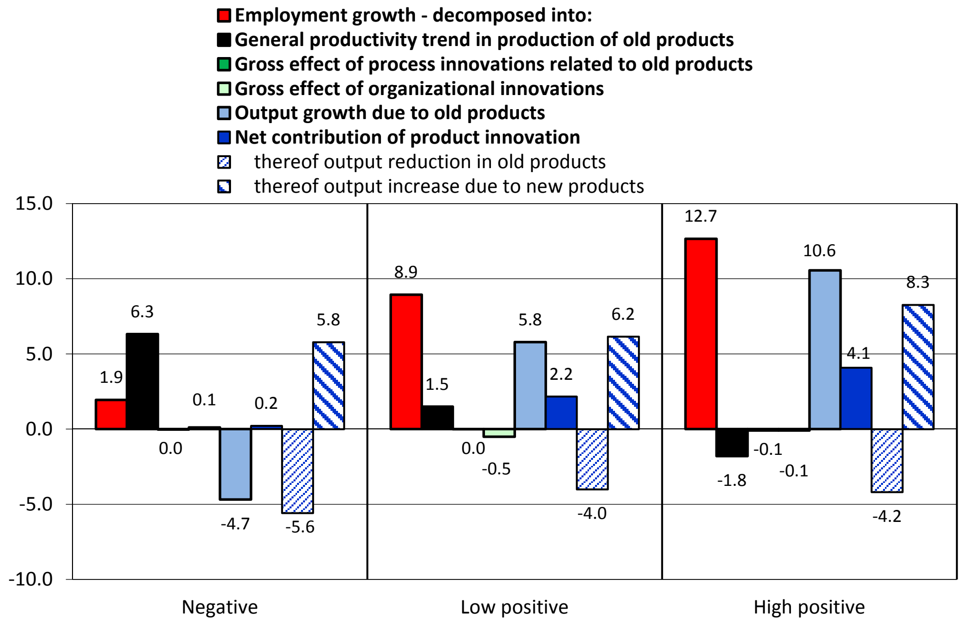



*Notes: Decomposition based on regressions in Table 5.5.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

The decomposition of the employment growth in the services sectors is displayed in Figure 5.18. Similar to manufacturing, negative economic growth again is strongly influenced by mainly the general productivity trend in production of old products (+6.3 percentage points) and the output growth due to old products (-4.7 percentage points). In the phase of high positive economic growth the output growth due to old products accounts for 10.6 percentage points of employment growth (12.7%), followed by the net contribution of product innovation (4.4 percentage points). Likewise, in the case for low positive economic growth, the output growth due to old products contributes with 5.8 percentage points to the total employment growth and the net contribution of product innovation accounts for 2.2 percentage points.

In general, the output growth due to old products and the net contribution of product innovation increase with stronger economic growth. Moreover, the gross effect of process innovations (related to old products) and the gross effect of organizational innovations only play a marginal role – in services and in manufacturing.

**Figure 5.18: Contribution of innovation to employment growth in phases of negative, low and high economic growth, services, 1998-2010**




*Notes: Decomposition based on regressions in Table 5.5.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

# Chapter 6.
# INNOVATION AND EMPLOYMENT GROWTH OVER THE BUSINESS CYCLE – SECTOR-LEVEL EVIDENCE

As it was explained in section 2.3.3., differences in demand expectations, technological opportunities and appropriablility conditions lead to differences in technology intensity of industries. This in turn might also cause heterogeneity in employment growth among industries and in the extent to which innovation contributes to employment growth. High-technology sectors, for example, have been growing faster than any other type of industry between 1995 and 2004 (Rincon-Aznar et al. 2009, p. 127). This may indicate that high-technology sectors are more confident in future demand growth, leading to faster employment growth in economic upswings. Moreover, faster technological change may lead to more opportunities for innovation in high-technology sectors compared to other sectors, which may turn into more employment growth via the demand effect. Another possible source for sectoral differences are appropriablility conditions, which denotes the ability of a firm to reap the full benefits of an innovation and avoid involuntary spillovers of new knowledge to competitors. Therefore, one can expect higher employment volatility in high-technology firms and manufacturing in general compared to low-technology firms and services.

In this chapter, we therefore aim at shedding light on industry heterogeneity in the relationship between innovation and firm-level employment growth. In chapter 5 we have already examined employment effects of innovation separately for manufacturing and service sectors, and we have seen some interesting differences between the two main business sectors over the business cycle. In this section we go a step further by differentiating between different industries. We use three different industry classifications. In section 6.1, we follow the traditional division of industries based on their technology intensity and distinguish between high- and low-tech industries. In section 6.2 we use a more disaggregated classification of 16 industries. Since we have shown that employment growth effects of innovation are strongly related to (expected) demand effects, we use the business cycle sensitivity of industries as alternative criteria for defining industry groups in section 6.3.

## 6.1. EMPLOYMENT EFFECTS OF INNOVATION BASED ON TECHNOLOGY INTENSITY OF SECTORS

Based on the technology intensity of industries – measured in terms of R&D intensity - Eurostat has suggested splitting manufacturing into high-tech manufacturing (HIGH) and low-tech manufacturing (LOW). Similarly, Eurostat splits services into knowledge-intensive services (KIS) and less-knowledge-intensive services (LKIS); see Table 11.1 in the Table Appendix.[18] Following their definition, we distinguish in this section four sector groups. In manufacturing, about four out of five firms belong to low-tech industries (79%) and every fifth firms is a high-tech firm (21%). In services, knowledge- and less knowledge-intensive services account for 35% and 65% of all firms. Like in in previous chapters all figures are weighted.

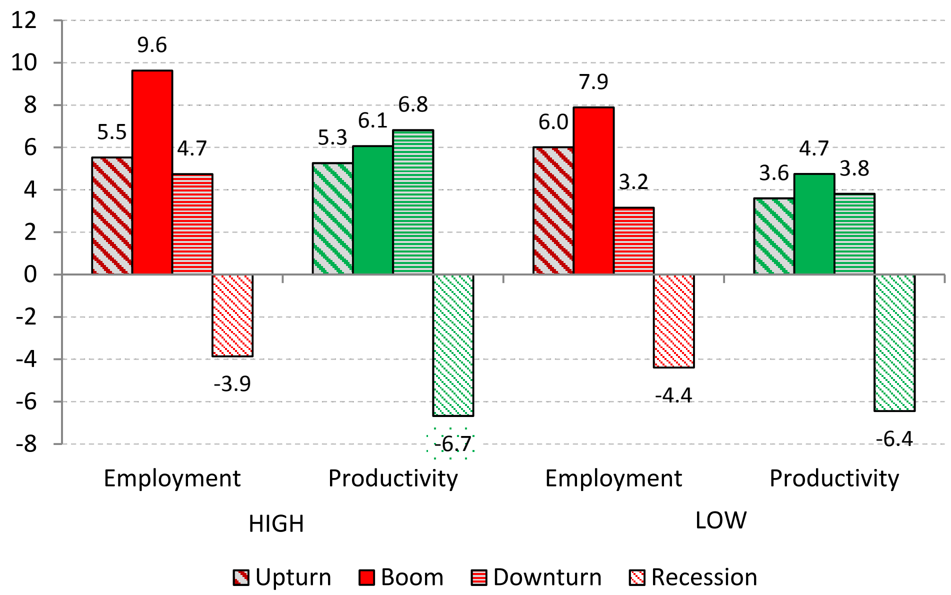
Figure 6.1 depicts the evolution of employment and productivity growth over the business cycle for high-tech and low-tech manufacturing. In both industry groups, the same pro-

[18] In contrast to section 4.4, we only use two sector groups for manufacturing, i.e. we aggregate Eurostat’s high-technology and medium-high-technology manufacturing groups to high-tech manufacturing (HIGH) and similarly low-technology and medium-low-technology manufacturing to low-technology manufacturing (LOW).

cyclical movement of average employment growth is observable. Both groups exhibit a clear negative employment growth in the recession phases, whereas the highest values of growth are noticeable again in the boom and upturn phases of the business cycle. In section 2.3.3 we put forward the hypothesis that high-tech firms grow faster than low-tech firms in all phases of the business cycle due to better demand expectations, technological opportunities and appropriability conditions. The data supports this hypothesis. In the observed period 1998-2010, employment growth is generally higher (or less negative) in high-tech manufacturing than in low-tech industries. Since innovation is much more important in high-tech manufacturing firms, this can already point towards differences in the innovation-employment link across industries.

In low-tech manufacturing, average real productivity growth also moves in line with the business cycle. That is, we observe the highest increase in real productivity in European firms in boom periods. In contrast, we do not observe pure pro-cyclicality of productivity in high-tech manufacturing since on average the strongest increase in productivity is experienced in downturn phases. But both sector groups suffer from a sharp decline in productivity of similar size in recession periods.

**Figure 6.1: Employment and productivity growth in high- and low-tech manufacturing, 1998-2010**

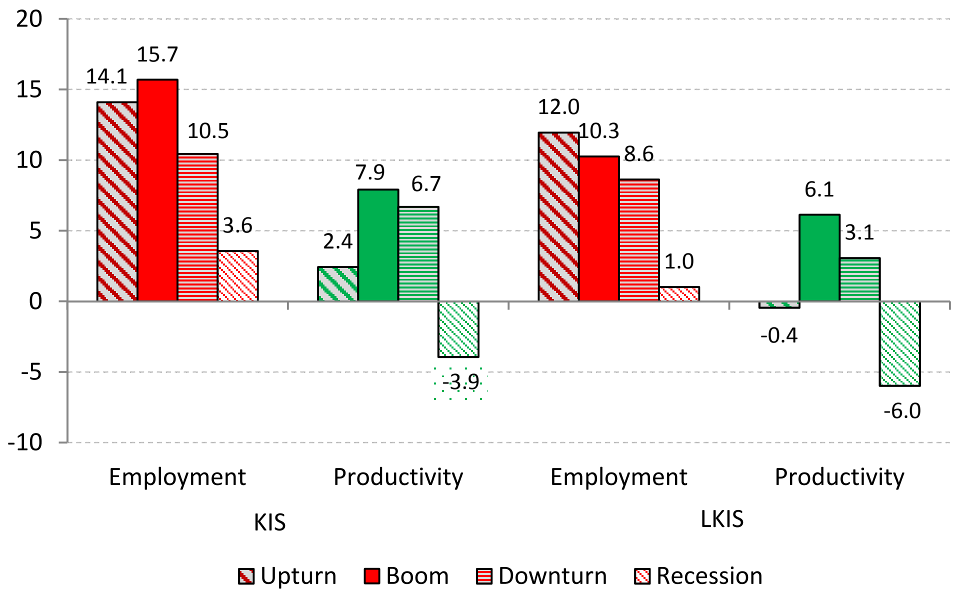



*Notes: Weighted figures. Depicted are two-year employment and real productivity growth rates, respectively.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

We gain further interesting insights when we compare employment and productivity growth. In both sector groups the increase in productivity is accompanied by a disproportionate employment growth in economic downturns. In contrast, employment even grows stronger on average than productivity in boom periods; in services this pattern also applies to upturns. In the recession, however, employment shrinks less than productivity in both industry groups, again pointing towards labour hoarding.

Figure 6.2 illustrates employment and productivity changes over the business cycle in services. Average employment growth also moves pro-cyclical in knowledge-intensive services. In less knowledge-intensive services this is only partly confirmed since the highest employment growth is observed in the upturn periods. Productivity is clearly pro-cyclical in both sector groups. In contrast to the findings for high-tech and low-tech manufacturing, employment growth exceeds productivity growth in all stages of the business cycle in both sector groups.

**Figure 6.2: Employment and productivity growth in knowledge-intensive and less knowledge-intensive services, 1998-2010**




*Notes: Weighted figures. Depicted are two-year employment and real productivity growth rates, respectively.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

Table 6.1 and Table 6.2 report the econometric evidence on how innovation affects employment growth over the business cycle in the four sector groups. The main take-away is that the employment gross effect of product innovation is significantly positive in all phases of the business cycle in all four sectors. Again, most coefficients are not significantly different from one, indicating that an increase in sales due to new products by one percent increases gross employment by one percent. In only one out of the 16 cases, we find this elasticity to be lower than one. In recession periods product innovations are associated with additional productivity effects in low-tech manufacturing.

For process innovation, we find a negative impact in upturns in both high- and low-tech manufacturing and also in downturns in low-tech manufacturing but surprisingly no effect in recession periods and also not in boom phases. This confirms findings for the manufacturing sector (see also the interpretation in section 5.5). In services, process innovations do not play a significant role for employment growth, neither in knowledge-intensive nor in less knowledge-intensive services.

A more mixed pattern emerges for the role of organizational innovation. In low-tech manufacturing, they have a significantly negative impact on employment growth in all phases of the business cycle except for the boom period. The effect is larger in upturns than in downturns and recessions. The latter might be again a reflection of labour hoarding.

**Table 6.1: Impact of innovation on employment growth over the business cycle in high- and low-tech manufacturing, 1998-2010**

| | **High-tech manufacturing** | | | | **Low-tech manufacturing** | | | |
|---|---|---|---|---|---|---|---|---|
| | **Upturn** | **Boom** | **Downturn** | **Recession** | **Upturn** | **Boom** | **Downturn** | **Recession** |
| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** | **(7)** | **(8)** |
| SGR_NEWPD | 0.995*** | 0.964*** | 1.021*** | 0.993*** | 0.972*** | 0.970*** | 0.997*** | 0.955*** |
| | (0.034) | (0.056) | (0.055) | (0.058) | (0.027) | (0.040) | (0.027) | (0.023) |
| PCONLY | -2.813* | 1.522 | -1.408 | 0.568 | -1.613* | -0.573 | -1.921* | -0.634 |
| | (1.559) | (2.121) | (1.649) | (2.478) | (0.930) | (1.382) | (1.060) | (1.100) |
| ORGA | -2.187** | -0.430 | -0.661 | 0.390 | -2.131*** | 1.007 | -1.553** | -0.822** |
| | (1.002) | (1.684) | (0.753) | (1.294) | (0.639) | (0.930) | (0.743) | (0.413) |
| GDPGR | 2.351** | -0.160 | -0.171 | 0.173 | 3.849*** | 3.533** | -0.722*** | -0.045 |
| | (0.979) | (0.406) | (0.248) | (0.523) | (0.117) | (1.689) | (0.200) | (0.314) |
| MEDIUM | -3.908*** | 1.022 | -2.283 | -3.285*** | -2.836*** | -0.398 | -1.037 | -1.721*** |
| | (1.007) | (2.161) | (1.466) | (0.762) | (0.468) | (0.884) | (0.639) | (0.561) |
| LARGE | -5.639*** | -2.986 | -2.671 | -5.526*** | -4.247*** | -3.813*** | -1.079 | -3.490*** |
| | (1.018) | (2.407) | (1.802) | (1.061) | (0.637) | (1.139) | (0.883) | (0.762) |
| DGP | -1.838** | 4.824*** | -0.386 | 3.543*** | -1.243 | 2.559** | 0.836 | 0.340 |
| | (0.919) | (1.623) | (1.711) | (1.134) | (0.828) | (1.163) | (0.707) | (0.640) |
| FGP | -0.007 | 2.216 | -0.448 | -1.152 | -1.736 | 0.474 | 0.550 | -2.007** |
| | (1.275) | (1.716) | (1.306) | (0.949) | (1.077) | (1.261) | (0.836) | (0.817) |
| Constant | -53.550*** | -9.650** | -20.328*** | -0.632 | -69.290*** | -39.935*** | -14.044*** | 3.554* |
| | (12.328) | (4.889) | (4.045) | (2.673) | (2.005) | (15.156) | (3.063) | (1.875) |

*Notes: Weighted IV regression. This table reports only the results of the main variables of interest. The full set of results can be found in the Table Appendix, Table 11.7 and Table 11.8.*

**Table 6.2: Impact of innovation on employment growth over the business cycle in knowledge-intensive and less knowledge-intensive services, 1998-2010**

| | **Knowledge-intensive services (KIS)** | | | | **Less knowledge-intensive services (LKIS)** | | | |
|---|---|---|---|---|---|---|---|---|
| | **Upturn** | **Boom** | **Downturn** | **Recession** | **Upturn** | **Boom** | **Downturn** | **Recession** |
| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** | **(7)** | **(8)** |
| SGR_NEWPD | 0.956*** | 0.996*** | 0.965*** | 1.001*** | 1.037*** | 0.867*** | 1.104*** | 1.060*** |
| | (0.051) | (0.086) | (0.041) | (0.037) | (0.101) | (0.093) | (0.100) | (0.084) |
| PCONLY | -2.454 | 7.958 | 0.573 | -1.992 | 0.774 | -4.282 | 1.587 | 1.021 |
| | (2.324) | (7.408) | (1.309) | (1.471) | (2.126) | (3.685) | (1.709) | (1.085) |
| ORGA | -1.903 | -4.599** | -1.826** | 2.642*** | -2.283** | 2.555 | -1.358 | -1.353** |
| | (1.320) | (1.975) | (0.916) | (0.824) | (0.956) | (2.132) | (1.487) | (0.557) |
| GDPGR | 3.285*** | -9.420** | -0.334 | 0.902 | 1.297 | -0.518 | -0.668*** | 0.932*** |
| | (1.197) | (3.988) | (0.387) | (0.566) | (2.827) | (2.401) | (0.258) | (0.220) |
| MEDIUM | -6.298*** | 2.204 | -4.333*** | -3.208*** | -3.298*** | -1.650 | -2.784*** | -4.903*** |
| | (1.272) | (3.901) | (1.049) | (0.901) | (1.207) | (1.877) | (0.800) | (0.745) |
| LARGE | -6.778*** | 0.687 | -7.541*** | -2.978* | -2.034 | -5.710** | -4.228*** | -6.929*** |
| | (2.152) | (2.747) | (1.990) | (1.740) | (1.921) | (2.810) | (1.080) | (1.199) |
| DGP | -1.828 | 1.150 | -1.135 | -0.110 | -0.347 | -0.126 | 0.743 | 0.735 |
| | (1.779) | (1.790) | (0.907) | (1.172) | (1.274) | (2.575) | (0.862) | (0.694) |
| FGP | -4.632** | 0.490 | 0.987 | 0.032 | -5.287*** | -3.215 | -0.371 | 0.336 |
| | (2.278) | (2.707) | (1.332) | (1.383) | (1.676) | (3.304) | (1.071) | (1.187) |
| Constant | -53.700*** | 59.986* | -14.326** | 16.192*** | -25.715 | -6.706 | -5.479 | 15.024*** |
| | (16.929) | (32.270) | (5.708) | (3.266) | (34.288) | (20.136) | (4.384) | (1.488) |

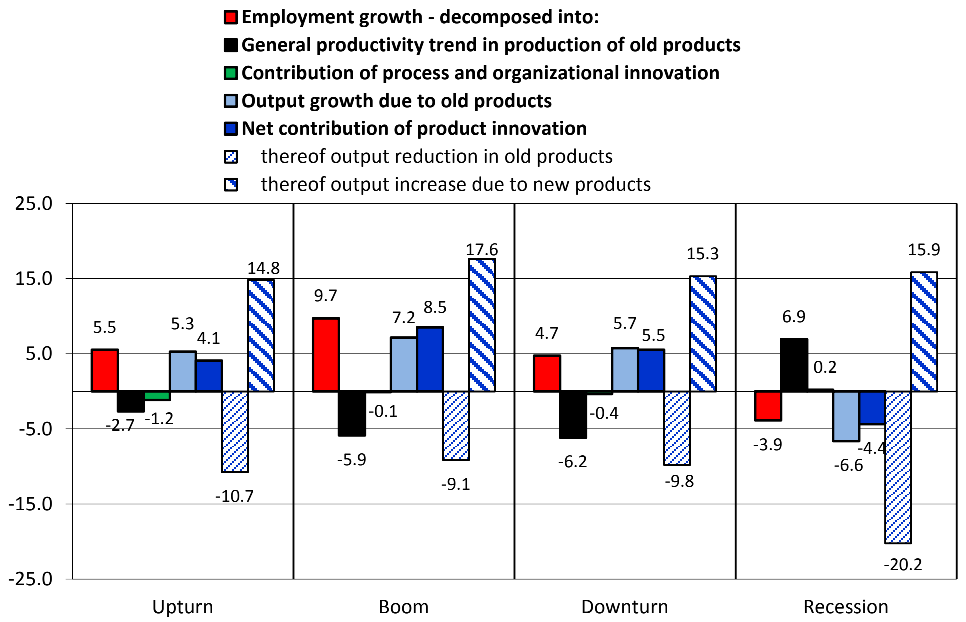
*Notes: Weighted IV regression. This table reports only the results of the main variables of interest. The full set of results can be found in the Table Appendix, Table 11.9 and Table 11.10.*

We find the same result for less-knowledge intensive services. In knowledge-intensive services, organizational innovation also negatively affects employment growth over most stages of the business cycle. Recession periods in knowledge-intensive services are an exception which is probably again a reflection of labour hoarding in the recession period. In high-tech manufacturing, organizational innovation is less employment-destructive. Only in upturns phases, organizational innovation is associated with significant labour saving.

The subsequent four figures illustrate the contribution of innovation to employment growth over the business cycle for each of the four sector groups. Figure 6.7 compares the contribution of three components – new products, old products and the general productivity trend – across sectors.

Outstanding is the pro-cyclical effect of product innovation in high-tech, low-tech and knowledge-intensive services (see dark blue bars). In all three industries, the net effect of product innovation on employment was significantly positive in upturn, boom, and downturn periods, and the effect was particularly high in absolute terms in the boom period. The decomposition further shows that in high-tech manufacturing and knowledge-intensive services product innovation is the main driver for employment growth in boom periods. In upturns and downturns, old products contribute the most to employment growth in these two industries. All in all, but not surprising, product innovation play a more important role for employment growth in both of these industries in all stages of the business cycle (see Figure 6.7).

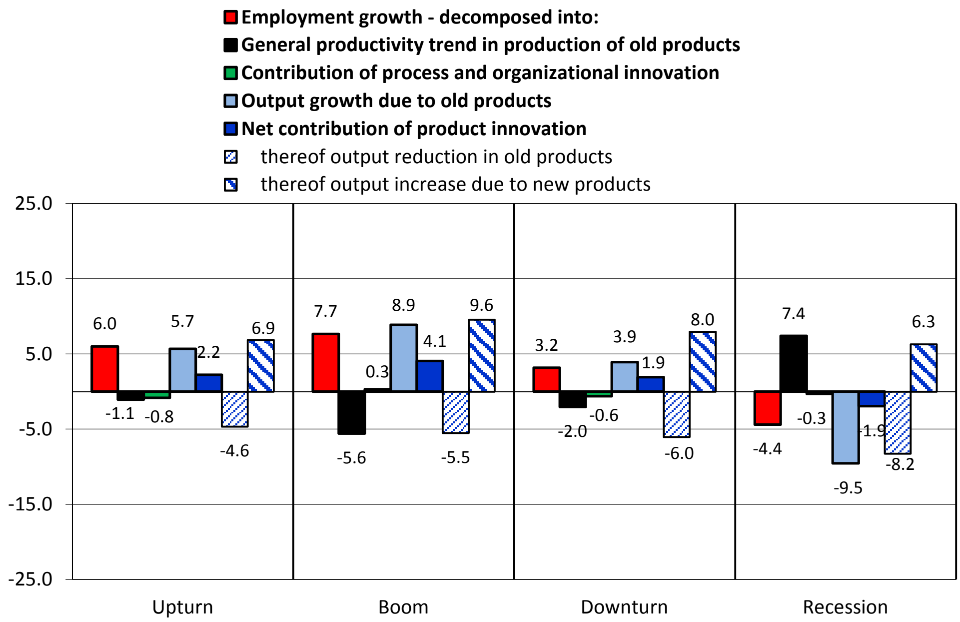
**Figure 6.3: Contribution of innovation to employment growth over the business cycle in high-tech manufacturing, 1998-2010**




*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

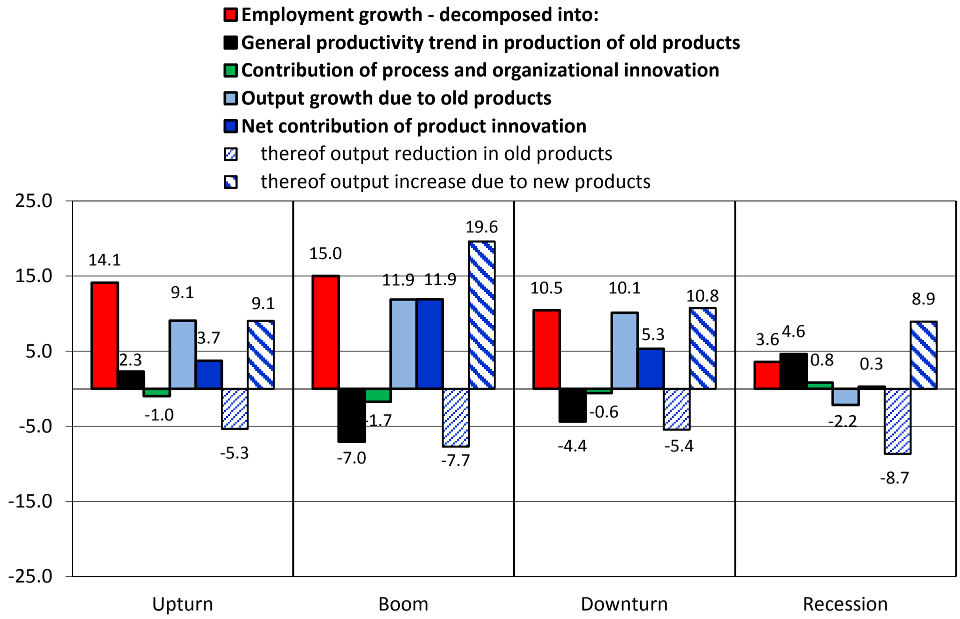
Remarkably is also the very stable demand increase due to new products over different phases of the business cycle in high-tech manufacturing (shaded dark blue bars) and to a lesser extent also in low-tech manufacturing and less knowledge-intensive services while we observe much more fluctuations in this demand component for knowledge-intensive services. Demand increases due to new products are particularly large in boom periods in the latter sector. This in turn stimulates employment growth to large extent.

**Figure 6.4: Contribution of innovation to employment growth over the business cycle in low-tech manufacturing, 1998-2010**



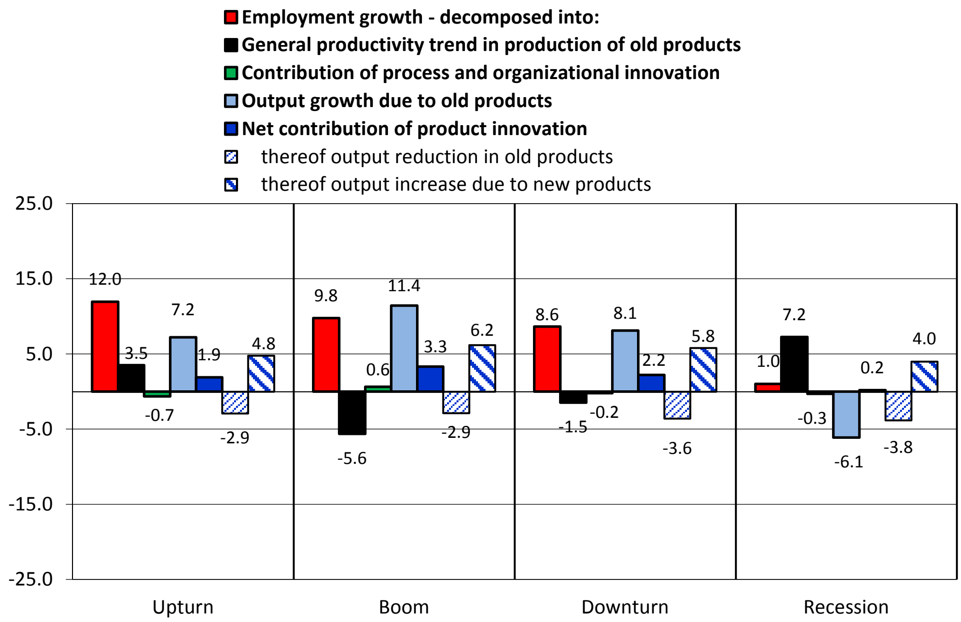

*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

**Figure 6.5: Contribution of innovation to employment growth over the business cycle in knowledge-intensive services, 1998-2010**




*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

**Figure 6.6: Contribution of innovation to employment growth over the business cycle in less knowledge-intensive services, 1998-2010**

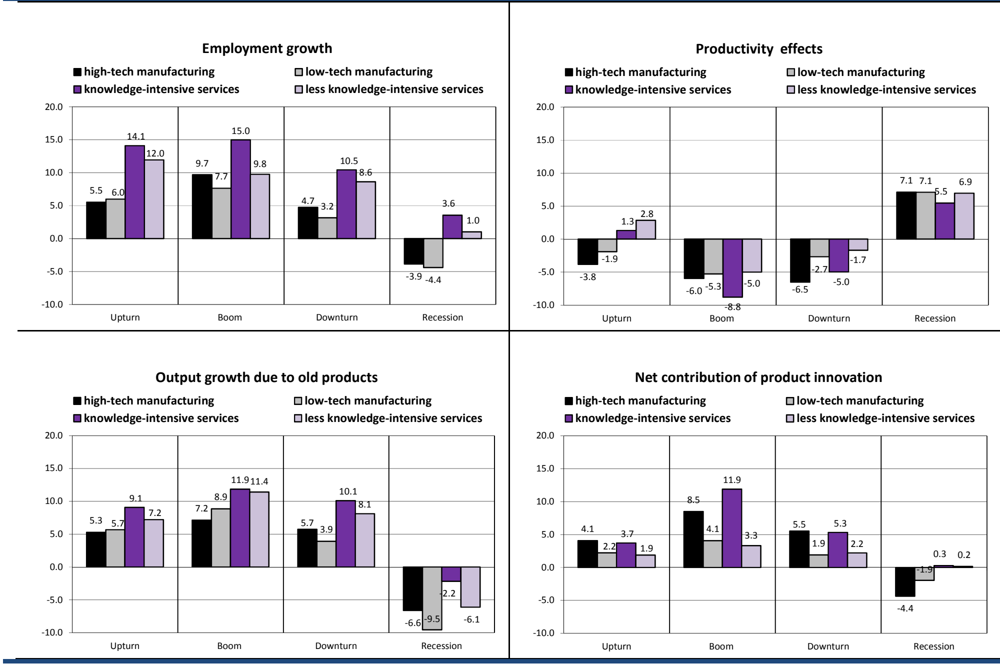



*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

Like in the overall sample, it is the role of product innovation in recession periods that is particularly intriguing. In both service industries product innovators are still able to create new employment, net of all productivity and substitution effects, in the recession period. This effect though is relatively small at about 0.3% in knowledge-intensive services and 0.2% in less knowledge-intensive services. In both manufacturing industries, it turns out that the net effect is negative implying a reduction in labour also for product innovators. However, we again observe the stabilizing effect of product innovation on employment in the recession period when we compare it with the employment destruction due to the demand for old products. Employment destruction due to lower demand for old products is particularly strong for low-tech manufacturing (-9.5%), but also relatively high for high-tech manufacturing (-6.6%) and less knowledge-intensive services (-6.1%). In comparison, knowledge-intensive services experience the lowest demand decrease (-2.2%).

Based on the literature, we have argued in section 2.3.3 that innovation-related employment fluctuations in services are likely to be smoother than in manufacturing. Based on the finding, we find this hypothesis only partly confirmed. Comparing the variance of the net contribution of product innovation over the business cycle, we indeed find the highest variance in high-tech manufacturing. However, innovation-induced employment growth fluctuations are larger in knowledge-intensive services than in low-tech manufacturing.

**Figure 6.7: Comparison of employment effects across sectors, 1998-2010**




*Notes: The productivity effect is the sum of the effects of process innovation, organisational innovation and the general productivity trend. These effects have been displayed separately in previous graphs.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

## 6.2. EMPLOYMENT EFFECTS OF INNOVATION – INDUSTRY-LEVEL RESULTS

This section goes beyond the analysis in section 6.1 by investigating potential heterogeneity in the innovation-employment link across industries using a more disaggregated industry classification. In chapter 2 it was explored that the employment effects of product and process innovation depend on a number of factors such as the demand and demand elasticity, the competitive pressure in an industry, the reaction time of competitors, production technology and type of technological progress. These factors are likely to differ between industries and hence we expect employment effects to differ between them as well. In the following, we focus on 11 manufacturing and 5 service industries.[19] The definition of industries can be found in Table 3.3.

Table 6.3 reports the estimation main results by industries and Table 6.4 disentangles the sources of employment growth for each industry.

[19] We left our consultancies, other business related services and media since they do not belong to the core CIS industries (in all waves) and hence are not provided by all countries.

**Table 6.3: Impact of innovation on employment growth over the business cycle by industry, 1998-2010**

| | | Food | Text | Wood | Chem | Plas | Nonm | Metal | Mach | Elec. | Vehi | Nec | Whole | Trans | Tele | Bank | Tech |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Upturn** | SGR_NEWPD | 1.03*** | 0.97*** | 1.03*** | 1.09*** | 1.10*** | 0.81*** | 1.05*** | 1.02*** | 1.08*** | 0.92*** | 1.00*** | 1.11*** | 1.01*** | 0.91*** | 1.18*** | 0.91*** |
| | PCONLY | -1.03 | 2.61 | -3.09 | -2.27 | 0.31 | -2.06 | 0.65 | -1.88 | 1.05 | 1.36 | 1.37 | 3.85** | -1.95 | -4.83 | 5.68* | -10.80*** |
| | ORGA | -5.64*** | -5.40*** | -5.59*** | -4.22** | -3.83** | -1.907 | -1.99 | -4.15** | -2.89 | -4.74*** | -5.78*** | -6.04*** | 1.43 | 1.27 | -1.39 | -4.37 |
| | β=1 | 0.66 | 0.62 | 0.66 | 0.30 | 0.13 | 0.00*** | 0.45 | 0.71 | 0.14 | 0.18 | 0.98 | 0.28 | 0.92 | 0.15 | 0.23 | 0.22 |
| | J | 0.11 | 0.84 | 0.25 | 0.77 | 0.31 | 0.95 | 0.47 | 0.80 | 0.45 | 0.14 | 0.46 | 0.26 | 0.94 | 0.56 | 0.52 | 0.86 |
| | KP Wald F | 144.1 | 115.2 | 155.1 | 148.0 | 91.9 | 56.4 | 96.3 | 118.6 | 152.1 | 85.3 | 95.8 | 89.4 | 47.9 | 101.8 | 10.9 | 183.0 |
| | Obs | 9,125 | 11,706 | 7,591 | 3,574 | 3,347 | 3,908 | 8,501 | 5,833 | 5,604 | 3,635 | 4,690 | 15,257 | 10,632 | 4,452 | 4,085 | 4,952 |
| **Boom** | SGR_NEWPD | 0.90*** | 1.16*** | 0.94*** | 0.94*** | 1.06*** | 1.00*** | 0.98*** | 0.96*** | 0.93*** | 1.07*** | 0.89*** | 0.49** | 1.23*** | 0.96*** | 0.68* | 1.05*** |
| | PCONLY | 1.48 | 0.25 | -3.85 | -1.08 | 5.39* | -0.15 | 0.33 | 5.22 | -2.96 | 4.13 | -1.93 | -11.66** | 2.79 | 1.95 | -10.23 | 20.17** |
| | ORGA | 0.65 | 3.06 | 1.10 | -2.75 | -2.47 | 4.59 | 1.49 | -1.05 | 2.71 | -0.36 | -2.75 | 4.10 | 2.09 | -2.38 | 0.18 | -4.93 |
| | β=1 | 0.30 | 0.15 | 0.62 | 0.61 | 0.53 | 0.98 | 0.73 | 0.62 | 0.48 | 0.39 | 0.14 | 0.02** | 0.43 | 0.83 | 0.35 | 0.80 |
| | J | 0.61 | 0.47 | 0.28 | 0.38 | 0.29 | 0.99 | 0.75 | 0.39 | 0.31 | 0.64 | 0.57 | 0.26 | 0.51 | 0.38 | 0.20 | 0.25 |
| | KP Wald F | 51.1 | 57.0 | 33.33 | 66.2 | 44.64 | 18.1 | 50.4 | 57.0 | 97.7 | 94.0 | 43.5 | 23.6 | 8.12 | 10.4 | 2.5 | 16.3 |
| | Obs | 1,988 | 1,940 | 1,761 | 1,045 | 915 | 892 | 2,180 | 1,434 | 1,645 | 942 | 1,119 | 2,404 | 1,630 | 906 | 1,023 | 1,387 |
| **Down turn** | SGR_NEWPD | 0.91*** | 1.12*** | 1.05*** | 1.12*** | 0.88*** | 1.11*** | 1.01*** | 1.07*** | 0.86*** | 1.00*** | 1.02*** | 0.97*** | 1.22*** | 0.96*** | 1.06*** | 1.02*** |
| | PCONLY | -3.49* | 0.09 | -0.76 | -0.87 | -3.83 | 3.45 | -2.16 | 2.50 | -6.44* | -4.81 | -5.22** | 0.04 | 2.90 | -2.78 | 3.72 | 0.99 |
| | ORGA | -1.23 | -0.93 | -4.38*** | -2.41 | -2.92 | -3.90 | -0.90 | -0.70 | 0.65 | 1.26 | -2.48 | 0.38 | -2.99 | 3.14 | -6.33** | -3.07 |
| | β=1 | 0.08* | 0.09* | 0.42 | 0.31 | 0.10* | 0.32 | 0.84 | 0.18 | 0.08* | 0.99 | 0.74 | 0.44 | 0.33 | 0.48 | 0.68 | 0.77 |
| | J | 0.92 | 0.69 | 0.61 | 0.57 | 0.28 | 0.10 | 0.30 | 0.10 | 0.92 | 0.33 | 0.78 | 0.59 | 0.15 | 0.79 | 0.16 | 0.20 |
| | KP Wald F | 194.3 | 177.2 | 184.9 | 73.4 | 59.6 | 86.5 | 211.3 | 147.4 | 83.1 | 57.1 | 116.1 | 345.8 | 14.0 | 291.5 | 39.5 | 172.4 |
| | Obs | 10,094 | 9,946 | 7,690 | 3,346 | 3,743 | 3,877 | 9,358 | 7,094 | 4,221 | 2,751 | 5,080 | 20,200 | 11,188 | 5,000 | 4,022 | 4,639 |
| **Reces sion** | SGR_NEWPD | 0.95*** | 0.88*** | 1.04*** | 0.82*** | 0.87*** | 1.13*** | 0.89*** | 1.03*** | 1.08*** | 1.06*** | 0.95*** | 1.07*** | 0.98*** | 1.05*** | 1.13*** | 1.03*** |
| | PCONLY | -1.91 | -0.78 | 0.06 | -4.35* | -7.03** | -0.21 | 1.20 | 2.57 | -0.20 | 4.78 | -2.77 | 0.68 | -0.07 | 0.36 | 3.95 | -3.22 |
| | ORGA | -1.52 | -0.63 | 0.37 | -0.14 | 1.80 | -1.95 | -1.47 | 1.55 | -0.51 | -5.06 | 0.51 | -0.65 | -1.97 | 3.05 | -0.07 | 2.08 |
| | β=1 | 0.40 | 0.09* | 0.45 | 0.06* | 0.12 | 0.26 | 0.11 | 0.63 | 0.36 | 0.78 | 0.37 | 0.57 | 0.86 | 0.46 | 0.58 | 0.75 |
| | J | 0.53 | 0.72 | 0.20 | 0.77 | 0.15 | 0.61 | 0.93 | 0.27 | 0.76 | 0.62 | 0.62 | 0.16 | 0.59 | 0.25 | 0.49 | 0.68 |
| | KP Wald F | 92.5 | 102.4 | 147.3 | 17.7 | 32.0 | 31.9 | 74.8 | 43.9 | 62.5 | 26.2 | 134.1 | 41.1 | 13.1 | 60.3 | 43.4 | 69.9 |
| | Obs | 7,667 | 5,344 | 5,783 | 2,740 | 3,021 | 2,817 | 7,966 | 6,181 | 3,503 | 2,224 | 3,947 | 15,482 | 9,260 | 5,170 | 3,285 | 4,789 |

*Notes: Additional regressors (not reported): dummies for size, foreign ownership, country, time. See also notes of Table 11.2.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

**Table 6.4: Decomposition of employment growth over the business cycle by industry, 1998-2010**

| | | Food | Text | Wood | Chem | Pla | Nonm | Metal | Mach | Elec. | Vehi | Nec | Whole | Trans | Tele | Bank | Tech |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Upturn** | Employment growth | **7.2** | **3.8** | 5.9 | 5.7 | 6.7 | 6.2 | **7.1** | 5.3 | 5.8 | **4.7** | 6.3 | **11.4** | 12.8 | 13.4 | 13.3 | **16.0** |
| | General productivity trend | **0.6** | **1.1** | -0.9 | -0.6 | **-6.4** | -3.2 | -1.2 | -2.7 | **-4.2** | -2.3 | -2.0 | 3.4 | 4.0 | 1.4 | **-5.5** | **7.1** |
| | Gross effect of process innovations | -0.1 | **0.2** | **-0.5** | -0.2 | 0.0 | **-0.3** | 0.1 | -0.2 | 0.1 | 0.1 | **0.2** | 0.5 | -0.2 | -0.3 | **0.7** | **-1.1** |
| | Gross effect of organizational innovation | -1.7 | -1.2 | -1.6 | **-1.8** | -1.5 | **-0.6** | **-0.7** | -1.7 | -1.2 | **-1.9** | **-1.8** | **-2.1** | 0.4 | **0.6** | -0.7 | -2.0 |
| | Output growth of old products for non-pd | 6.3 | **2.6** | 6.5 | **3.3** | **8.4** | **8.2** | 6.3 | 5.7 | 5.3 | 5.5 | 5.7 | 7.2 | 7.1 | **4.9** | **12.1** | 8.8 |
| | Net contribution of product innovations | **2.2** | **1.1** | 2.3 | 5.1 | **6.2** | **2.2** | 2.6 | 4.1 | **5.8** | 3.3 | 4.2 | 2.4 | **1.5** | **6.8** | **6.8** | 3.1 |
| | Thereof output reduction in old products | -3.2 | -4.8 | -4.6 | -7.8 | -5.7 | -4.3 | -4.7 | -10.3 | -13.0 | -8.9 | -6.3 | -3.1 | -2.5 | -14.6 | -2.9 | -6.4 |
| | Thereof output increase in new products | 5.3 | 6.0 | 7.0 | 12.8 | 11.8 | 6.5 | 7.3 | 14.4 | 18.7 | 12.2 | 10.5 | 5.5 | 3.9 | 21.4 | 9.7 | 9.6 |
| **Boom** | Employment growth | 7.3 | **4.8** | 6.3 | 8.6 | 8.3 | **5.7** | **10.0** | 9.8 | 9.4 | **12.4** | 9.5 | 9.8 | 11.1 | **25.2** | **8.2** | 11.5 |
| | General productivity trend | **-1.4** | -5.0 | -5.8 | **-1.6** | -8.6 | **-9.6** | -6.6 | -6.2 | -6.3 | **-8.9** | -5.6 | **-0.9** | **-11.2** | -5.7 | -5.0 | -7.4 |
| | Gross effect of process innovations | 0.2 | 0.0 | **-0.7** | -0.1 | **0.5** | 0.0 | 0.0 | **0.4** | **-0.2** | **0.4** | -0.2 | **-1.0** | 0.3 | 0.1 | **-1.0** | **2.0** |
| | Gross effect of organizational innovation | 0.3 | 0.9 | 0.4 | **-1.4** | -1.2 | **1.7** | 0.7 | -0.6 | **1.3** | -0.2 | **-1.0** | **1.7** | 0.9 | -1.4 | 0.1 | **-2.8** |
| | Output growth of old products for non-pd | **4.9** | 5.2 | 9.2 | **5.1** | 9.8 | 10.7 | **11.8** | 7.1 | 6.7 | **12.6** | 9.8 | 8.7 | **16.4** | 10.6 | **7.8** | 10.3 |
| | Net contribution of product innovations | 3.5 | 3.7 | **3.2** | 6.6 | 7.7 | **2.9** | 4.1 | **9.1** | 7.9 | **8.4** | 6.4 | **1.3** | 4.8 | **21.5** | 6.3 | 9.5 |
| | Thereof output reduction in old products | -4.3 | -5.5 | -4.8 | -5.9 | -7.3 | -7.4 | -4.5 | -9.5 | -10.6 | -7.1 | -9.1 | -2.5 | -3.4 | -11.6 | -5.0 | -9.2 |
| | Thereof output increase in new products | 7.8 | 9.2 | 8.0 | 12.5 | 15.0 | 10.3 | 8.5 | 18.6 | 18.5 | 15.5 | 15.5 | 3.8 | 8.2 | 33.1 | 11.3 | 18.7 |
| **Down** | Employment growth | 4.1 | **1.2** | **1.9** | 4.0 | 4.8 | **1.9** | 4.3 | **5.3** | 4.2 | **6.0** | 2.9 | 9.0 | **7.7** | **14.7** | 13.6 | 10.6 |
| **turn** | General productivity trend | -0.9 | **-0.3** | -3.5 | -1.4 | -1.5 | **1.0** | -3.9 | **-7.2** | -5.5 | **-8.2** | -2.4 | **0.6** | -4.1 | **-10.2** | 0.5 | -5.3 |
| | Gross effect of process innovations | -0.4 | 0.0 | -0.1 | -0.1 | -0.4 | **0.5** | -0.3 | **0.2** | **-0.5** | **-0.5** | **-0.5** | 0.0 | 0.3 | **-0.2** | **0.4** | 0.1 |
| | Gross effect of organizational innovation | -0.3 | -0.2 | **-1.1** | **-1.1** | -1.0 | -1.0 | -0.3 | -0.2 | **0.2** | **0.5** | -0.7 | 0.1 | -0.8 | **1.4** | **-2.7** | -1.1 |
| | Output growth of old products for non-pd | 3.9 | **0.7** | 4.6 | 2.4 | 4.6 | **-0.7** | 6.4 | **7.2** | 5.7 | **8.4** | 3.8 | **6.8** | 9.4 | **14.1** | 8.5 | 11.3 |
| | Net contribution of product innovations | **1.8** | **1.0** | 2.1 | **4.2** | 3.0 | 2.1 | 2.3 | 5.3 | 4.2 | **5.7** | 2.7 | **1.5** | 2.7 | **9.6** | 6.9 | 5.7 |
| | Thereof output reduction in old products | -5.0 | -6.3 | -4.8 | -13.4 | -8.8 | -7.2 | -5.4 | -7.3 | -10.6 | -7.5 | -9.0 | -4.1 | -3.2 | -9.1 | -2.8 | -7.5 |
| | Thereof output increase in new products | 6.9 | 7.2 | 6.9 | 17.6 | 11.8 | 9.3 | 7.7 | 12.5 | 14.8 | 13.2 | 11.7 | 5.7 | 6.0 | 18.7 | 9.7 | 13.2 |
| **Reces** | Employment growth | **0.0** | -5.4 | -5.2 | **-0.4** | -3.7 | **-7.9** | -6.5 | -3.6 | -4.4 | **-7.2** | -4.7 | **0.1** | 1.7 | **7.1** | 3.4 | 3.4 |
| **sion** | General productivity trend | 4.8 | **4.0** | 5.0 | 4.2 | 5.5 | **11.7** | **11.7** | 9.4 | **3.0** | 7.9 | 7.1 | **8.6** | 6.2 | **3.6** | 7.4 | 6.9 |
| | Gross effect of process innovations | -0.2 | -0.1 | 0.0 | **-0.4** | **-0.9** | 0.0 | **0.2** | **0.2** | 0.0 | **0.5** | -0.2 | 0.1 | 0.0 | 0.0 | **0.5** | **-0.3** |
| | Gross effect of organizational innovation | -0.4 | -0.1 | 0.1 | -0.1 | **0.6** | **-0.5** | **-0.5** | **0.6** | -0.2 | **-1.8** | 0.1 | -0.2 | **-0.5** | **1.5** | 0.0 | 0.9 |
| | Output growth of old products for non-pd | **-3.5** | -7.6 | -9.7 | **-2.5** | -5.9 | **-16.4** | **-14.4** | -8.8 | -5.3 | -9.9 | -9.3 | **-8.2** | -4.4 | **-0.5** | -3.5 | -4.1 |
| | Net contribution of product innovations | **-0.7** | -1.6 | **-0.6** | -1.6 | -3.0 | -2.7 | -3.5 | **-4.9** | -1.9 | **-3.8** | -2.4 | -0.1 | 0.4 | **2.5** | **-0.9** | 0.2 |
| | Thereof output reduction in old products | -5.5 | -7.3 | -7.2 | -15.2 | -11.0 | -9.2 | -9.3 | -19.2 | -18.7 | -17.8 | -11.3 | -5.0 | -2.8 | -17.8 | -6.6 | -9.3 |
| | Thereof output increase in new products | 4.8 | 5.6 | 6.6 | 13.6 | 7.9 | 6.4 | 5.8 | 14.3 | 16.8 | 13.9 | 8.9 | 4.9 | 3.2 | 20.4 | 5.7 | 9.4 |

*Notes: Black and blue cells indicate the highest and lowest values separately for manufacturing and services, respectively.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

Table 6.3 reports the estimation main results by industries. Most strikingly, we also find a significantly positive impact of product innovation on employment growth in all 16 industries. Compared to the results in section 6.1, however, we detect stronger heterogeneity in the size of the effect among industries. In 11 out of 60 cases, i.e. in nearly 20% of the time, the coefficient of product innovation is now significantly smaller than 1 indicating that an increase in the sales growth due to new product innovation by one percent leads to an increase in gross employment but by less than one percent.[20] Most of these 11 cases are in downturn and recession periods and in low-tech manufacturing, e.g. in food, plastics, metal and textile. However, with electrical engineering (downturns) and chemicals (recession) also two high-tech manufacturing industries show additional productivity effects of product innovation and thus disproportionate employment gains.

In contrast, results illustrate that in 5 out of 60 cases (i.e. in 10% of the cases), product innovations are associated with a coefficient of larger than 1 implying that an increase in the sales growth due to new product innovation by one percent leads to an increase in gross employment by more than one percent. This disproportionate increase is mainly observed in upturn and boom periods in manufacturing industries. Despite this larger heterogeneity, results indicate that in the majority of industries and business cycle periods the gross employment effect of an increase in the sales growth due to new products is one percent.

Results for process innovation remain weak at the industry level and they largely confirm findings from section 6.1 with three exceptions. First, while we found a significantly negative impact of process innovation in high-tech manufacturing in upturn phases in general, we cannot establish this relationship at the industry level for any industry. The smaller sample size might explain this finding. Second, process innovation was responsible for a significant job loss in electrical engineering in downturn periods and in the chemical and plastic industry during the recent recession period. Both results have not been detected at the more aggregated level. Third, at the industry level process innovation turns out to play a more important role than what we have seen in section 6.1. In particular, in upturn and boom periods process innovation matter for wholesale, banks and technical services, however with mixed signs.

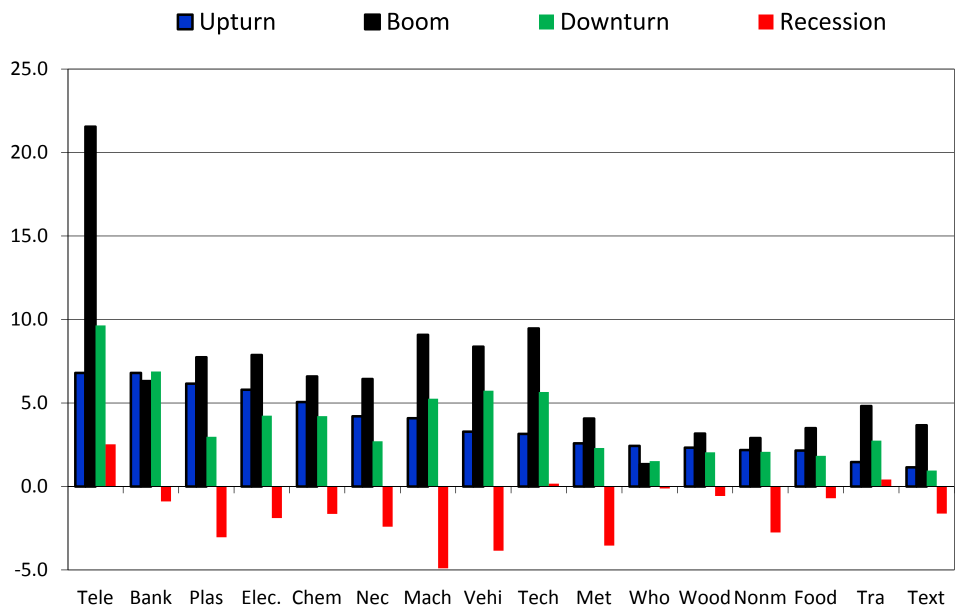
Table 6.4 reports the decomposition of average employment growth in European firms by industry and business cycle. Additionally, Figure 6.8 compares the net contribution of product innovation to employment growth over the business cycle by industry. In a nutshell, we can conclude the following: Employment growth fluctuations are larger in high-tech manufacturing industries, in particular in machinery and vehicles. Both industries experience a strong employment growth during boom and downturn periods but also a strong decline during the recession. This is to a large degree driven by the contribution of product innovation. The net contribution of product innovation fluctuates much more over the business cycle in machinery and vehicles and in high-tech manufacturing in general than in low-tech manufacturing industries (see Figure 6.8). Process innovations reinforce this effect in boom and downturn periods in both industries while they attenuate the decline in employment in the recession.

Among services, telecommunication firms show the fastest employment growth in nearly all business cycle phases. Like in manufacturing this is mainly driven by product innovation. That is, within telecommunication firms product innovation matters most for employment growth except for the downturn period where old products are most important. Compared across service industries, we furthermore find the employment contribution of product innovation to be highest in telecommunication, even higher than in all high-tech manufacturing industries. Interestingly the results also point towards a large absolute contribu-

[20] Statement is based on one-sided t-tests.

tion of product innovation in the banking and insurance industry which seems to be also larger than the product innovation induced employment effect in high-tech manufacturing.

**Figure 6.8: Net contribution of product innovation to employment growth over the business cycle by sector, 1998-2010**




*Notes: Based on Table 6.4.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

## 6.3. EMPLOYMENT EFFECTS OF INNOVATION BASED ON BUSINESS CYCLE SENSITIVITY OF SECTORS

One of the main argument why innovation induced employment reactions differ over the business cycle relates to differences in (expected) demand. Changes in industry-level demand over the business cycle, however, are not uniform across industries. Economic sectors vary considerably in terms of their reaction to general business fluctuations measured by changes in output (Zislin and Barret 2009, p 254f). Particular sectors may be more volatile than the economy overall, and expand and contract less than the whole economy in a boom or recession. We refer to this observation as the cyclical sensitivity of sectors. Cyclical sensitivity is related to the price and income elasticities of the main products of a sector, but also to characteristics of production such as the time it needs to react to perceived changes in demand, the position in the value chain, or industrial organisation of the sector. Cyclical and non-cyclical sectors are not necessarily sectors with high or low growth rates; is it rather the degree of persistence of growth rates over the business cycle which characterizes cyclical sensitivity.

In the context of innovation and employment growth, cyclical sensitivity means that the demand effect and the price effect in this particular sector may be stronger than in other parts of the economy. Moreover, firms in non-cyclical sectors which face a more stable demand may be more confident about future demand growth in an upswing, and reveal less labour hoarding. Therefore, we assume that firms in cyclical sectors experience larger employment growth in upswings, but also larger losses in downswings compared to firms in non-cyclical sectors.

Some sectors may be more volatile than the economy overall or, on the contrary, expand and contract less than the whole economy in a boom or recession. We refer to this observation as the cyclical sensitivity of sectors. Information on the cyclical sensitivity of sectors is taken from the Competitiveness Report 2008 which investigated drivers of growth and competitiveness at the sectoral level (Peneder 2009). As a part of this project, Zislin and Barret (2009) estimated elasticities of value added per capita with respect to GDP per capita for each sector from the 1970s up until 2007. The elasticities reported by Zislin and Barret (2009, p. 239 and 255) were used to distinguish between sectors of

- low business cycle sensitivity (elasticity smaller than 1),
- medium business cycle sensitivity (elasticity between 1 and 1.25) and
- high business cycle sensitivity (elasticity larger than 1.25).

Table 6.5 gives for each sector the elasticity of sectoral value added per capita on GDP per capita and the classification of cyclical sensitivity. Comparing the sensitivity-based and technology-based classifications, we observe a partial but not complete overlap. For instance, machinery and motor vehicles are characterized by both high technology-intensity and business cycle sensitivity whereas high-tech industries such as chemicals and electrical machinery are found to be of medium and low sensitivity to the business cycle. In contrast, low-technology industries such as rubber and plastics or non-metal mineral products are sectors that show disproportionately high fluctuations over the business cycle.

Figure 6.9 illustrates the innovation behaviour of firms in industries that differ in their business cycle sensitivity. Interestingly, European manufacturing firms in industries that exhibit a low or medium sensitivity with respect to the aggregate business cycle focus their innovation activities more strongly on process innovation. In contrast, in highly sensitive industries product innovations are more frequent than process innovations. This finding is driven by the high-tech industries. Note, however, that this is a purely descriptive observation and does not allow us to draw any causality conclusion.

The illustration of employment growth and productivity growth related to the sensitivity of sectors (see Figure 6.10) shows that in manufacturing in all sensitivity classes the productivity growth exceeds the employment growth. However, in both cases, sectors with low business cycle sensitivity exhibit the highest growth, followed by sectors with high business cycle sensitivity. While, in services productivity growth is clearly higher for sectors with low business cycle sensitivity, employment growth is the highest for sectors with high sensitivity. For both, employment and productivity growth, sectors with medium business cycle sensitivity have the lowest growth. In comparison to the manufacturing sectors, in services, the employment growth by far exceeds the productivity growth.

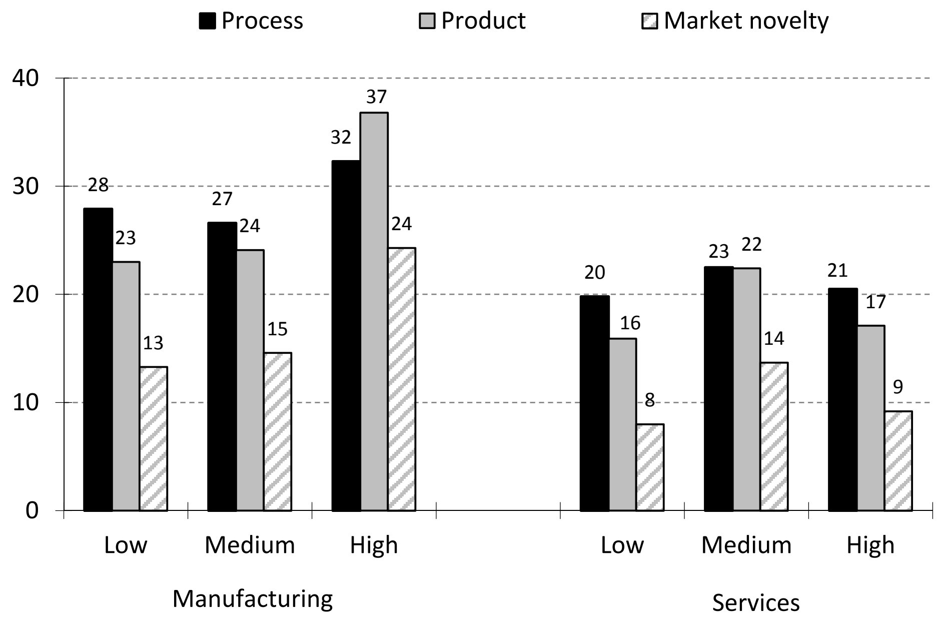
Figure 6.11 displays the sales growth according to the classes of business cycle sensitivity. In manufacturing, sales growth due to new products increases with rising business cycle sensitivity while sales growth due to old products decreases and even turns negative with increasing sensitivity. Nevertheless, the net sales growth of existing and new products is positive for all sensitivity classes. In services, sales growth due to existing as well as due to new products is positive in all sensitivity classes. Whereas, in sectors with medium business cycle sensitivity, sales growth due to new products is the highest, sales growth due to existing products is the lowest. Furthermore, in sectors with low and high sensitivity, sales growth due to existing products is higher than growth due to new products. A comparison of manufacturing and services indicates that sales growth in manufacturing sectors actually depends on the business cycle sensitivity, while such distinct differences are not observable in the services sectors.

**Table 6.5 Cyclical sensitivity at the sectoral level, EU15**

| NACE | Description | Elasticity | Sensitivity |
|---|---|---|---|
| 15-16 | Manufacturing: food, beverages, tobacco | 0.28 | Low |
| 65 | Financial intermediation | 0.44 | Low |
| 64 | Post and telecommunications | 0.54 | Low |
| 40-41 | Electricity, gas, water supply | 0.56 | Low |
| 23 | Manufacturing: coke, refined petrol. | 0.63 | Low |
| 55 | Hotels and restaurants | 0.63 | Low |
| 45 | Construction | 0.66 | Low |
| 21 | Manufacturing: pulp, paper | 0.69 | Low |
| 63 | Supporting and auxiliary transport activities | 0.75 | Low |
| 31 | Manufacturing: electric machinery | 0.77 | Low |
| 60 | Land transport | 0.79 | Low |
| 20 | Manufacturing: wood | 0.85 | Low |
| 28 | Manufacturing: fabricated metal products | 0.88 | Low |
| 52 | Retail trade | 0.89 | Low |
| 50 | Sale, maintenance, repair of motor vehicles | 0.92 | Low |
| 73 | Research and development | 0.99 | Low |
| | | | |
| 66 | Insurance and pension funds | 1.03 | Medium |
| 70 | Real Estate | 1.03 | Medium |
| 18 | Manufacturing: clothing | 1.05 | Medium |
| 22 | Publishing, printing, reproduction | 1.07 | Medium |
| 36-37 | Manufacturing: furniture, recycling | 1.08 | Medium |
| 51 | Wholesale trade | 1.09 | Medium |
| 24 | Manufacturing: chemicals | 1.18 | Medium |
| 27 | Manufacturing: basic metals | 1.19 | Medium |
| 72 | Computer and related activities | 1.19 | Medium |
| 17 | Manufacturing: textiles | 1.25 | Medium |
| 19 | Manufacturing: leather | 1.25 | Medium |
| 35 | Manufacturing: Other transport equipment | 1.29 | Medium |
| | | | |
| 71 | Renting of machinery and equipment | 1.31 | High |
| 74 | Other business activities | 1.31 | High |
| 33 | Manufacturing: medical instruments, watches, clocks | 1.33 | High |
| 25 | Manufacturing: rubber, plastics | 1.39 | High |
| 29 | Manufacturing: machinery and equipment | 1.43 | High |
| 34 | Manufacturing: motor vehicles, trailers | 1.48 | High |
| 62 | Air transport | 1.52 | High |
| 32 | Manufacturing: radio & tv | 1.55 | High |
| 61 | Water transport | 1.56 | High |
| 26 | Manufacturing: other non-metallic mineral products | 1.73 | High |
| 30 | Manufacturing: office, machinery, computers | 2.24 | High |
| 26 | Auxiliary financial intermediation activities | 1.73 | High |

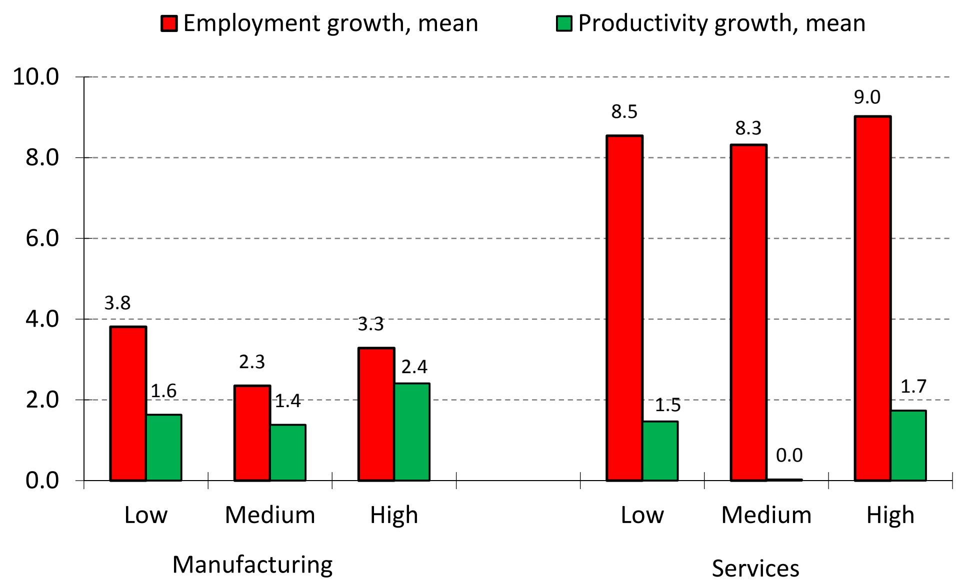
*Notes: Elasticity refers to the elasticity of sectoral value added per capita on GDP per capita. Classification is based on NACE Rev. 1.1. For CIS2008 and CIS2010 a concordance between NACE 1 and NACE 2 has been used. A few sectors like hotels and restaurants, construction and real estate have been excluded since they are not covered by the CIS, see also Table 3.3. Auxiliary financial intermediation activities (67) have been included in financial intermediation (65).*
*Source: Zislin and Barret (2009, p. 255)*

**Figure 6.9: Innovator shares in industries of high, medium and low business cycle sensitivity, 1998-2010**



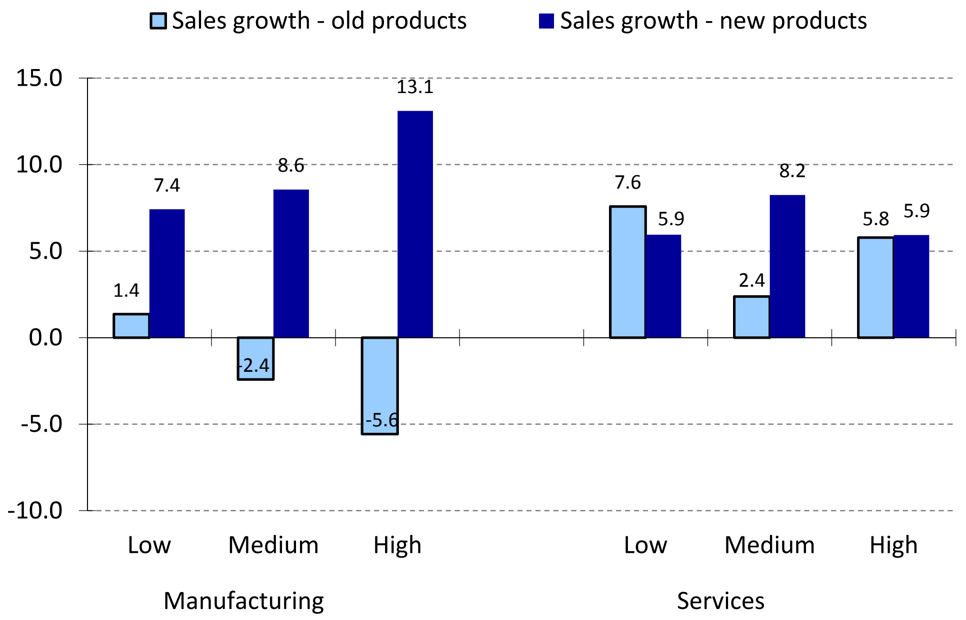

*Notes: Weighted figures.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

**Figure 6.10: Employment and productivity growth in industries of high, medium and low business cycle sensitivity, 1998-2010**




*Notes: Weighted figures. Depicted are average two-year employment and real productivity growth rates, respectively.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

**Figure 6.11: Sales growth due to new and old products in industries of high, medium and low business cycle sensitivity, 1998-2010**




*Notes: Weighted figures. Depicted are two-year nominal sales growth rates due to new and old products, respectively.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

Regarding the econometric estimations of the impact of innovation variables on employment growth in industries of high, medium, and low business cycle sensitivity in Table 6.6, a positive relationship between sales growth due to new products (SGR_NEWPD) is confirmed. Whereas for manufacturing industries with low and medium business cycle sensitivity the coefficients are slightly smaller than one, respective coefficients in the services sector are slightly larger than one. In contrast, coefficients larger than one are provided for the case of industries with high business cycle sensitivity for the case of manufacturing, while coefficients smaller than one are provided for services. Following the same rationale like in section 5.5, employment grows not as fast as sales from new products in manufacturing industries with low and mediums business cycle sensitivity, while for the case of highly sensitive industries, for the production of new products more labour input is need than for old products.

In the services sector, however, new products are produced with a higher productivity and less labour output is needed in industries which have high business cycle sensitivity, whereas, the opposite holds true for the industries with low and medium sensitivity. The variable of process innovation (PC) is correlates negatively with employment growth; however, the coefficients are not significant for any of the specifications. The coefficient of organizational innovation (ORGA) is negative and significant in manufacturing – for all three classes of business sensitivity. This suggests that firms with organisational innovations exhibit smaller employment growth rates than firms with no organizational innovation. However, this effect is stronger for firms in industries with low and medium business sensitivity. The estimation for the impact of the real GDP growth rate (GDPGR) on employment growth yields significant and negative coefficients only for services industries with low as well as high business cycle sensitivity. Negative and highly significant are the coefficients for the firm size dummies (MEDIUM and LARGE). That is, small firms contribute, ceteris paribus, more to the overall employment growth than medium and large firms do, regardless of the business sensitivity of the industry. These findings are in line with findings in previous sections relating to different phases in the business cycle.

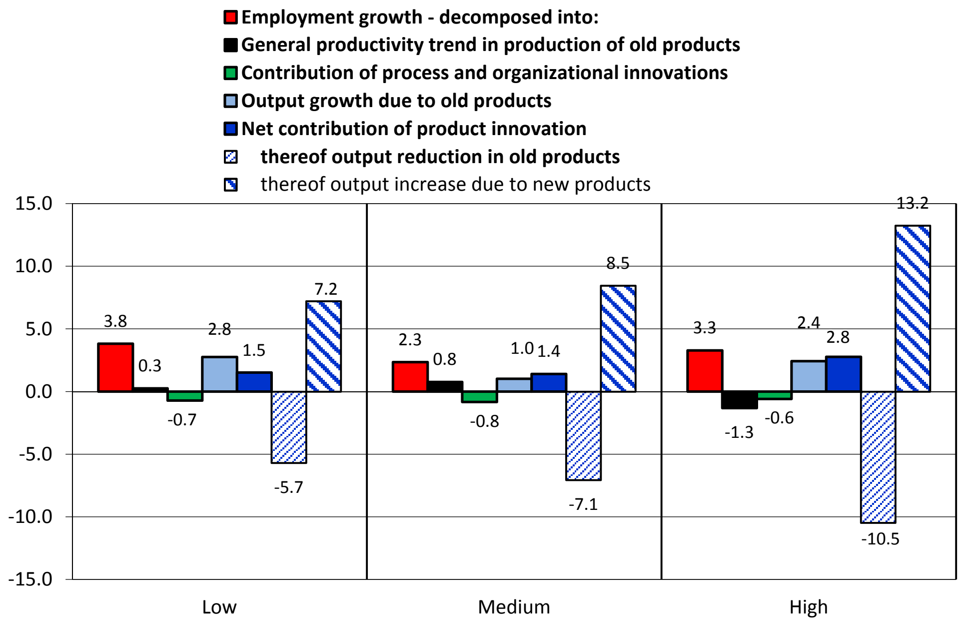
**Table 6.6: Impact of innovation on employment growth in industries of high, medium and low business cycle sensitivity, 1998-2010**

| | Manufacturing | | | Services | | |
|---|---|---|---|---|---|---|
| | Low | Medium | High | Low | Medium | High |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| SGR_NEWPD | 0.995*** | 0.998*** | 1.028*** | 1.037*** | 1.027*** | 0.902*** |
| | (0.033) | (0.029) | (0.043) | (0.083) | (0.035) | (0.042) |
| PCONLY | -0.567 | -0.458 | -0.259 | -0.346 | -0.106 | -0.843 |
| | (1.065) | (0.618) | (1.319) | (1.623) | (0.699) | (1.639) |
| ORGA | -3.087*** | -3.221*** | -2.022*** | 0.782 | -1.765 | -0.697 |
| | (0.782) | (1.132) | (0.725) | (1.686) | (1.120) | (1.085) |
| GDPGR | 0.192 | 0.730 | -0.206 | -0.978*** | 0.110 | -0.906*** |
| | (0.405) | (0.532) | (0.327) | (0.324) | (0.459) | (0.351) |
| SGR_NEWPD x GDPGR2 | -0.007** | -0.003 | -0.005 | -0.010 | -0.011* | 0.012** |
| | (0.003) | (0.004) | (0.005) | (0.010) | (0.006) | (0.006) |
| PCONLY x GDPGR2 | -0.288* | -0.339*** | -0.046 | -0.025 | -0.255* | 0.114 |
| | (0.150) | (0.129) | (0.209) | (0.209) | (0.148) | (0.344) |
| ORGA X GDPGR2 | 0.389*** | 0.229 | 0.169 | 0.106 | 0.204* | -0.376** |
| | (0.099) | (0.142) | (0.107) | (0.237) | (0.122) | (0.160) |
| MEDIUM | -1.571*** | -2.036*** | -1.532** | -4.025*** | -3.092*** | -4.254*** |
| | (0.543) | (0.491) | (0.667) | (0.623) | (0.630) | (1.227) |
| LARGE | -3.037*** | -4.290*** | -3.501*** | -5.527*** | -4.243*** | -5.666*** |
| | (0.767) | (0.532) | (0.942) | (1.171) | (0.927) | (1.167) |
| DGP | 1.291 | 1.078 | 1.073* | 0.511 | 0.543 | -0.244 |
| | (0.986) | (0.741) | (0.610) | (0.880) | (0.813) | (1.091) |
| FGP | 0.561 | -1.215 | -0.068 | 0.002 | -2.348** | -0.438 |
| | (0.788) | (0.826) | (0.656) | (1.303) | (0.917) | (1.416) |
| Constant | -20.665*** | -31.949*** | -17.336*** | 0.815 | -10.345 | -14.354** |
| | (5.554) | (7.330) | (4.710) | (6.113) | (6.842) | (6.299) |

*Notes: Weighted IV regression. This table reports only the results of the main variables of interest. The full set of results can be found in the Table appendix, Table 11.6*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation*

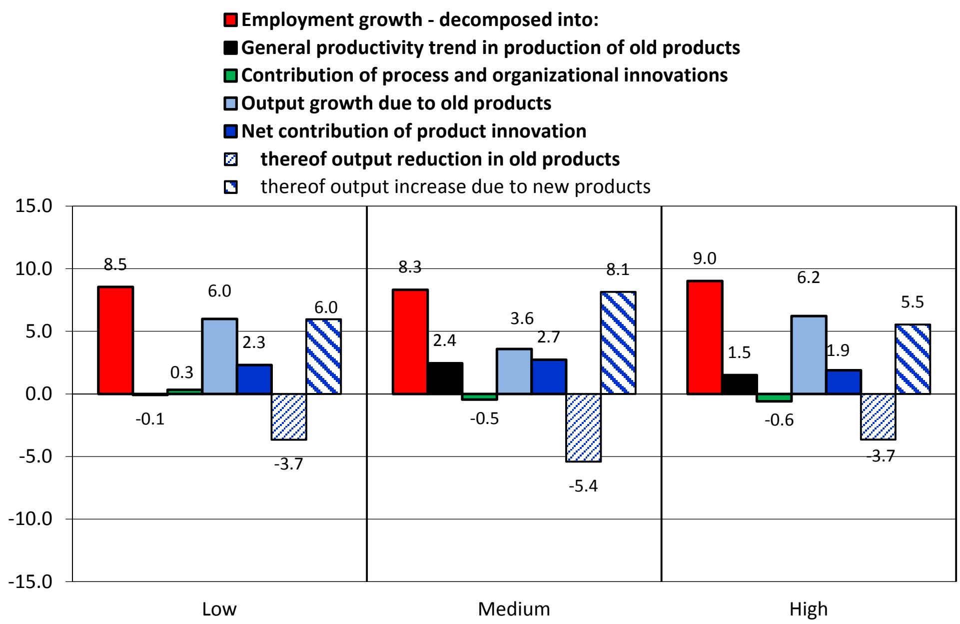
Figure 6.12 shows the decomposition of employment growth in manufacturing industries as proposed in section 5.4 for the three classes of business cycle sensitivity. For industries with low business cycle sensitivity, the main source of employment growth is the output growth due to old products, while the main component for employment growth for industries with medium and high business sensitivity is the net contribution of product innovation (i.e. the difference between the output reduction in old products and the output increase due to new products). In both latter cases, the second main source is the output growth due to old products. Interestingly, we can observe that gains due to new products are increasing with increasing business cycle sensitivity of the industries. At the same time, losses from old products also increase with higher business cycle sensitivity. This confirms our assumption from 2.4 that firms in cyclical sectors experience larger employment growth but also larger losses from the demand effect than firms in non-cyclical sectors.

**Figure 6.12: Contribution of innovation to employment growth in manufacturing industries of high, medium and low business cycle sensitivity, 1998-2010**




*Notes: Weighted figures.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

**Figure 6.13: Contribution of innovation to employment growth in service industries of high, medium and low business cycle sensitivity, 1998-2010**




*Notes: Weighted figures.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

The decomposition of the employment growth in services industries is displayed in Figure 6.13. Throughout all defined business sensitivity classes, the main component of employment growth is the output growth due to old products; however, the contribution of this component is considerably larger in industries with low and high business cycle sensitivity, with 6.0 and 6.2 percentage points, respectively. Furthermore, the net contribution of product innovation has also a relatively high impact on the overall employment growth. As a third part, the general productivity trend in the production of old products contributes to the employment growth in the classes of medium and high business cycle sensitivity as well.

# Chapter 7.
# FIRM HETEROGENEITY, INNOVATION AND EMPLOYMENT GROWTH OVER THE BUSINESS CYCLE

A main advantage of firm-level data is the possibility to investigate heterogeneity in the link between innovation and employment growth between different sub-groups of firms. This allows us to identify e.g. sub-populations of firms in which innovation matters more for employment growth than in others. In chapter 2.3 we have put forward theoretical arguments of why firm size and foreign ownership might play an important role for the effect innovation exerts on employment growth. In this chapter we will first examine in the role of firm size in section 7.1, followed by an analysis whether foreign ownership matters for employment effects of innovation in section 0.

## 7.1. FIRM SIZE

One of the most important differences between firms which can also explain heterogeneity in the relationship between innovation and employment growth is firm size. Here, many arguments go along the discussion on specific advantages and disadvantages of small and large firms in the innovation process (Kleinknecht 1989, Dogson and Rothwell 1994, Cohen 1995, 2010). The main argument in favour of large firms is that they have large internal financial means and access to external funds to finance innovation projects more easily and can manage risk more easily through diversification and distribution of the cost of failures over a larger number of projects. Large, diversified firms have also more potential applications for new knowledge (Rosenberg 1990). Another advantage of size is specialisation and a more intense division of labour between different scientific disciplines and persons of different qualifications. Data from the financial crisis of 2008-2009 provides evidence that innovation activities in larger firms have been less affected by the recession and support the view that large firms have advantages in the innovation process (Paunov 2012, Rammer 2012, Archibugi et al. 2013).

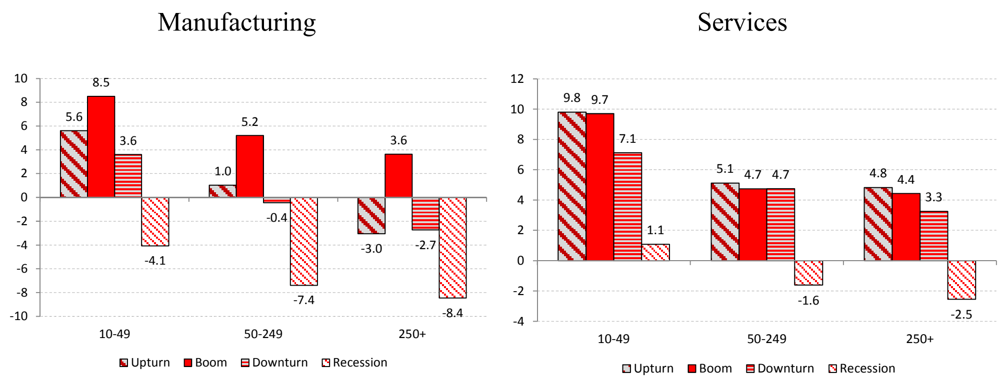
Small enterprises, in contrast, are more flexible to react to new opportunities, are able to survive in niche markets where large enterprises are not willing to operate, and benefit from the personal engagement of an entrepreneur who brings in his/her knowledge of technologies and markets.

Empirical evidence has found that especially young SMEs exhibit high net employment growth rates, whereas large, old firms are found to have the lowest rates (Fort et al. 2013, Haltiwanger et al. 2013). This pattern is confirmed for European manufacturing firms (see Figure 7.1). Their employment growth decreases as the firm size increases. That is, small firms grow faster in all stages of the business cycle compared to medium-sized and large firms. For services we also find employment growth rates to be higher for small businesses though there is hardly any difference between medium and large service firms.

Fort et al. (2013) furthermore found pro-cyclicality of employment growth for young, small and medium-sized as well as for old, large firms in the US, however, net job creation rates for young SMEs and old, small businesses declined substantially during times of recession. They explain this finding by the fact that small firms are more often credit constrained.

Figure 7.1 depicts employment growth rates for small, medium and large companies over the business cycle, separately for manufacturing and services in Europe. Not surprisingly, the figure confirms that a pro-cyclical development of employment growth for all firm sizes, in manufacturing as well as in services. That is, employment growth is much higher in booms and upturns for all size classes, which points to the importance of the demand effect. Job creation is substantially smaller in downturns and recession periods and even negative in the recession phase for all size classes, except for small service firms. In manufacturing job cuts are already observed for downturn phases in medium and large firms. An interesting finding is that on average large firms in Europe have not grown at all except in boom times. Calculating the standard deviation of employment growth rates over different phases of the business cycle by size class, we find employment growth to be more volatile in small businesses (5.4 in manufacturing and 4.1 in services) than in large firms (4.9 in manufacturing and 3.4 in services).

**Figure 7.1: Employment growth over the business cycle by firm size, 1998-2010**

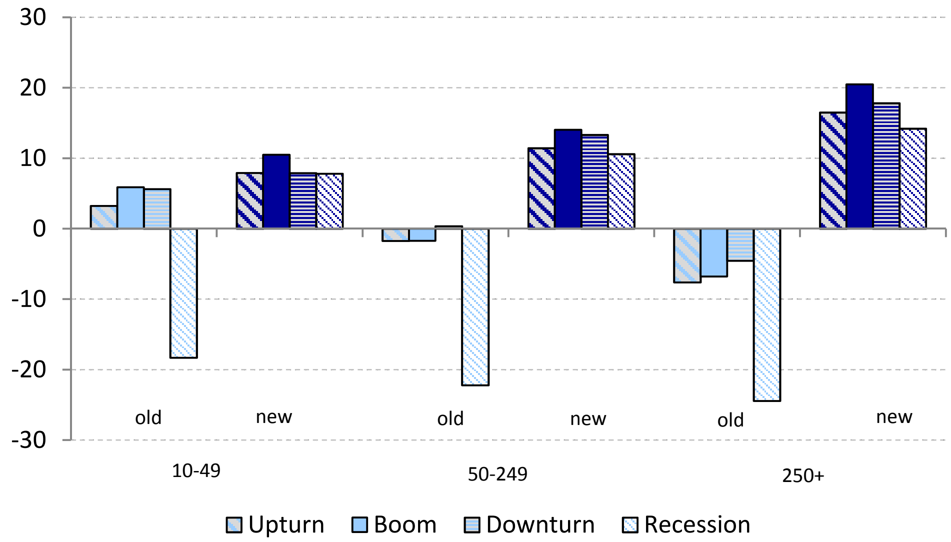



*Notes: Depicted are two-year employment growth rates.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

As was shown in the previous chapter, innovation output is one of the key determinants for employment growth. Figure 7.2 therefore reveals differences in sales growth due to new and old products between small, medium and large firms in the manufacturing sector. Large firms have the highest sales growth from new products, followed by medium sized firms and small firms. In other words, large firms reap the highest benefits from innovation measured by sales from new products. Still, the expected pro-cyclical behaviour is recognizable in all three size classes. This is not the case for sales growth due to old products for medium and large firms. But note that a substantial part of the decline in the demand for old products is provoked by the introduction of new products. Losses in sales from old products are in general larger for medium and large companies as more firms in these size classes offer new products. Moreover, growth from old products decreases with increasing firm size, where medium and large firms have losses in all phases of the business cycle. Recessions have a particularly strong impact on the sales growth of old products.

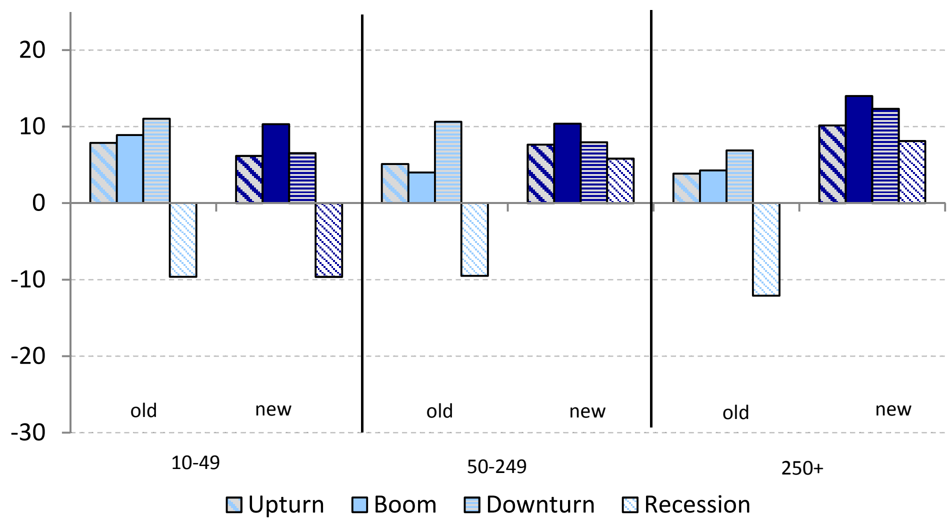
Compared to the manufacturing sector, in the service sector the differences in sales growth between small, medium and large enterprises are not that large (see Figure 7.3). As it has been observed for manufacturing, sales growth due to new products moves pro-cyclical in services and it increases with increasing firm size, although less than in manufacturing. Interestingly, we do not observe a pro-cyclical pattern for the sales growth rate due to old products in any of the size classes. Instead, service firms of all size classes tend to have higher sales growth rates with old products during phases of economic downswing. In the recession, the sales growth rate with old products is negative and slightly increasing with firm size.

**Figure 7.2: Sales growth due to new and old products over the business cycle by size classes, manufacturing, 1998-2010**




*Notes: Depicted are two-year nominal sales growth rates due to new and old products, respectively. Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

**Figure 7.3: Sales growth due to new and old products over the business cycle by size classes, services, 1998-2010**




*Notes: Depicted are two-year nominal sales growth rates due to new and old products, respectively. Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

Like in the previous chapters, we estimate the employment model for two size classes and for manufacturing and services separately. The regression results are reported in Table 7.1, while Table 7.2 delivers the results of the decomposition. The results of the regression fit well with the results reported in previous chapters. In most size classes, sectors and business cycle phases, the coefficients for SGR_NEWPD are close to one which indicates a stable relationship between innovation output and employment growth in all sub-groups evaluated. The coefficients are highly significant in all regressions. Two exceptions are small service firms in boom phases and large service firms in in recession periods. In both cases an increase in innovation output led to a disproportionate growth in employment.

**Table 7.1: Impact of innovation on employment growth over the business cycle in SME and large enterprises in manufacturing, 1998-2010**

| | Manufacturing,10-249 | | | | Manufacturing, 250+ | | | |
|---|---|---|---|---|---|---|---|---|
| | Upturn | Boom | Downturn | Recession | Upturn | Boom | Downturn | Recession |
| SGR_NEWPD | 0.989*** | 0.965*** | 1.010*** | 0.971*** | 0.953*** | 1.015*** | 1.025*** | 0.994*** |
| | (0.026) | (0.029) | (0.026) | (0.027) | (0.031) | (0.054) | (0.041) | (0.046) |
| PCONLY | -1.278 | -0.453 | -1.727* | -0.547 | -2.999*** | -0.130 | 0.427 | 0.696 |
| | (0.821) | (1.483) | (0.981) | (1.071) | (1.107) | (2.266) | (1.177) | (1.275) |
| ORGA | -2.012*** | 0.639 | -1.629** | -0.674 | -2.871*** | -1.710 | -0.743 | -1.022* |
| | (0.449) | (0.703) | (0.655) | (0.509) | (0.695) | (1.049) | (0.730) | (0.560) |
| | Services,10-249 | | | | Services, 250+ | | | |
| | Upturn | Boom | Downturn | Recession | Upturn | Boom | Downturn | Recession |
| SGR_NEWPD | 0.981*** | 0.735*** | 1.024*** | 1.003*** | 1.040*** | 0.951*** | 0.898*** | 0.854*** |
| | (0.044) | (0.113) | (0.048) | (0.046) | (0.096) | (0.128) | (0.150) | (0.053) |
| PCONLY | 0.603 | -3.362 | 0.912 | -0.646 | -0.180 | 5.494 | -1.607 | -1.965 |
| | (1.390) | (2.967) | (1.148) | (0.873) | (1.701) | (5.157) | (1.642) | (1.405) |
| ORGA | -1.247 | 1.302 | -1.110 | 0.640 | -1.200 | 1.967 | 0.139 | 0.433 |
| | (0.821) | (1.411) | (0.819) | (0.571) | (1.815) | (2.620) | (1.119) | (1.176) |

*Notes: Method: Weighted instrumental variables estimation. ***, ** and * indicate significance at the 1%, 5% and 10% level. Reported is only the impact of innovation on employment growth. The full set of results including first stage results and specification tests are provided in the Table Appendix Table 11.12 and Table 11.13.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

**Table 7.2: Decomposition of employment growth in SME and large enterprises over the business cycle, 1998-2010**

| | Up-turn | Boom | Down-turn | Reces-sion | Up-turn | Boom | Down-turn | Reces-sion |
|---|---|---|---|---|---|---|---|---|
| | Manufacturing,10-249 | | | | Manufacturing, 250+ | | | |
| **Employment growth** | **4.8** | **7.4** | **2.8** | **-4.7** | **-3.0** | **3.7** | **-2.7** | **-8.4** |
| *Decomposed into* | | | | | | | | |
| **(1) General productivity trend** | **-2.4** | **-5.6** | **-2.9** | **7.4** | **-7.0** | **-7.2** | **-8.0** | **3.6** |
| **(2) Gross effect of process innovation** | **-0.2** | **-0.1** | **-0.2** | **-0.1** | **-0.3** | **0.0** | **0.0** | **0.1** |
| **(3) Gross effect of orga. innovation** | **-0.6** | **0.3** | **-0.5** | **-0.2** | **-1.7** | **-1.1** | **-0.4** | **-0.6** |
| **(4) Output growth of old products for non-pd** | **5.4** | **8.0** | **3.9** | **-9.4** | **2.2** | **3.0** | **1.3** | **-5.6** |
| (4a) for non-innovators | 4.2 | 6.4 | 2.9 | -8.4 | 1.6 | 2.1 | 0.7 | -4.3 |
| (4b) for process innovators | 1.2 | 1.6 | 1.0 | -1.0 | 0.6 | 0.9 | 0.6 | -1.3 |
| **(5) Net contrib. of product innov.** | **2.6** | **4.8** | **2.5** | **-2.4** | **3.8** | **9.0** | **4.4** | **-5.9** |
| (5a) output reduction in old prod. | -5.9 | -6.1 | -6.5 | -10.6 | -12.0 | -11.6 | -13.9 | -20.0 |
| (5b) output increase in new prod. | 8.4 | 10.8 | 9.1 | 8.1 | 15.7 | 20.6 | 18.3 | 14.1 |
| | Services, 10-249 | | | | Services, 250+ | | | |
| **Employment growth** | **9.1** | **8.3** | **6.8** | **0.6** | **4.8** | **3.9** | **3.3** | **-2.5** |
| *Decomposed into* | | | | | | | | |
| **(1) General productivity trend** | **0.5** | **-5.2** | **-3.2** | **5.7** | **-3.5** | **-12.6** | **-7.5** | **3.5** |
| **(2) Gross effect of process innovation** | **0.1** | **-0.3** | **0.1** | **-0.1** | **0.0** | **0.5** | **-0.3** | **-0.2** |
| **(3) Gross effect of orga. innovation** | **-0.4** | **0.6** | **-0.3** | **0.2** | **-0.7** | **1.2** | **0.2** | **0.1** |
| **(4) Output growth of old products for non-pd** | **6.7** | **9.8** | **7.5** | **-5.3** | **4.8** | **5.8** | **6.4** | **-3.5** |
| (4a) for non-innovators | 5.7 | 8.2 | 6.5 | -5.1 | 3.5 | 4.7 | 5.0 | -2.3 |
| (4b) for process innovators | 1.1 | 1.6 | 1.0 | -0.2 | 1.3 | 1.2 | 1.4 | -1.2 |
| **(5) Net contrib. of product innov.** | **2.3** | **3.3** | **2.7** | **0.0** | **4.3** | **8.8** | **4.4** | **-2.4** |
| (5a) output reduction in old prod. | -4.0 | -4.3 | -4.2 | -5.4 | -6.3 | -4.6 | -6.1 | -9.7 |
| (5b) output increase in new prod. | 6.3 | 7.7 | 6.9 | 5.4 | 10.6 | 13.4 | 10.5 | 7.3 |

*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

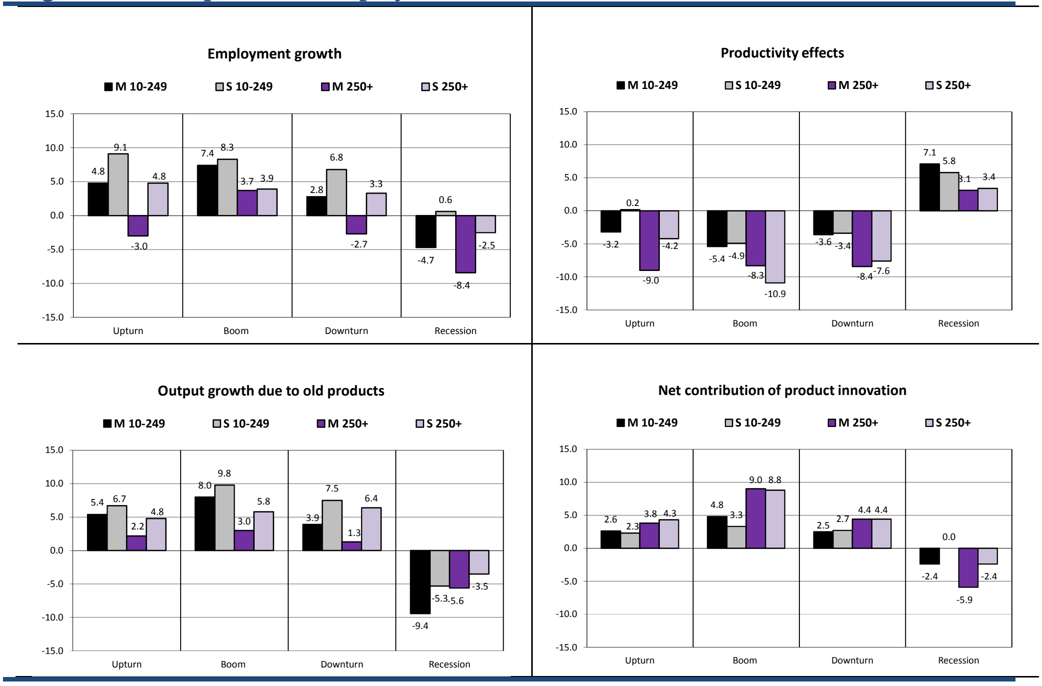
Coefficients for process and organisational innovation, in contrast are only rarely significant. The largest significant values for the two coefficients can be observed in large manufacturing firms during an upswing which points to more opportunities in large firms for the productivity effect of process innovation.

The decomposition analysis reveals why large firms generate less employment growth than small firms, despite higher sales from new products as shown above; large firms have considerably higher gains from general productivity trends, which overcompensate gains from new products and turn employment development into negative. This reflects a higher capital intensity, more opportunities to realize productivity gains from economics of scale, or better management practices of large firms. All these factors are related to a higher productivity, but cannot be accounted separately by this model. Large firms are the only group in the analysis of this chapter where race between innovation and productivity is permanently won by productivity, leading to jobless growth.

The results from Table 7.2 are illustrated in Figure 7.4. The figure clearly reveals that employment losses in large manufacturing firms are not because these firms do not innovate; new products (lower right quadrant), in contrast, are a much bigger source of employment creation in large than in small and medium sized firms. Employment gains from new products and also from demand growth for old products, however, are compensated by productivity gains from process and organisational innovation and general productivity increases which are much bigger in large manufacturing firms than in SMEs. Boom periods with large demand effects are an exception.

A comparison between SME and large firms in services reveal a similar pattern though demand effects are in general large enough to compensate for productivity gains in large service firms.

**Figure 7.4: Comparison of employment effects across size classes, 1998-2010**




*Notes: Based on Table 7.2.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

In turn, the contribution of old products is much larger in SMEs. Consequently, SMEs also suffer much higher losses from dropping sales of older products in recessions than large firms.

### 7.2. FOREIGN OWNERSHIP

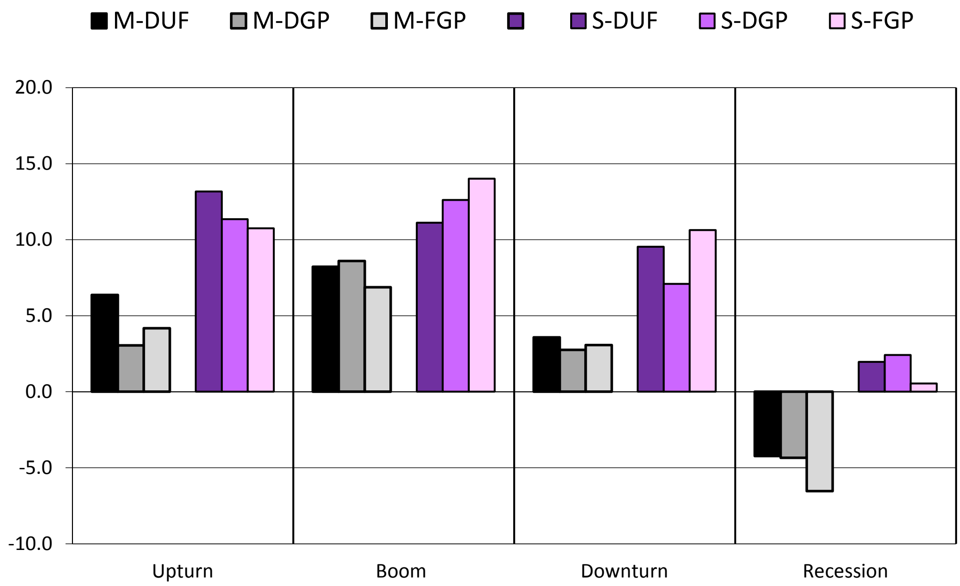
The extent to which innovation creates or destroys employment over the business cycle is also likely to differ between domestic and foreign owned firms. Based on the arguments in section 2.3.2, we expect employment volatility to be higher over the business cycle in foreign-owned firms, in part provoked by a higher volatility of innovation-induced employment effects.

Based on information provided in CIS data, we distinguish between domestically owned unaffiliated firms (DUF), firms that belong to a group with a domestic headquarter (DGP) and foreign-owned firms (FGP). The latter describe domestic firms that belong to a group having its headquarter abroad. The large majority of firms in Europe are domestic unaffiliated firms. In manufacturing its share is about 812%. 13.4% of the firms in Europe are owned by a domestic group and 5.4% are foreign-owned. In services, we observe a slightly higher proportion of foreign-owned firms (8.2%) and firms that belong to a domestic group (18.7). This finding can be explained by the fact that large and multinational companies often have large service distribution networks.

Figure 7.5 shows employment growth rates over the business cycle by type of ownership. The following three stylized facts can be observed:

- First of all, employment growth shows a *pro-cyclical pattern* for all six types of firms in Europe, except for domestic unaffiliated services firms (S-DUF). That is more employment is created in boom and upturn phases than in downturn and recession phases.
- Second, *foreign-owned firms in manufacturing grow less* than domestic unaffiliated firms in *upturn, boom and downturn* periods. In part this can be explained by the fact that foreign-owned firms are larger on average than domestic unaffiliated firms. The pattern is less clear when we compare foreign-owned and domestically-owned group firms in Europe. On the other hand, foreign owned manufacturing firms clearly *cut more jobs during recessions* than both types of domestic firms. This confirms that multinational firms have on average a tendency to cut jobs more easily abroad than at home. Taking both findings together, it is not obvious at first glance whether employment growth is more volatile in foreign-owned firms over the business cycle. However, calculating the standard deviation as a measure for volatility, the results supports the hypothesis that employment growth is *more volatile* over the business cycle in foreign-owned firms (s.d. 5.8) than in domestic unaffiliated firms (s.d.5.5) and domestic group firms (s.d.5.3).
- Third, the pattern slightly differs for *foreign-owned firms in services*. They indeed experienced a *faster employment growth in boom* periods and still in downturn phases, but also create much *less employment in recessions* and upturn phases compared to their domestic counterparts. These findings clearly show that employment growth is also *more volatile* in foreign-owned service firms (s.d. 5.8) than in domestic unaffiliated firms (s.d.4.9) and domestic group firms (s.d.4.6).
- Overall, the Polish finding (Kolasa et al. 2010) that foreign ownership provided a higher degree of resilience against the crisis due to better intra-firm lending opportunities, is not generalizable to foreign-owned firms in Europe as a whole.

**Figure 7.5: Employment growth over the business cycle by firm ownership, 1998-2010**




*Notes: Depicted are 2-year employment growth rates.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

What drives the higher volatility of foreign-owned firms over the business cycle? In particular to what extent is this driven by innovation? In order to answer this question, we estimate the impact of innovation on employment growth over the business cycle in domestic unaffiliated firms (see Table 11.14), domestically-owned group firms (see Table 11.15) and foreign-owned firms (see Table 11.16). Based on these results, Table 7.3 decomposes employment growth into its different sources. Figure 7.6 graphically compares the main sources of employment growth.

The results show three interesting findings. First, the estimates confirm that product innovation has a significantly positive impact on employment growth in both domestic and foreign-owned firms. However, the coefficient of sales growth due to new products tends to be smaller in foreign-owned firms than in their domestic counterparts. We observe this pattern for manufacturing firms in all business cycle phases and in services for three out of four phases although the difference is statistically significant only in some cases. This implies that a given innovation output (sales growth due to new products) tends to be translated into less employment growth in foreign-owned firms due to a stronger productivity effect of product innovation. However, this effect is overcompensated by a larger innovation output (demand effect) and a higher proportion of product innovators among foreign-owned firms. Taking all three effects together and taking account of substitution effects related to old products, we observe the largest positive net contributions of product innovation in foreign-owned firms in upturn, boom and downturn phases.

**Table 7.3: Decomposition of employment growth in domestic and foreign-owned firms over the business cycle, 1998-2010**

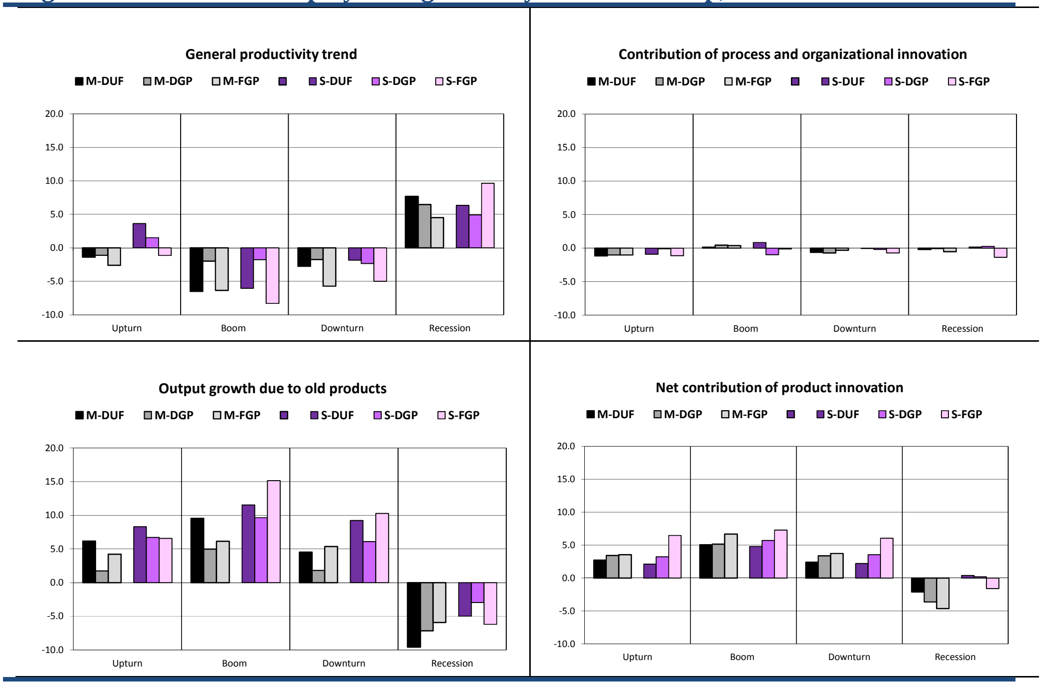
| | Up-turn | Boom | Down-turn | Reces-sion | Up-turn | Boom | Down-turn | Reces-sion | Up-turn | Boom | Down-turn | Reces-sion |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Manufacturing - DUF** | | | | **Manufacturing - DGP** | | | | **Manufacturing - FGP** | | | |
| **Employment growth** | **6.4** | **8.2** | **3.6** | **-4.2** | **3.1** | **8.6** | **2.7** | **-4.3** | **4.2** | **6.9** | **3.1** | **-6.5** |
| *Decomposed into* | | | | | | | | | | | | |
| **(1) General productivity trend** | **-1.4** | **-6.5** | **-2.7** | **7.7** | **-1.1** | **-2.0** | **-1.7** | **6.5** | **-2.6** | **-6.3** | **-5.7** | **4.5** |
| **(2) Gross effect of process innovation** | **0.1** | **0.1** | **-0.1** | **0.0** | **-0.1** | **-0.3** | **-0.2** | **0.0** | **-0.5** | **-0.2** | **-0.6** | **-0.2** |
| **(3) Gross effect of organizational innovation** | **-1.2** | **0.1** | **-0.5** | **-0.2** | **-0.9** | **0.7** | **-0.6** | **0.0** | **-0.6** | **0.6** | **0.3** | **-0.3** |
| **(4) Output growth of old products for non-pd** | **6.2** | **9.5** | **4.5** | **-9.6** | **1.8** | **5.0** | **1.8** | **-7.1** | **4.2** | **6.1** | **5.4** | **-5.9** |
| (4a) for non-innovators | 4.9 | 7.8 | 3.5 | -8.6 | 0.8 | 3.5 | 1.2 | -5.8 | 3.0 | 4.8 | 3.9 | -5.0 |
| (4b) for process innovators | 1.3 | 1.7 | 1.0 | -1.0 | 0.9 | 1.5 | 0.6 | -1.4 | 1.2 | 1.3 | 1.5 | -0.9 |
| **(5) Net contribution of product innovation** | **2.7** | **5.0** | **2.4** | **-2.1** | **3.4** | **5.1** | **3.4** | **-3.6** | **3.5** | **6.7** | **3.7** | **-4.6** |
| (5a) output reduction in old products | -5.3 | -6.3 | -6.2 | -9.8 | -9.6 | -7.3 | -8.8 | -15.1 | -9.1 | -5.7 | -9.9 | -16.3 |
| (5b) output increase in new products | 8.1 | 11.3 | 8.6 | 7.7 | 13.1 | 12.4 | 12.2 | 11.4 | 12.7 | 12.4 | 13.6 | 11.7 |
| | **Services - DUF** | | | | **Services - DGP** | | | | **Services - FGP** | | | |
| **Employment growth** | **13.2** | **11.1** | **9.5** | **2.0** | **11.4** | **12.6** | **7.1** | **2.4** | **10.8** | **14.0** | **10.6** | **0.5** |
| *Decomposed into* | | | | | | | | | | | | |
| **(1) General productivity trend** | **3.6** | **-6.0** | **-1.8** | **6.4** | **1.5** | **-1.8** | **-2.3** | **4.9** | **-1.1** | **-8.3** | **-5.0** | **9.7** |
| **(2) Gross effect of process innovation** | **0.0** | **0.0** | **0.0** | **0.0** | **0.1** | **-0.3** | **-0.1** | **0.1** | **0.0** | **-1.3** | **0.2** | **-0.2** |
| **(3) Gross effect of organizational innovation** | **-0.9** | **0.8** | **-0.1** | **0.2** | **-0.2** | **-0.7** | **-0.1** | **0.2** | **-1.2** | **1.1** | **-0.9** | **-1.1** |
| **(4) Output growth of old products for non-pd** | **8.3** | **11.5** | **9.2** | **-5.0** | **6.7** | **9.7** | **6.1** | **-2.9** | **6.6** | **15.1** | **10.3** | **-6.2** |
| (4a) for non-innovators | 7.2 | 10.3 | 8.2 | -4.9 | 5.5 | 7.0 | 5.0 | -2.7 | 5.3 | 11.9 | 8.6 | -5.6 |
| (4b) for process innovators | 1.1 | 1.2 | 1.0 | -0.1 | 1.3 | 2.6 | 1.1 | -0.2 | 1.3 | 3.3 | 1.7 | -0.6 |
| **(5) Net contribution of product innovation** | **2.1** | **4.8** | **2.2** | **0.4** | **3.2** | **5.7** | **3.5** | **0.2** | **6.5** | **7.3** | **6.0** | **-1.6** |
| (5a) output reduction in old products | -3.4 | -4.3 | -3.8 | -4.8 | -5.3 | -3.9 | -5.2 | -6.5 | -4.7 | -6.1 | -5.5 | -11.0 |
| (5b) output increase in new products | 5.5 | 9.1 | 6.0 | 5.2 | 8.5 | 9.6 | 8.8 | 6.7 | 11.2 | 13.3 | 11.5 | 9.4 |

*Notes: DUF- domestically owned unaffiliated firms, DGP – domestically owned group firms, FGP – foreign-owned group firms*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation*

In the recent crisis, however, these counter-effects have not been strong enough due to a shrinking demand. Overall, this has led to a negative net contribution of product innovation which turned out to be larger in foreign-owned firms than in domestic firms in Europe. More detailed results show that foreign-owned firms created more employment than domestic firms from increases in output of product innovation during the recession, but also lost much more than domestic firms due to substitution effects leading to a lower net contribution of product innovation. Based on CIS data it is not feasible to distinguish the sources of demand (domestic demand versus exports), however our results are in line with findings showing that exports dropped faster during the crisis than domestic demand and thus that the crisis had a more severe impact on export-oriented firms (Paunov 2012, Rammer 2012, Archibugi et al. 2013). To sum up, the contribution of product innovation is more volatile in foreign-owned firms and thus has contributed to larger employment volatility in foreign-owned firms over the business cycle.

Second, in upturn, boom and downturn periods foreign-owned firms grow less because of larger general productivity gains than domestic firms. This result holds for both manufacturing and services. These larger productivity gains reflect benefits from internal technology transfer and learning effects in the corporate network. In the recession, however, all three types of firms show a positive general productivity trend. This implies that employment destruction would have been even larger if firms would not have been willing to accept a worsening of productivity – for instance as a result of labour hoarding. In manufacturing, this effect is smallest for foreign-owned firms implying that they experience a stronger decline in employment during the recession. This supports the view that in manufacturing multinational firms have on average a tendency to cut jobs more easily abroad than at home during a recession. In services, however, the contrary is observed.

**Figure 7.6: Sources of employment growth by firm ownership, 1998-2010**




*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

Third, in contrast to the contribution of product innovation, demand of old products and the general productivity trend process and organizational innovation are of minor importance for employment growth (and in most cases not significant). The effect is consistently negative in foreign-owned service firms, ranging between -1.4% in the recession period and -0.1% in the boom period. In manufacturing, results are mixed with respect to process innovation.

To sum up, our results show that employment growth is more volatile in foreign-owned firms than in domestic firms. The main source of this finding can be traced back to the impact of product innovation. That is, foreign-owned firms create more employment due to more product innovation and a stronger demand effect in upturn, boom and downturn periods (overcompensating stronger productivity effects of product innovation). At the same time, they lost more jobs due to product innovation during the recent crisis which affected export-oriented firms more strongly. Overall, the larger volatility in product innovation impacts in foreign-owned firms has contributed to larger employment volatility in foreign-owned firms over the business cycle. In upturn, boom and downturn phases of the business cycle, the positive effect of product innovation is somewhat dampened by the larger general productivity gains in foreign-owned firms due to benefits from internal technology transfer and learning effects. In the recession, however, the general productivity trend reinforces the employment growth disadvantage of foreign-owned firms in manufacturing.

# Chapter 8. INNOVATION AND EMPLOYMENT GROWTH OVER THE BUSINESS CYCLE – REGIONAL DIFFERENCES

Results from section 4.3 have shown that innovation strategies vary between firms from different regions in Europe. In particular results have revealed that the level of innovation activity is on average higher but surprisingly also more business-cycle dependent in North-west European countries than in South-east Europe. In North-western European countries firms are most frequently engaged in innovation activities in boom phases, but all three types of innovator shares – product, process and organizational - are also relatively high in recession periods. An obvious question immediately followed by this pattern is whether and to what extent this behaviour affects firm growth.

Unfortunately, CIS data provided at Eurostat's safecenter do not allow us to perform a comparative analysis at the EU member states level for all countries since not all countries are observed in all business cycle stages; see also section 3.2.[21] As alternative, we aggregate EU member states countries into three groups: North-west Europe, South and East Europe. The three regions comprise the following countries:

- *North-west Europe*: Belgium, Germany, Denmark, France, Finland, Ireland, Luxemburg, the Netherlands, Sweden, Iceland and Norway.
- *South Europe*: Cyprus, Spain, Greece, Italy, Malta and Portugal.
- *East Europe*: Czech Republik, Estonia, Latvia, Lithuania, Slovakia, Slovenia, Romania, Hungary, Bulgaria and Croatia.

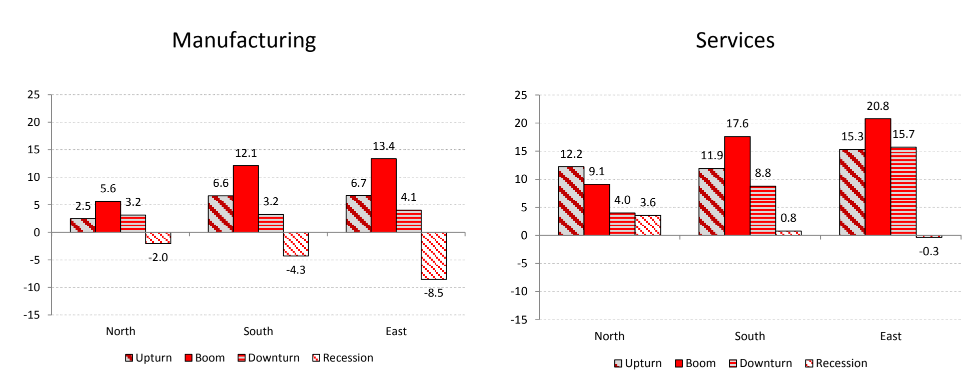
Separately for manufacturing and services, Figure 8.1 depicts average two-year employment growth rates for firms from North-west, South and East Europe during the period 1998-2010. In manufacturing, employment growth changes follow a plain pro-cyclical development in all three regions. Interestingly, this pro-cyclical pattern is much more pronounced in Southern and Eastern European countries. During upturn and boom phases employment growth rates among surviving firms in Southern and Eastern European countries are on average 2.5 times larger than for firms in North-western European countries. This may be a sign of a higher labour intensity in these countries compared to North-western Europe. But on the contrary, average employment losses turn out to be 2.5 and 4.5 times larger in Southern and Eastern European countries during recessions than in North-west Europe.

In services, employment changes also follow a pro-cyclical development in South and East Europe. North-west Europe, however, deviates from this pattern as the highest average employment growth rate is observed during the upturn. Furthermore, even during recession periods, service firms in North-west Europe have created employment, and this increase in employment was nearly as high as in downturn phases (+3.6%). On the contrary, average

[21] At the country level, estimates have also been conducted for France and Spain which are observed for all business cycle phases. Both countries are large representatives of North-western and Southern European countries and hence results are similar. Results are available upon request.

employment growth was slightly above or below zero in South (+0.8%) and East Europe (-0.3%).

**Figure 8.1: Employment growth over the business cycle by region, 1998-2010**




*Notes: Weighted figures. Depicted are two-year employment growth rate.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

The observed differences in employment growth among firms from different regions in Europe might the due to differences in innovation engagement and innovation success over the business cycle, but they might also reflect differences in GDP growth, firm size, wage development, investments, institutions, and other factors that affect employment growth. In order to isolate the impact of innovation on employment growth over the business cycle, we make use of the methodology explained in section 5.1. We estimate the model separately for different regions and business cycle stages. Table 8.1and Table 8.2 report the estimation results for manufacturing and services, respectively. Table 8.3 depicts the decomposition results for both sectors which are also illustrated in Figure 8.2 to Figure 8.7.

Results confirm findings at the European level for product innovation. Higher sales growth rates due to new products are associated with significantly higher employment growth in upturns and boom periods as well as in downturn and recession periods. That is in all three regions product innovations are a major driver of employment growth in manufacturing in all phases of the business cycle. In South and East Europe, the coefficient of the sales growth due to new products variable is not significantly different from 1 in all stages of the business cycle, indicating the same efficiency of old and new products and thus no additional productivity effects and labour savings due to the introduction of new products. In North-western European countries, however, the coefficient is significantly smaller than 1 in boom, downturns and recession periods where it shows values between 0.92 and 0.95 (based on one-sided tests). This implies that product innovators in North-western European countries increase the efficiency of the production of new products compared to the efficiency of the production of old products in these phases of the business cycle. On the one hand, an increase in efficiency implies less labour per unit of output. But on the other hand, higher efficiency raises firm's competitiveness and output with new products.

Both process and organizational innovation play only a minor role for employment growth in North-western European countries. The coefficients of organizational innovation are rather small and insignificant in all four stages. The effect of process innovation is negative in all phases except for the recession period but only significantly negative in the downturn period.

**Table 8.1: Impact of innovation on employment growth in manufacturing by region, 1998-2010**

| | North-west Europe | | | | South Europe | | | | East Europe | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Upturn (1)** | **Boom (2)** | **Downturn (3)** | **Recession (4)** | **Upturn (5)** | **Boom (6)** | **Downturn (7)** | **Recession (8)** | **Upturn (9)** | **Boom (10)** | **Downturn (11)** | **Recession (12)** |
| SGR | 1.010*** | 0.944*** | 0.950*** | 0.916*** | 1.021*** | 1.161*** | 1.051*** | 1.150*** | 0.968*** | 1.002*** | 0.943*** | 0.963*** |
| _NEWPD | (0.038) | (0.040) | (0.032) | (0.048) | (0.029) | (0.096) | (0.043) | (0.118) | (0.034) | (0.025) | (0.036) | (0.030) |
| PCONLY | -2.478 | -1.841 | -2.116** | 0.488 | -1.098 | 3.358 | -0.502 | 1.627 | 0.041 | 0.215 | -4.750* | -2.368** |
| | (2.270) | (1.806) | (0.920) | (1.705) | (0.897) | (2.599) | (1.322) | (2.213) | (1.668) | (2.583) | (2.466) | (1.089) |
| ORGA | 0.045 | -0.618 | 0.166 | -0.850 | -2.718*** | 0.746 | -2.559*** | -2.606** | -4.780*** | -1.174 | -1.450 | -1.296* |
| | (0.842) | (0.921) | (0.621) | (1.171) | (0.619) | (1.446) | (0.833) | (1.249) | (1.241) | (1.175) | (1.330) | (0.701) |
| GDPGR | -1.262*** | 1.069* | 0.241 | -1.192 | -2.045*** | 0.535 | -0.205 | -1.142*** | 5.388*** | 0.807 | -0.087 | -0.407*** |
| | (0.392) | (0.571) | (0.386) | (1.698) | (0.331) | (2.874) | (0.217) | (0.333) | (0.667) | (0.645) | (0.173) | (0.073) |
| MEDIUM | -3.383*** | -0.988 | -1.372** | -0.636 | -2.090*** | 0.089 | -2.968*** | -1.414 | -5.489*** | 2.684** | 1.553 | -5.032*** |
| | (0.820) | (1.123) | (0.611) | (0.585) | (0.669) | (1.509) | (0.848) | (1.132) | (0.939) | (1.280) | (1.388) | (0.530) |
| LARGE | -6.018*** | -4.391*** | -0.822 | -1.911** | -2.299** | -2.945 | -4.162*** | -1.729 | -7.636*** | 1.428 | 1.628 | -8.290*** |
| | (1.110) | (1.481) | (1.051) | (0.759) | (0.969) | (2.377) | (1.051) | (1.345) | (1.197) | (1.639) | (1.470) | (0.679) |
| DGP | 1.709* | 4.469*** | 0.257 | 1.516** | -2.656** | 0.576 | 1.102 | 0.458 | 1.491 | -1.473 | 1.605 | 1.574* |
| | (0.883) | (1.222) | (0.781) | (0.766) | (1.325) | (2.709) | (1.070) | (1.291) | (1.375) | (2.050) | (1.715) | (0.837) |
| FGP | 0.951 | 1.644 | 1.066 | 0.411 | -0.850 | -2.362 | -0.032 | -3.183** | 1.307 | 0.114 | -3.396*** | -4.056*** |
| | (1.011) | (1.443) | (1.324) | (0.885) | (1.545) | (2.454) | (0.970) | (1.262) | (1.796) | (1.171) | (1.247) | (0.803) |
| Constant | 4.343 | -4.624 | -4.920** | 0.110 | 12.657*** | -6.604 | 4.858*** | -1.527 | -49.756*** | -26.304*** | -7.104** | 9.036*** |
| | (4.511) | (3.582) | (2.468) | (2.582) | (1.724) | (28.590) | (1.432) | (1.577) | (6.132) | (9.714) | (3.233) | (0.840) |

*Notes: Weighted IV regression. This table reports only the results of the main variables of interest. The full set of results can be found in the Table appendix, Table 11.17, Table 11.18 and Table 11.19.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

The pattern is more mixed in South and East Europe. In both regions organizational innovation tend to significantly increase efficiency and thus reduce labour inputs in all phases of the business cycle though the coefficients are not significant in all stages. Boom periods in South Europe are an exception where we find a significantly positive impact from organizational innovation. The effect of process innovation is also mixed. In Eastern European countries they significantly increase efficiency and thus reduce employment in downturns (-4.75%) and recessions (-2.4%). In South Europe, this effect is also negative but not significant. Interestingly, process innovation do not significantly increase efficiency in upturn and boom periods in both regions.

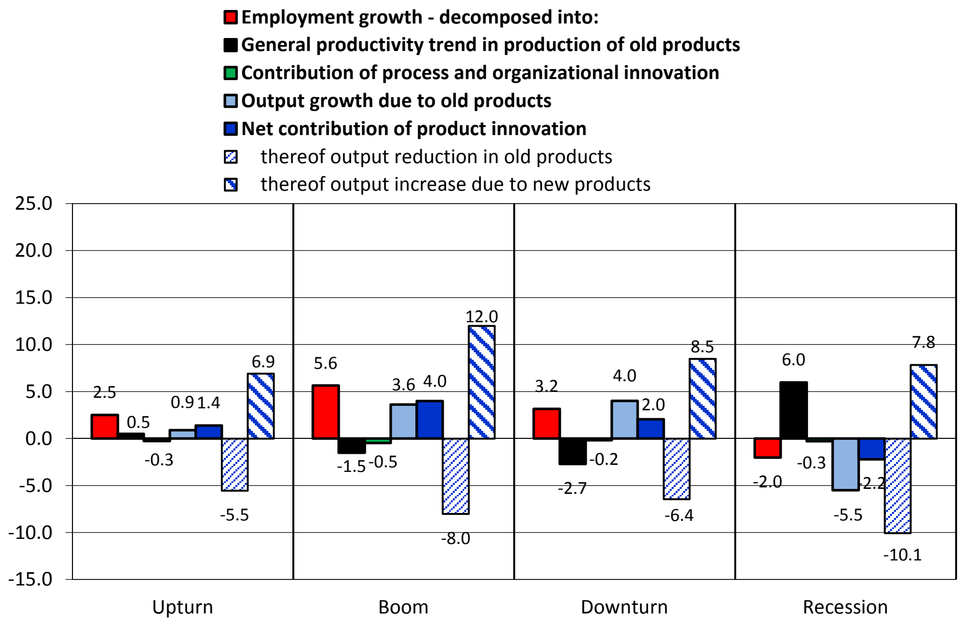
Figure 8.2, Figure 8.3 and Figure 8.4 illustrate the decomposition of employment growth for the three regions. In all three regions, product innovation tends to create much more employment due to the demand effect than it destroys due to the productivity effect and substitution effects between old and new products in upturns, booms and downturns. That is, the net employment contribution of product innovation is positive in these three phases of the business cycle and not surprisingly the net effect is highest in boom periods in all three regions.

At the European level results have shown that, despite the positive contribution of product innovation, old products are the main driver of employment changes (see section 5). This result is confirmed for South and East Europe where we find the contribution of sales growth due to old products to be larger than the net contribution of product innovation. In contrast to that we find product innovation to play a more important role in firm growth in North-western European countries. That is, in upturns, product innovation is the main contributor to employment growth accounting for roughly half of the increase in employment. In boom periods, new and old products contribute to employment growth to a similar extent.

A second main finding from section 5 was that product innovation has a stabilizing effect in recessions. That is, the absolute employment creation effects of product innovation shrink and become negative in recessions but less than those of old products. This finding is corroborated for all three regions. Employment losses were smallest for product innovators in North-western European countries whereas employment losses due to old products were particularly large in East and South Europe.

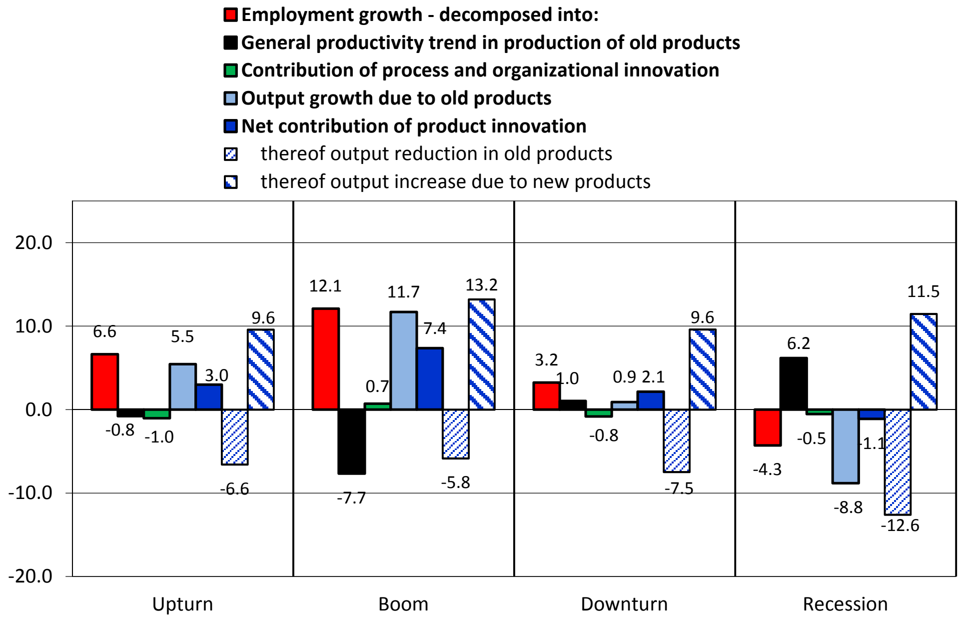
Results at the European level have also pointed towards major labour hoarding effects during the recession periods. The general productivity trend shows that this effect can also be observed when we split the sample into three regions. This effect varies between 6% in North-western European countries and 10% in East Europe.

**Figure 8.2: Contribution of innovation to employment growth in manufacturing in North-west Europe, 1998-2010**



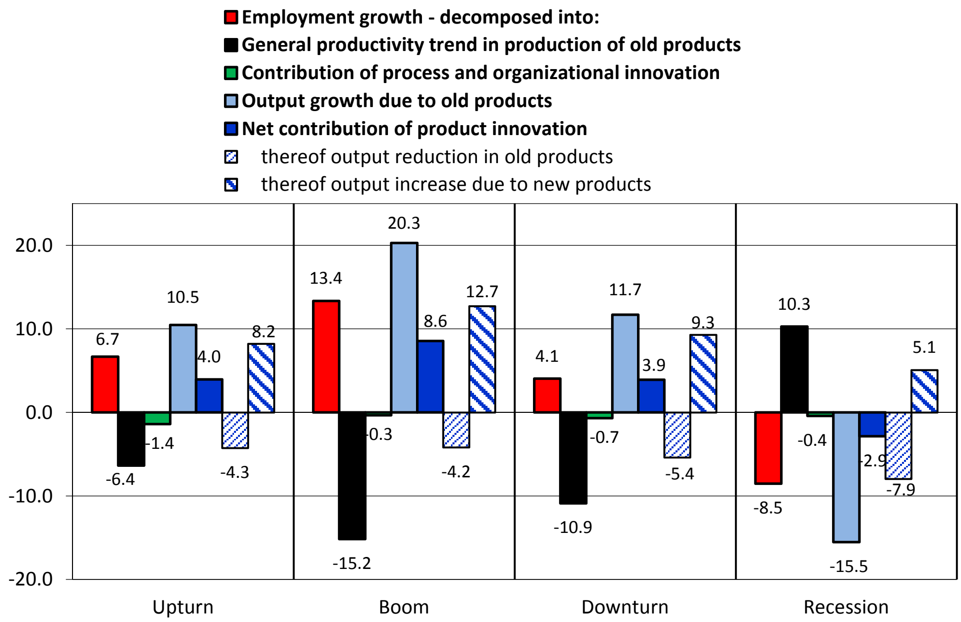

*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

**Figure 8.3: Contribution of innovation to employment growth in manufacturing in South Europe, 1998-2010**




*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

**Figure 8.4: Contribution of innovation to employment growth in manufacturing in East Europe, 1998-2010**




*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

Table 8.2 shows corresponding estimation results for services. Product innovation also significantly affects employment growth in services. It turns out the coefficients do not vary much across different stages of the business cycle and they are not significantly different from 1 in all cases, except for South Europe in boom periods. That is, in general, an increase in sales growth due to new products of 1% leads to an increase in gross employment by 1%. Or to put differently, in general new products are produced with the same efficiency and thus labour input per unit than old products.

Like in manufacturing, process and organizational innovation only play a minor role for employment creation in services in North-western European countries. The effects turn out to be not significant. Only in the recession period, we find organizational innovators to experience significantly higher employment growth than non-innovators.

Also like in manufacturing, we find the effect of organizational innovation to be mostly negative in South and East Europe though they are in general less significant than for manufacturing. The only exception is again the boom period in South Europe. For process innovation, we do not find a clear pattern in both regions across different stages of the business cycle.

Figure 8.5, Figure 8.6 and Figure 8.7 illustrate the decomposition of employment growth in service firms from North-west, South and East Europe. We find similar results as in manufacturing.

**Table 8.2: Impact of innovation on employment growth in services by region, 1998-2010**

| | North-west Europe | | | | South Europe | | | | East Europe | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Upturn** | **Boom** | **Downturn** | **Recession** | **Upturn** | **Boom** | **Downturn** | **Recession** | **Upturn** | **Boom** | **Downturn** | **Recession** |
| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** | **(7)** | **(8)** | **(9)** | **(10)** | **(11)** | **(12)** |
| SGR | 1.034*** | 0.780*** | 0.973*** | 1.055*** | 0.943*** | 0.822*** | 1.128*** | 1.031*** | 0.935*** | 0.999*** | 0.980*** | 0.918*** |
| _NEWPD | (0.076) | (0.150) | (0.066) | (0.056) | (0.064) | (0.105) | (0.082) | (0.033) | (0.069) | (0.060) | (0.045) | (0.060) |
| PCONLY | 0.057 | -2.807 | 0.392 | -0.481 | -2.244* | -6.271** | 3.947** | 0.130 | -1.466 | 3.319 | -4.307** | -1.072 |
| | (2.724) | (5.696) | (1.333) | (1.535) | (1.278) | (2.486) | (1.612) | (0.840) | (2.882) | (2.092) | (2.030) | (2.252) |
| ORGA | -1.870 | 0.142 | -1.581 | 1.599* | -2.490** | 4.855** | -2.477 | -0.853 | 0.827 | -2.814 | -1.902 | -2.431** |
| | (1.288) | (2.411) | (1.049) | (0.920) | (1.053) | (2.071) | (1.532) | (0.771) | (3.300) | (2.067) | (1.435) | (1.152) |
| GDPGR | -0.915 | 1.413 | 2.476*** | -1.093 | -1.709*** | 8.202** | -0.790*** | -0.875*** | 2.871 | 1.288 | -0.399* | -0.575*** |
| | (0.707) | (0.873) | (0.262) | (1.242) | (0.395) | (3.644) | (0.252) | (0.268) | (2.055) | (1.283) | (0.210) | (0.106) |
| MEDIUM | -5.861*** | -1.651 | -2.494*** | -4.498*** | -3.031* | -1.715 | -3.032*** | -3.146*** | -4.753*** | -2.245 | -3.765** | -4.877*** |
| | (1.330) | (2.190) | (0.828) | (0.876) | (1.808) | (1.551) | (0.833) | (0.874) | (1.630) | (1.946) | (1.602) | (0.822) |
| LARGE | -9.590*** | -5.375** | -3.522* | -5.788*** | 0.083 | -5.068 | -6.286*** | -2.063 | -8.121*** | 3.468 | -7.868*** | -7.183*** |
| | (2.490) | (2.263) | (1.936) | (1.678) | (1.923) | (3.174) | (1.745) | (1.355) | (2.562) | (3.760) | (2.056) | (1.071) |
| DGP | 1.557 | 2.938 | -0.249 | 1.497 | -3.134* | 0.715 | -0.643 | -0.794 | -3.502 | 4.020 | 4.881** | -2.049 |
| | (1.706) | (2.096) | (0.873) | (0.975) | (1.705) | (1.044) | (0.874) | (1.012) | (2.841) | (2.446) | (2.264) | (1.620) |
| FGP | 0.702 | -0.788 | 0.800 | 3.732*** | -8.452*** | -2.212 | -0.851 | -2.467 | -9.196*** | -1.287 | 0.299 | -2.028* |
| | (1.820) | (3.108) | (1.265) | (1.357) | (1.720) | (3.540) | (0.918) | (1.506) | (2.803) | (1.489) | (2.308) | (1.176) |
| Constant | 8.821 | -9.699** | -12.223*** | 2.903 | 10.845*** | -83.815** | 9.920*** | 5.130*** | -21.060 | -23.936 | -0.539 | 15.016*** |
| | (6.180) | (4.856) | (1.093) | (2.302) | (1.797) | (36.065) | (1.060) | (0.984) | (17.738) | (19.348) | (4.211) | (0.908) |

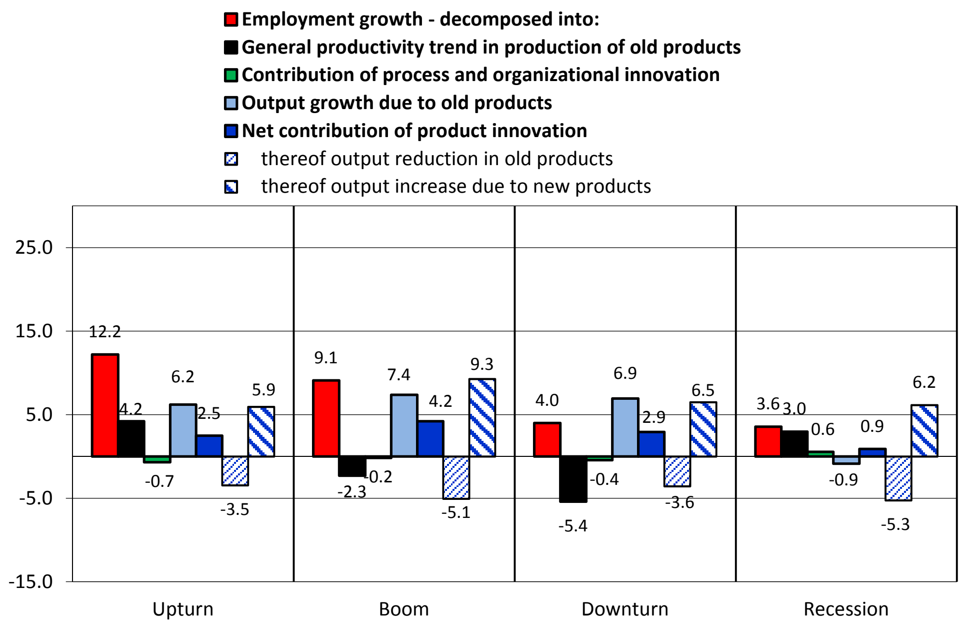
*Notes: Weighted IV regression. This table reports only the results of the main variables of interest. The full set of results can be found in the Table appendix,Table 11.20, Table 11.21 and Table 11.22.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation*

First, in all three regions the net contribution of product innovation to employment growth is positive in upturn, boom and downturn periods. The effect is strongest in boom phases though the net effect of product innovation is rather stable in North-west and South Europe. The business cycle dependency is stronger in East Europe. At first glance, this might contradict our finding in terms of innovation engagement which shows a rather stable innovation activity in East Europe over the business cycle. This finding can be explained by the fact that innovation success, measured as the sales growth due to new products, shows stronger fluctuations over the business cycle. Notably, even in recessions product innovator show on average a positive employment growth in North-west Europe.

The finding, that despite the positive net contribution of product innovation, old products are the main driver of employment changes, is also confirmed for all three regions in services. The importance of old products is particularly strong in South and East Europe, and less so for North-west Europe.

The stabilizing effect of product innovation in recessions is also confirmed in services for all three regions. This effect is particularly strong in East and South Europe where the sales due to old products for non-product innovators and as a result employment have declined to a considerable extent (-5.6% and -14.3%). This decline was much smaller for product innovators and could be accounted for by employment stimulating effects from sales with new products. As a result they slightly increase employment (+0.1%) or only reduce employment by -1.5%.

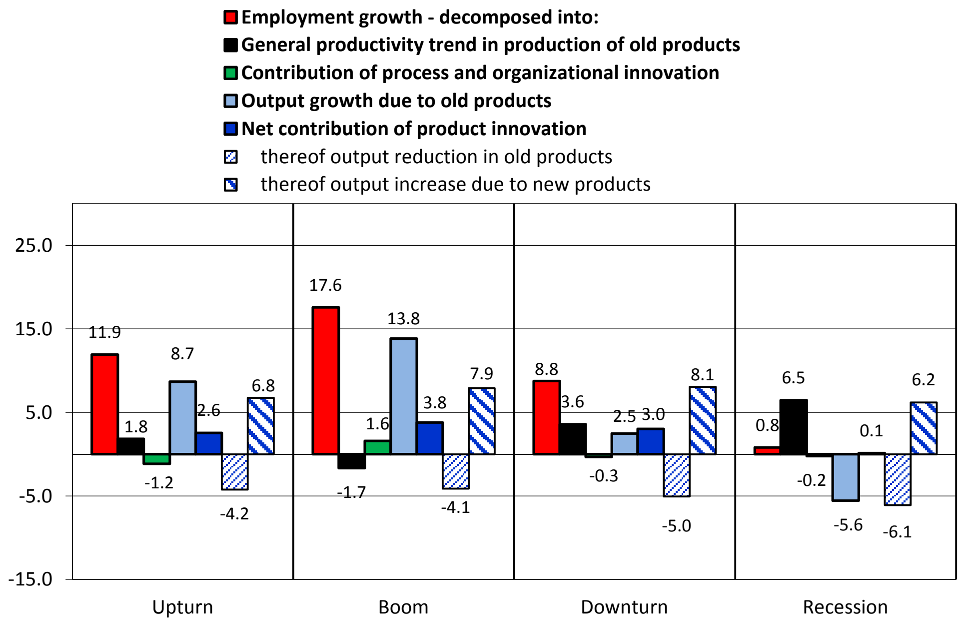
**Figure 8.5: Contribution of innovation to employment growth in services in North-west Europe, 1998-2010**




*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

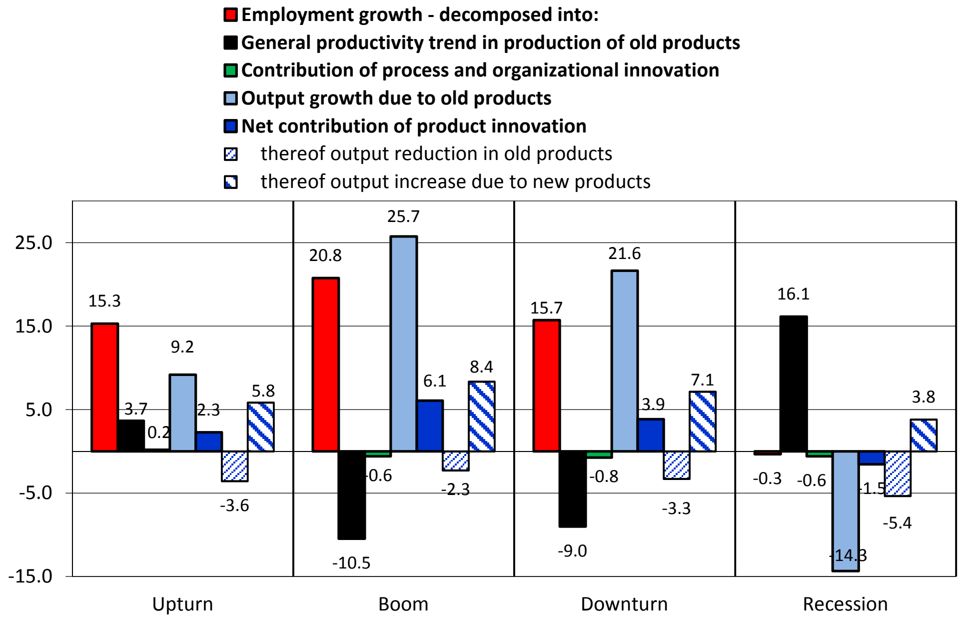
Finally, results also point towards labour hoarding in services in all three regions. Compared to manufacturing, this effect is more dispersed across the three regions, but the effect is again smallest in North-west Europe (3%), followed by South Europe (6.5%) and East Europe (16%).

**Figure 8.6: Contribution of innovation to employment growth in services in South Europe, 1998-2010**




*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

**Figure 8.7: Contribution of innovation to employment growth in services in East Europe, 1998-2010**




*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

**Table 8.3: Contribution of innovation to employment growth over the business cycle by region, 1998-2010**

| | North-west Europe | | | | South Europe | | | | East Europe | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Upturn | Boom | Down-turn | Reces-sion | Upturn | Boom | Down-turn | Reces-sion | Upturn | Boom | Down-turn | Reces-sion |
| | Manufacturing | | | | | | | | | | | |
| **Employment growth** | **2.5** | **5.6** | **3.2** | **-2.0** | **6.6** | **12.1** | **3.2** | **-4.3** | **6.7** | **13.4** | **4.1** | **-8.5** |
| *Decomposed into* | | | | | | | | | | | | |
| **(1) General productivity trend in production of old products** | **0.5** | **-1.5** | **-2.7** | **6.0** | **-0.8** | **-7.7** | **1.0** | **6.2** | **-6.4** | **-15.2** | **-10.9** | **10.3** |
| **(2) Gross effect of process innovations related to old products** | **-0.3** | **-0.2** | **-0.2** | **0.1** | **-0.2** | **0.4** | **-0.1** | **0.2** | **0.0** | **0.0** | **-0.3** | **-0.2** |
| **(3) Gross effect of organizational innovation** | **0.0** | **-0.3** | **0.1** | **-0.3** | **-0.9** | **0.3** | **-0.8** | **-0.7** | **-1.4** | **-0.4** | **-0.3** | **-0.3** |
| **(4) Output growth of old products for non-product innovators** | **0.9** | **3.6** | **4.0** | **-5.5** | **5.5** | **11.7** | **0.9** | **-8.8** | **10.5** | **20.3** | **11.7** | **-15.5** |
| (4a) Thereof for non-innovators | 0.4 | 2.7 | 3.1 | -4.6 | 3.8 | 9.5 | 0.1 | -7.7 | 9.7 | 17.2 | 10.1 | -14.5 |
| (4b) Thereof for process innovators | 0.5 | 1.0 | 0.9 | -0.9 | 1.6 | 2.2 | 0.8 | -1.1 | 0.8 | 3.1 | 1.6 | -1.0 |
| **(5) Net contribution of product innovations** | **1.4** | **4.0** | **2.0** | **-2.2** | **3.0** | **7.4** | **2.1** | **-1.1** | **4.0** | **8.6** | **3.9** | **-2.9** |
| (5a) Thereof output reduction in old products | -5.5 | -8.0 | -6.4 | -10.1 | -6.6 | -5.8 | -7.5 | -12.6 | -4.3 | -4.2 | -5.4 | -7.9 |
| (5b) Thereof output increase in new products | 6.9 | 12.0 | 8.5 | 7.8 | 9.6 | 13.2 | 9.6 | 11.5 | 8.2 | 12.7 | 9.3 | 5.1 |
| | Services | | | | | | | | | | | |
| **Employment growth** | **12.2** | **9.1** | **4.0** | **3.6** | **11.9** | **17.6** | **8.8** | **0.8** | **15.3** | **20.8** | **15.7** | **-0.3** |
| *Decomposed into* | | | | | | | | | | | | |
| **(1) General productivity trend in production of old products** | **4.2** | **-2.3** | **-5.4** | **3.0** | **1.8** | **-1.7** | **3.6** | **6.5** | **3.7** | **-10.5** | **-9.0** | **16.1** |
| **(2) Gross effect of process innovations related to old products** | **0.0** | **-0.2** | **0.0** | **0.0** | **-0.3** | **-0.6** | **0.4** | **0.0** | **-0.1** | **0.3** | **-0.3** | **-0.1** |
| **(3) Gross effect of organizational innovation** | **-0.7** | **0.1** | **-0.5** | **0.6** | **-0.9** | **2.2** | **-0.8** | **-0.3** | **0.3** | **-0.9** | **-0.5** | **-0.5** |
| **(4) Output growth of old products for non-product innovators** | **6.2** | **7.4** | **6.9** | **-0.9** | **8.7** | **13.8** | **2.5** | **-5.6** | **9.2** | **25.7** | **21.6** | **-14.3** |
| (4a) Thereof for non-innovators | 5.5 | 6.0 | 6.0 | -1.2 | 7.0 | 12.1 | 1.7 | -5.1 | 8.7 | 22.9 | 19.6 | -13.5 |
| (4b) Thereof for process innovators | 0.8 | 1.3 | 0.9 | 0.3 | 1.7 | 1.7 | 0.7 | -0.4 | 0.5 | 2.8 | 2.0 | -0.8 |
| **(5) Net contribution of product innovations** | **2.5** | **4.2** | **2.9** | **0.9** | **2.6** | **3.8** | **3.0** | **0.1** | **2.3** | **6.1** | **3.9** | **-1.5** |
| (5a) Thereof output reduction in old products | -3.5 | -5.1 | -3.6 | -5.3 | -4.2 | -4.1 | -5.0 | -6.1 | -3.6 | -2.3 | -3.3 | -5.4 |
| (5b) Thereof output increase in new products | 5.9 | 9.3 | 6.5 | 6.2 | 6.8 | 7.9 | 8.1 | 6.2 | 5.8 | 8.4 | 7.1 | 3.8 |

*Notes: Decomposition based on regressions of Table 8.1 and Table 8.2.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation*

# Chapter 9. INNOVATION AND EMPLOYMENT GROWTH – PANEL DATA EVIDENCE FOR GERMANY

This section investigates the impact of innovation on employment growth for German firms. Unfortunately, Eurostat CIS data does not allow us to trace firms over time and hence e.g. to control for individual heterogeneity. In order to address this issue and check whether this has an impact on the main conclusions that we have drawn so far, this section makes use of the German Mannheim Innovation Panel (MIP, see subsection 3.3). It extends the analysis on EU level presented in section 5.4, in the following four dimensions:

- Accounting for individual heterogeneity: The German MIP data set is constructed as a panel data set. We will exploit this type of information and control for unobserved individual heterogeneity among firms. Individual heterogeneity is an important factor that should be taken into account since it may explain a considerable share of the total variance in the data. In the German sample for instance it turns out that the share of total variance explained by individual effects is about 45 %.
- Including very small firms with 5-9 employees into the analysis. The target population of the German MIP data covers all firms with at least 5 employees whereas the threshold is 10 employees in CIS surveys of other countries. Assessing the impact of firms having 5-9 employees on the relationship between innovation and employment might be important since these small firms might affect the estimation results considerably as changes in the labour force due to the small size may result in large growth rates.
- Accounting for long-term effects of innovation on employment growth. The panel data structure also allows us to include longer lags and assess whether innovation has additional long-term effects.
- Testing for non-linearities. We will also use the German MIP data to investigate whether there is a non-linear relationship between product innovation and employment growth.

Since Germany is the largest single economy in Europe it is furthermore an interesting country case to study the dynamics of innovation and employment over the course of the business cycle. Before we present econometric results in section 9.2 and the decomposition analysis in section 9.3, we start by investigating whether general trends in employment growth and innovation performance over the business cycle that have been found for Europe also hold for the German economy.

## 9.1. COMPARISON OF INNOVATION PERFORMANCE AND EMPLOYMENT GROWTH BETWEEN GERMANY AND EUROPE

In contrast to the European CIS data, the German MIP data allows us to exploit a longer time period. The analysis covers the time period from 1994-2012. Table 9.1 and Table 9.2 present descriptive statistics for the sample of firms used to estimate the effect of innovation on employment growth over the business cycle. The statistics are differentiated by sector (manufacturing versus services) and phases of the business cycle. Like for most of the European exercises we use the 4-phases two-year business cycle indicator.

**Table 9.1: Descriptive statistics, sample of German manufacturing firms, 1994-2012**

| | Upturn | | Boom | | Downturn | | Recession | | Total | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | SD | Mean | SD | Mean | SD | Mean | SD | Mean | SD |
| EMPGR | 0.48 | 15.69 | 2.37 | 15.50 | 2.03 | 15.28 | -1.35 | 15.50 | 0.75 | 15.56 |
| SGR_NEWPD | 17.12 | 26.34 | 14.91 | 23.24 | 17.18 | 26.68 | 11.59 | 20.38 | 15.50 | 24.82 |
| SGR_OLDPD | -5.89 | 32.17 | -2.67 | 29.83 | -8.72 | 31.28 | -16.10 | 26.91 | -8.75 | 30.73 |
| PRICE GROWTH | 3.78 | 12.56 | 3.49 | 9.11 | 5.02 | 16.05 | 1.51 | 13.21 | 3.55 | 13.51 |
| PCONLY | 0.09 | 0.29 | 0.08 | 0.27 | 0.08 | 0.28 | 0.10 | 0.29 | 0.09 | 0.28 |
| SMALL | 0.44 | 0.50 | 0.41 | 0.49 | 0.43 | 0.50 | 0.47 | 0.50 | 0.44 | 0.50 |
| MEDIUM | 0.33 | 0.47 | 0.34 | 0.47 | 0.34 | 0.47 | 0.33 | 0.47 | 0.34 | 0.47 |
| LARGE | 0.22 | 0.42 | 0.25 | 0.43 | 0.22 | 0.42 | 0.20 | 0.40 | 0.22 | 0.42 |
| DUF | 0.65 | 0.48 | 0.66 | 0.48 | 0.65 | 0.48 | 0.68 | 0.47 | 0.66 | 0.47 |
| DGP | 0.25 | 0.43 | 0.24 | 0.43 | 0.26 | 0.44 | 0.24 | 0.42 | 0.25 | 0.43 |
| FGP | 0.10 | 0.30 | 0.10 | 0.30 | 0.09 | 0.28 | 0.09 | 0.28 | 0.10 | 0.29 |
| *Instruments* | | | | | | | | | | |
| RANGE | 0.32 | 0.47 | 0.38 | 0.49 | 0.34 | 0.47 | 0.29 | 0.45 | 0.33 | 0.47 |
| RD | 0.37 | 0.48 | 0.36 | 0.48 | 0.36 | 0.48 | 0.34 | 0.47 | 0.36 | 0.48 |
| Obs | 6,004 | | 2,530 | | 5,395 | | 4,440 | | 18,369 | |

*Notes: SD denotes the standard deviation. Industry dummies are not reported. Statistics presented for the sample of firms used for instrumental variable regressions with fixed effects (IVFE), see Table 9.1.*
*Source: Mannheim Innovation Panel, own calculation.*

Employment growth has been significantly lower in Germany during upturn, boom and downturn periods compared to the EU. This observation is particularly pronounced in the service sector. On the contrary, during recessions the negative employment growth in Germany is significantly lower in manufacturing whereas there is almost no difference between the employment growth in the service sector between Germany and the EU. Despite differences in the level of employment growth, we corroborate a clear pro-cyclical pattern of employment growth in Germany as well; that is higher (lower) average employment growth rates are experienced during boom (recession) periods. Like for Europe as a whole, we find that German manufacturing firms cut jobs during recessions while the average employment growth is smaller but still positive for service firms.

In German manufacturing, the share of product innovators is about 51% compared to 29% in German services. In particular for product innovation these numbers turn out to be higher than the respective shares in Europe. Concerning the innovation performance it furthermore turns out that German firms yield a higher average sales growth due to new products (*SGR_NEWPD*) than the average European firm (see Figure 5.8 in section 5.4.3). In manufacturing, we observe a total mean value of about 15.5 % compared to 9.4% in Europe. In services, the difference is smaller with 8.4% compared to 7.3%. This lead in innovation performance is observed during all phases of the business cycle with the exception of boom periods in services. Despite differences in the level of innovation performance, it turns out that the innovation performance is comparable with respect to its movement over the business cycle. That is, innovation performance of German firms also shows a pro-cyclical pattern though it is not as stringent as at the European level. In services, the average sales growth due to new products is slightly higher during upturn and boom periods (about 9 %) than during downturn and recession periods (about 7.5 %). In manufacturing, firms least benefit from product innovation in terms of increasing sales during recession periods. A bit surprising is the relatively weak innovation performance during boom periods in manufacturing.[22] Overall, however, German data mirrors the finding at the European level that the sales growth due to new products is relatively less affected by the business cycle, a bit more in manufacturing than in services.

**Table 9.2: Descriptive statistics, sample of German service firms, 1994-2012**

| | Upturn | | Boom | | Downturn | | Recession | | Total | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | SD | Mean | SD | Mean | SD | Mean | SD | Mean | SD |
| EMPGR | 2.28 | 19.92 | 4.3 | 19.52 | 2.75 | 18.85 | 1.36 | 19.05 | 2.44 | 19.36 |
| SGR_NEWPD | 9.15 | 22.28 | 8.81 | 21.67 | 8.30 | 20.47 | 7.13 | 18.59 | 8.35 | 20.80 |
| SGR_OLDPD | -2.55 | 30.36 | -1.58 | 28.41 | -2.81 | 27.96 | -5.33 | 28.09 | -3.21 | 28.88 |
| PRICE GROWTH | 2.96 | 4.68 | 4.61 | 2.65 | 2.65 | 5.27 | 2.29 | 4.67 | 3.32 | 4.72 |
| PCONLY | 0.13 | 0.33 | 0.12 | 0.32 | 0.11 | 0.31 | 0.13 | 0.34 | 0.12 | 0.33 |
| SMALL | 0.60 | 0.49 | 0.60 | 0.49 | 0.59 | 0.49 | 0.59 | 0.49 | 0.59 | 0.49 |
| MEDIUM | 0.24 | 0.43 | 0.24 | 0.43 | 0.24 | 0.43 | 0.24 | 0.43 | 0.24 | 0.43 |
| LARGE | 0.16 | 0.37 | 0.15 | 0.36 | 0.17 | 0.37 | 0.17 | 0.37 | 0.16 | 0.37 |
| NOGP | 0.73 | 0.44 | 0.73 | 0.44 | 0.73 | 0.44 | 0.74 | 0.44 | 0.73 | 0.44 |
| DGP | 0.23 | 0.42 | 0.22 | 0.42 | 0.23 | 0.42 | 0.23 | 0.42 | 0.23 | 0.42 |
| FGP | 0.04 | 0.19 | 0.04 | 0.21 | 0.04 | 0.19 | 0.03 | 0.18 | 0.04 | 0.19 |
| *Instruments* | | | | | | | | | | |
| RANGE | 0.18 | 0.39 | 0.22 | 0.41 | 0.17 | 0.37 | 0.15 | 0.36 | 0.17 | 0.38 |
| RD | 0.16 | 0.37 | 0.15 | 0.36 | 0.15 | 0.36 | 0.16 | 0.36 | 0.16 | 0.36 |
| Observations | 4,654 | | 1,889 | | 4,033 | | 3,676 | | 14,252 | |

*Notes: Columns with heading SD display the standard deviation. Industry dummies are not included. Statistics presented for the sample of firms used for instrumental variable regressions with fixed effects (IVFE), see Table 9.1.*
*Source: Mannheim Innovation Panel, own calculation.*

A difference compared to the European results relates to the negative average sales growth rates due to old products over all phases of the business cycle. This can be explained by the larger proportion of innovators in Germany and the fact that for about 80% of the product innovators the sales growth due to old products is negative because of the replacement of old with new products. Like in Europe as a whole we observe a sharp decline in the sales growth rate due to old products in Germany during the recession. This fall has been much stronger in manufacturing and was larger than the increase in demand with new products. In services, the demand increase in new products was on average still larger than the loss of demand for old products.

For the instrument variables *RANGE* and *RD* we observe significantly higher shares in the manufacturing sample. Recall that *RANGE* measures whether the product innovation was aimed at increasing the product range. The data show that regardless of the sector a higher share of firms innovate products in order to increase the product range during boom phases while in recession phases the shares are lowest. The share of firms performing continuous R&D activities as measured by *RD* is stable throughout the business cycle for both samples.

The descriptive statistics furthermore reveal some structural differences between manufacturing and service firms. We find a higher share of mere process innovators in the service

[22] One of the few boom periods in the sample was the period 1998-2000. Changes in the CIS 3 questionnaire have led to a decline in the share of sales with new products from this time onwards and might partly explain the lower value for the sales growth rate due to new products.

sample. Regardless of industry affiliation the share is relatively constant over the business cycle. The same pattern is observed for the share of small firms, i.e. firms with less than 50 employees and for the share of firms that do not belong to an enterprise group. The share of these firms among the service firms is higher compared to manufacturing. Correspondingly, in the manufacturing sample we observe a higher share of medium and large firms and of firms belonging to domestic or foreign enterprise groups.

## 9.2. ECONOMETRIC EVIDENCE

This section investigates the impact of innovation on employment growth for German firms. As mentioned, it extends the analysis on EU level in four dimensions: accounting for individual heterogeneity, including very small firms with 5-9 employees, accounting for long-term effects of innovation on employment growth, and testing for non-linearities.

### 9.2.1. Accounting for individual heterogeneity

Like in section 5.4, we estimate equation (5.3) (see section 5.1) separately for manufacturing and services. However, our model specification deviates in two aspects: First, we only consider the effect of product innovation and process innovation (SGR_NEWPD, PCONLY) and leave out organisational innovations as the variable is not continuously available for the time span we are interested in.[23] Second, due to the lower number of observations we do not estimate the model separately for all four phases but instead include dummy variables indicating different phases of the business cycle (GDPGR_i with $i = D$ (downturn), $U$ (upturn), $B$ (boom)) and interaction terms between the innovation variables and the business cycle dummies. The recession period is the reference business cycle phase in the estimation. As controls we likewise include firm size dummies (LARGE, MEDIUM), ownership dummies (DGP, FGP), and industry dummies but we have to leave out time dummies. The independent variables are defined as described in section 5.2.4. As already explained, we do not observe firm-level price changes and use price deflators at the industry level instead. In contrast to the previous estimations, we use producer price indices not at the country but at the industry level (4-, 3- and 2-digit NACE rev. 2).[24]

Our estimation strategy is as follows: First, we conduct OLS estimations as baseline estimations (columns (1) and (5) of Table 9.3). Then we apply fixed effects estimations in order to control for individual heterogeneity of the firms (columns (2) and (6) of Table 9.3). Subsequently, we conduct instrumental variables estimations to examine the impact of endogeneity on the estimated effects. Again, we provide estimation results without considering individual heterogeneity (columns (3) and (7)) and with taking account of individual heterogeneity (columns (4) and (8)).

For the instrumental variable estimations described in section 5.2 we applied the instruments RANGE which is defined as a dummy variable indicating whether the product innovation was aimed at increasing the product range (0/1) and RD which reflects continuous R&D activities of a firm (0/1). As we have interaction terms of SGR_NEWPD we also have to instrument these interactions. In order to do so we have to include additional instruments as otherwise it would be impossible to identify the endogenous variables. Hence, we used interactions between *RANGE* and the business cycle dummy variables as further instruments.

Recall that the coefficient of the sales growth rate due to new products (SGR_NEWPD) reflects the gross change in employment growth as a reaction to a one percent increase in

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[23] This should not have a large impact on the results. We estimated the model at the European level also without organisational innovation and all results for product and process innovation were confirmed.

[24] All indices are elaborated and published by the German Statistical Office (Destatis).

the firm's sales due to new products. In line with the findings from the European data, we also find for German firms across all specifications a positive and significant coefficient. The results illustrate that all estimated elasticities without accounting for endogeneity are considerably smaller than one. However, we expect these elasticities to be downward biased due to measurement error. As soon as we account for endogeneity by instrumenting, estimated elasticities become closer to one. The impact of individual heterogeneity on the regression results is less obvious. While the estimated coefficient decreases from OLS to fixed effect estimations for both sectors, the same effect is observed for the manufacturing sample comparing IV with IVFE results. For the service sample however, the estimated coefficient increases from IV to IVFE. The effect of individual heterogeneity on estimated coefficients after controlling for endogeneity is relatively small though. Therefore, the following discussion of the results will concentrate on the estimations using the instrumental variable approach (IV and IVFE).

Further inspection shows that using IV the coefficients of SGR_NEWPD are not significantly different from one in manufacturing. This finding is in line with the European findings and tells us that on average an increase in the sales of new products by 1 % leads to an increase in gross employment by 1 % in German manufacturing firms. That is, new products are produced with the same productivity and hence need the same labour input as the production of old products. For services the elasticity estimates are significantly smaller than one for the simple IV approach which disappears however if individual heterogeneity is accounted for. Hence, the result indicates that – as in manufacturing – new products are produced with the same productivity as old products.

Moreover the results show that all interaction terms between SGR_NEWPD and business cycle indicators become insignificant in the instrumental variable estimations. In both sectors the gross employment effect of new products (SGR_NEWPD*)* thus does not vary over the business cycle. An exception is the interaction between SGR_NEWPD and the upturn dummy variable GDPGR_U in the service sector. The estimated coefficient is weakly significant but this effect disappears if individual heterogeneity is accounted for. This again corroborates our findings at the European level where we also found elasticities that are not significantly different from one in all business cycle periods. That is, variations in employment growth over the business cycle are not dampened by productivity effects of product innovation. But product innovation impacts employment growth over the business cycle via demand and substitution effects as we will see in subsection 9.3.

Our results further confirm the finding that the displacement effect of process innovation is rather marginal. It is insignificant in most specifications regardless of the sector under investigation. Surprisingly, we find a significantly negative effect in services. But again, as we take account of individual heterogeneity this effect disappears.[25] For manufacturers we find a weakly significant effect of the interaction term between PCONLY and the downturn dummy variable *GDPGR_D* (see column (5)). This indicates that in downturn compared to the other phases of the business cycle the displacement effect of process innovations is relevant and affects employment growth for German manufacturers negatively.

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[25] Note however, that it is not possible to completely disentangle the displacement effect from the compensation effect of introducing new products for firms which introduced both, product and process innovation in the same period. Therefore it is possible that the estimated coefficient of SGR_NEWPD is underestimated if a firm introduced a new product but at the same time implemented a new process increasing efficiency in the production of old products (see also section 5.2.2).

**Table 9.3: Impact of innovation on employment growth, accounting for individual heterogeneity and endogeneity, German manufacturing and service firms, 1994-2012**

| | **Manufacturing** | | | | **Services** | | | |
|---|---|---|---|---|---|---|---|---|
| **Dep var:** | **OLS** | **FE** | **IV** | **IVFE** | **OLS** | **FE** | **IV** | **IVFE** |
| $EMP = l - (g_1 - \hat{\pi}_1)$ | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** | **(7)** | **(8)** |
| SGR_NEWPD | 0.803*** | 0.732*** | 0.951*** | 0.930*** | 0.864*** | 0.797*** | 0.864*** | 0.912*** |
| | (0.016) | (0.025) | (0.050) | (0.090) | (0.022) | (0.036) | (0.045) | (0.089) |
| PCONLY | -1.878 | -0.435 | -0.015 | 1.546 | -3.191*** | -2.171 | -2.946*** | -1.094 |
| | (1.201) | (1.798) | (1.374) | (1.734) | (1.079) | (1.781) | (1.129) | (1.500) |
| GDPGR_D | -5.145*** | -6.253*** | -5.312*** | -4.858*** | -1.228** | -1.552* | -1.516** | -1.711** |
| | (0.529) | (0.789) | (0.931) | (1.106) | (0.565) | (0.874) | (0.743) | (0.820) |
| GDPGR_U | -9.711*** | -11.228*** | -10.431*** | -11.268*** | -2.299*** | -2.843*** | -4.540*** | -3.991*** |
| | (0.519) | (0.796) | (1.028) | (1.152) | (0.582) | (0.894) | (0.772) | (0.847) |
| GDPGR_B | -9.826*** | -11.225*** | -10.983*** | -12.161*** | -0.869 | -0.486 | -1.540* | -0.126 |
| | (0.654) | (0.976) | (1.030) | (1.230) | (0.712) | (1.113) | (0.875) | (1.043) |
| SGR_NEWPD | 0.071*** | 0.091*** | 0.016 | -0.032 | 0.001 | 0.017 | 0.053 | 0.087 |
| x GDPGR_D | (0.019) | (0.030) | (0.056) | (0.073) | (0.027) | (0.042) | (0.056) | (0.066) |
| SGR_NEWPD | 0.099*** | 0.111*** | 0.016 | -0.018 | 0.050** | 0.075* | 0.101* | 0.048 |
| x GDPGR_U | (0.017) | (0.026) | (0.060) | (0.070) | (0.025) | (0.039) | (0.055) | (0.063) |
| SGR_NEWPD | 0.092*** | 0.070** | 0.089 | 0.027 | -0.025 | 0.003 | 0.051 | -0.020 |
| x GDPGR_B | (0.024) | (0.034) | (0.060) | (0.076) | (0.032) | (0.050) | (0.058) | (0.074) |
| PCONLY | -3.089** | -3.930* | -3.236* | -4.761** | 1.391 | 1.057 | 1.886 | 2.185 |
| x GDPGR_D | (1.484) | (2.215) | (1.718) | (2.120) | (1.427) | (2.275) | (1.519) | (1.867) |
| PCONLY | 0.303 | -1.204 | -0.210 | -2.415 | 2.187 | 0.270 | 3.867** | 1.247 |
| x GDPGR_U | (1.523) | (2.214) | (1.818) | (2.142) | (1.436) | (2.263) | (1.539) | (1.817) |
| PCONLY | -0.883 | -0.431 | -0.476 | -0.064 | 0.855 | -0.811 | 1.695 | -0.583 |
| x GDPGR_B | (1.854) | (2.629) | (2.099) | (2.557) | (1.827) | (2.820) | (1.933) | (2.406) |
| Obs | 27,908 | 27,908 | 22,394 | 18,369 | 21,163 | 21,163 | 18,290 | 14,252 |

*Notes: Methods: OLS, Fixed Effects (FE), Instrumental variables (IV) and Instrumental variables with fixed effects (IVFE) estimations. ***, ** and * indicate significance at the 1%, 5% and 10% level. Reported are only the main variables of interest. Remaining variables including specification tests are presented in the Table Appendix in Table 11.23 and Table 11.24.*
*Source: Mannheim Innovation Panel, own calculation.*

Employment growth among the sample of German firms does not benefit from economic growth per se. Our estimations yield negative coefficients for all phases of the business cycle in all specifications with a larger magnitude for upturn and boom phases. This finding is counterintuitive as it suggests that compared to a recession period all other periods exhibit lower employment growth. Note however that firms' individual demand effects are already captured by the sales growth due to old and new products and by industry-specific demand effects by the industry dummies implying that other factors must be picked up by the dummy variables capturing the business cycle.

The coefficients of the size dummies (MEDIUM, LARGE) are negative in manufacturing and services regardless of the economic conditions with a larger magnitude for the coefficient of the large firms. This finding indicates that medium and large firms have a lower employment growth compared to small firms. A possible explanation for this finding is that small firms are still on the way to their optimum size and thus hire personnel whereas medium and large firms may have already reached their optimum size. In addition, employment growth in German firms is not affected by the type of ownership. Whether or not a firm belongs to domestic or a foreign-owned group does not have an impact on the employment growth.

In a nutshell, the results found at the European level using pooled cross-sectional data are confirmed when we account for individual heterogeneity in a panel of German firms.

### 9.2.2. Assessing the impact of firms having 5-9 employees

As a second robustness check we test for the impact of very small firms on the results. We run all regressions again without the firms having 5-9 employees. The results are presented in Table 9.4. Previous findings do not substantially change when we exclude the very small firms. With respect to the innovation variables we find a slight increase in the coefficient estimates. That is, in column (4) of Table 9.3 the estimated coefficient of SGR_NEWPD is 0.930 whereas it is 0.947 in column (4) of Table 9.4. For the estimations using the service sector sample the increase is from 0.912 in column (8) of Table 9.3 to 0.930 in column (8) of Table 9.4. Also for the significant coefficient estimates of PCONLY and the business cycle dummy variables we find that the exclusion of the very small firms does lead to a small increase. For the subsample of the service firms we find that in contrast to the full sample the dummy variable GDPGR_D turns insignificant. Hence, the service firms having 5-9 employees apparently exhibit lower employment growth during downturns compared to firms with 10 or more employees. Our conclusion from the findings of Table 9.4 is accordingly, that very small firms tend to have only a marginal impact on the estimated effects of innovation on employment growth.

### 9.2.3. Non-linear effects of innovation on employment

So far, we have assumed a linear relationship between innovation and employment growth. However, the link between innovation and employment growth might be more complex and non-linear. In order to test for non-linearities, we added a quadratic term of the sales growth due to new products ($SGR\_NEWPD^2$) to the model specification. Note that we only test for non-linear effects of SGR_NEWPD since it is a continuous variable. In contrast, we cannot test whether process innovation has a non-linear effect on employment growth since it is only measured as dummy variable. We therefore refrain from including squared values of PCONLY since this would not lead to meaningful results in the detection of non-linearities. We limit the presentation of the results to the findings of the instrumental variable estimations with fixed effects for the manufacturing sample. Since we did not find significant differences in the estimated elasticities of product innovation over the business cycle in section 9.2.1, we dropped the interactions between the business cycle dummy variables and innovation variables.

**Table 9.4: Impact of innovation on employment growth excluding firms with 5-9 employees, German manufacturing and service firms, 1994-2012**

| | Manufacturing | | | | Services | | | |
|---|---|---|---|---|---|---|---|---|
| **Dep var:** | **OLS** | **FE** | **IV** | **IVFE** | **OLS** | **FE** | **IV** | **IVFE** |
| $EMP = l - (g_1 - \hat{\pi}_1)$ | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** | **(7)** | **(8)** |
| SGR_NEWPD | 0.799*** | 0.726*** | 0.964*** | 0.947*** | 0.877*** | 0.841*** | 0.877*** | 0.930*** |
| | (0.016) | (0.026) | (0.054) | (0.096) | (0.024) | (0.035) | (0.048) | (0.093) |
| PCONLY | -2.591** | -1.057 | -0.432 | 1.258 | -2.353** | -1.492 | -2.129* | -0.939 |
| | (1.233) | (1.852) | (1.440) | (1.830) | (1.119) | (1.825) | (1.175) | (1.531) |
| GDPGR_D | -5.387*** | -6.394*** | -5.326*** | -4.373*** | -1.211** | -1.394 | -1.543* | -1.410 |
| | (0.562) | (0.827) | (1.028) | (1.222) | (0.601) | (0.932) | (0.802) | (0.863) |
| GDPGR_U | -10.161*** | -11.686*** | -10.625*** | -11.464*** | -1.980*** | -2.510*** | -4.038*** | -3.590*** |
| | (0.545) | (0.837) | (1.142) | (1.276) | (0.620) | (0.949) | (0.833) | (0.901) |
| GDPGR_B | -10.164*** | -11.495*** | -11.411*** | -12.574*** | -1.033 | -0.577 | -1.919** | -0.588 |
| | (0.683) | (1.013) | (1.113) | (1.333) | (0.757) | (1.163) | (0.942) | (1.097) |
| SGR_NEWPD | 0.076*** | 0.097*** | 0.005 | -0.059 | 0.010 | 0.006 | 0.060 | 0.050 |
| x GDPGR_D | (0.020) | (0.031) | (0.060) | (0.079) | (0.028) | (0.041) | (0.060) | (0.069) |
| SGR_NEWPD | 0.104*** | 0.120*** | 0.001 | -0.029 | 0.033 | 0.041 | 0.068 | 0.009 |
| x GDPGR_U | (0.018) | (0.027) | (0.065) | (0.076) | (0.027) | (0.038) | (0.058) | (0.065) |
| SGR_NEWPD | 0.085*** | 0.066* | 0.080 | 0.025 | -0.030 | -0.008 | 0.051 | -0.023 |
| x GDPGR_B | (0.025) | (0.035) | (0.064) | (0.081) | (0.034) | (0.051) | (0.062) | (0.078) |
| PCONLY | -2.764* | -3.875* | -3.230* | -5.180** | 0.408 | 0.059 | 0.851 | 0.559 |
| x GDPGR_D | (1.534) | (2.255) | (1.811) | (2.240) | (1.485) | (2.330) | (1.580) | (1.906) |
| PCONLY | 0.912 | -0.467 | 0.184 | -1.831 | 1.814 | -0.358 | 3.395** | 0.989 |
| x GDPGR_U | (1.561) | (2.244) | (1.914) | (2.248) | (1.494) | (2.347) | (1.606) | (1.866) |
| PCONLY | -0.310 | -0.018 | 0.146 | 1.000 | 0.673 | -0.729 | 1.622 | 0.056 |
| x GDPGR_B | (1.905) | (2.673) | (2.184) | (2.670) | (1.868) | (2.858) | (1.980) | (2.433) |
| Obs | 25,407 | 25,407 | 20,215 | 16,657 | 17,428 | 17,428 | 15,003 | 11,741 |

*Notes: Methods: OLS, Fixed Effects (FE), Instrumental variables (IV) and Instrumental variables with fixed effects (IVFE) estimations. ***, ** and * indicate significance at the 1%, 5% and 10% level. Reported are only the main variables of interest. Remaining variables including specification tests are presented in the Appendix in Table 11.25 and Table 11.26.*
*Source: Mannheim Innovation Panel, own calculation.*

The findings are presented in column (1) of Table 9.5. Including the squared term of SGR_NEWPD does lead to insignificant coefficient estimates of both the SGR_NEWPD as well as the $SGR\_NEWPD^2$ coefficient. All other estimates are similar to the previously presented estimations. Overall, our estimation results do not support the hypothesis of non-linear effects of innovation on employment growth.

**Table 9.5: Non-linear and long-term impact of innovation on employment growth, German manufacturing firms 1994-2012**

| | Non-Linearities | Two-Period Lag | Three-Period Lag |
|---|---|---|---|
| | (1) | (2) | (3) |
| SGR_NEWPD | 0.894 | 1.040*** | 1.132*** |
| | (0.583) | (0.098) | (0.136) |
| PCONLY | -0.578 | -1.938 | -0.853 |
| | (1.006) | (1.589) | (1.896) |
| GDPGR_D | -5.809*** | -5.930*** | -7.613*** |
| | (1.360) | (0.850) | (1.020) |
| GDPGR_U | -11.804*** | -13.316*** | -13.751*** |
| | (1.605) | (0.878) | (1.032) |
| GDPGR_B | -11.773*** | -13.582*** | -13.526*** |
| | (0.735) | (1.119) | (1.217) |
| $SGR\_NEWPD^2$ | 0.000 | | |
| | (0.011) | | |
| $SGR\_NEWPD_{t-2}$ | | 0.094*** | |
| | | (0.023) | |
| $SGR\_NEWPD_{t-3}$ | | | 0.083*** |
| | | | (0.026) |
| $PCONLY_{t-2}$ | | 1.163 | |
| | | (1.277) | |
| $PCONLY_{t-3}$ | | | 0.910 |
| | | | (1.621) |
| MEDIUM | -5.231*** | -5.008** | -3.736 |
| | (1.632) | (2.400) | (2.802) |
| LARGE | -8.086* | -6.109 | 0.810 |
| | (4.419) | (3.964) | (4.028) |
| DGP | -0.660 | 0.016 | -2.759 |
| | (1.164) | (1.566) | (1.825) |
| FGP | -1.098 | -3.513 | -7.399** |
| | (4.437) | (3.099) | (3.195) |

*Notes: IV regression with fixed effects. This table reports only the results of the main variables of interest. The full set of results and specification tests can be found in the Table appendix, Table 11.27. Source: Mannheim Innovation Panel, own calculation.*

### 9.2.4. Long-term effects of innovation on employment

In this subsection we investigate whether innovation has some additional long-run effects that we have missed in the previous estimations. So far, we have considered employment effects of innovation within a (maximum of) three-year period. However, it might well be that innovation affects employment growth over a longer period of time.

While it is sensible to assume that displacement effects of process or product innovations will not be lagging much to the time of their introduction, compensation effects of product and process innovations may appear with a certain delay. This would imply that we have underestimated the employment creation effects of innovation. Estimating the time period in which compensation effects of product innovations arise is complicated in particular due to 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.

In order to test the hypothesis of long-run effects we added lagged values of SGR_NEWPD and PCONLY, either lagged by t-2 or t-3. Note that in our dependent variable we use employment growth (EMPGR) between year t-2 and t and we relate this to the sales growth due to new products (SGR_NEWPD) between year t-2 and t. Hence, $SGR\_NEWPD_{t-2}$ measures the sales growth due to new products between t-4 and t-2. Accordingly $SGR\_NEWPD_{t-3}$ captures the innovation success for the period t-5 and t-3. Again we only show results for IVFE in manufacturing. Columns (2) and (3) in Table 9.5 report the estimation results with lagged SGR_NEWPD and PCONLY.

With respect to the long-run effect of innovation on employment growth it turns out both lagged values of SGR_NEWPD are significantly positive. Hence, our results confirm that the introduction of new products is associated with long-run effects on a firm's employment growth. As expected the coefficient of lag *t-2* is smaller than of lag *t-3* indicating fading effects over time. In contrast, we do not find significant long-run displacement effects of process innovations. In fact the coefficient estimates for the lagged values of PCONLY have a positive sign. Though not significant this may hint in the direction that process innovations have a positive effect on employment growth in the long-run by improving a firm's competitiveness.

## 9.3. DECOMPOSITION OF EMPLOYMENT GROWTH

As in section 5.4 we finish the analysis by assessing the contribution of old and new products, process innovation and general productivity trend to employment growth. Since we do not consider organizational innovation the third term in equation (5.4) is dropped.[26]

Therefore, we will decompose employment growth into:

a. the contribution of the *general trend in productivity* in the production of *old products,*

b. changes in employment due to the introduction of *process innovation* applied in the production of *old* products,

c. employment shifts which originate from the real *growth of output in old products* for firms that do *not* introduce any new products,

d. and the *net* contribution of *product innovation* to employment growth for product innovators.

The components add up to total employment growth. The components listed under (c) and (d) can be further decomposed into the contribution of non-innovators and mere process innovators as well as the output reduction in old products and the output increase in new products respectively (see section 5.4). The decomposition is carried out for all phases of the business cycle separately. Results are reported in Table 9.6. In addition, Figure 9.1 and Figure 9.2 provide a graphical illustration of the decomposition in the manufacturing and service sector, separately.

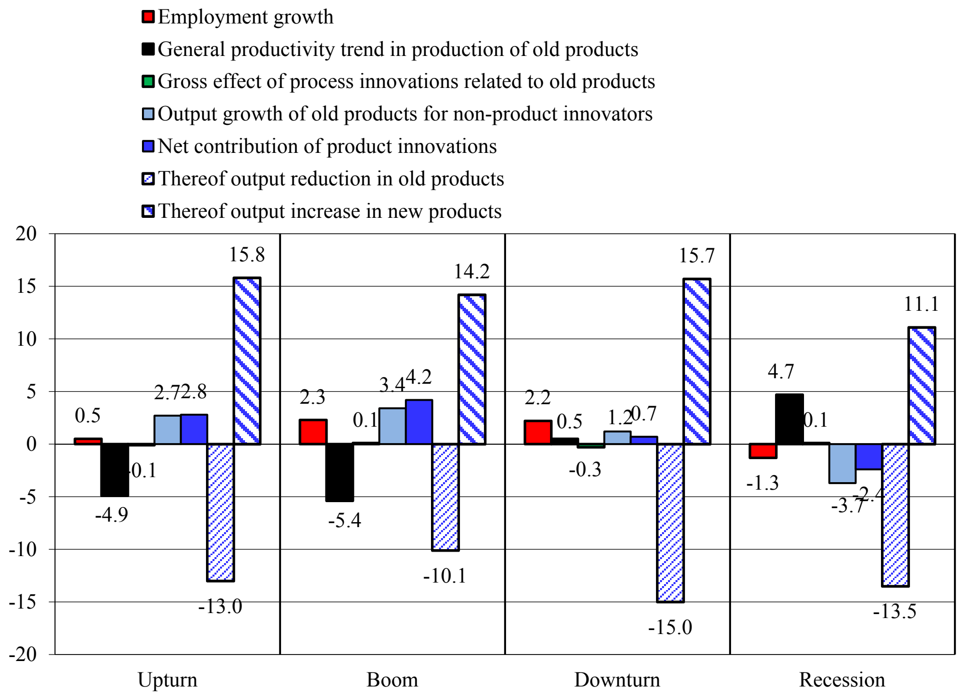
[26] Note that the European results include the contribution of organizational innovations which are not considered in the German case. The contribution of organizational innovations is very small though implying that a comparison of German and EU results is reasonable.

**Table 9.6: Decomposition of employment growth over the business cycle in Germany, manufacturing and Services 1994-2012**

| | Manufacturing | | | | Services | | | |
|---|---|---|---|---|---|---|---|---|
| | **Upturn** | **Boom** | **Down-turn** | **Reces.** | **Up-turn** | **Boom** | **Down-turn** | **Reces.** |
| **Employment growth** | **0.5** | **2.3** | **2.2** | **-1.3** | **2.5** | **4.0** | **3.4** | **1.6** |
| *Decomposed into* | | | | | | | | |
| **(1) General productivity trend** | **-4.9** | **-5.4** | **0.5** | **4.7** | **-0.8** | **2.4** | **1.2** | **2.9** |
| **(2) Gross effect of process innovation** | **-0.1** | **0.1** | **-0.3** | **0.1** | **0.0** | **-0.2** | **0.1** | **-0.1** |
| **(3) Gross effect of orga. innovation** | **2.7** | **3.4** | **1.2** | **-3.7** | **1.9** | **0.3** | **0.4** | **-1.2** |
| **(4) Output growth of old products for non-pd** | **2.0** | **2.6** | **0.5** | **-3.1** | **1.4** | **0.1** | **0.1** | **-1.5** |
| (4a) for non-innovators | 0.7 | 0.8 | 0.7 | -0.7 | 0.5 | 0.2 | 0.3 | 0.3 |
| (4b) for process innovators | 2.8 | 4.2 | 0.7 | -2.4 | 1.4 | 1.5 | 1.7 | 0.0 |
| **(5) Net contribution of product innov.** | **-13.0** | **-10.1** | **-15** | **-13.5** | **-7.7** | **-7.0** | **-7.2** | **-6.9** |
| (5a) output reduction in old prod. | 15.8 | 14.2 | 15.7 | 11.1 | 9.1 | 8.6 | 8.9 | 6.9 |
| (5b) output increase in new prod. | 0.5 | 2.3 | 2.2 | -1.3 | 2.5 | 4.0 | 3.4 | 1.6 |

*Notes: Decompositions based on regressions (4) and (8) of Table 9.3.*
*Source: Mannheim Innovation Panel, own calculations.*

**Figure 9.1: Contribution of innovation to employment growth in different phases of the business cycle in Germany, manufacturing 1994-2012**



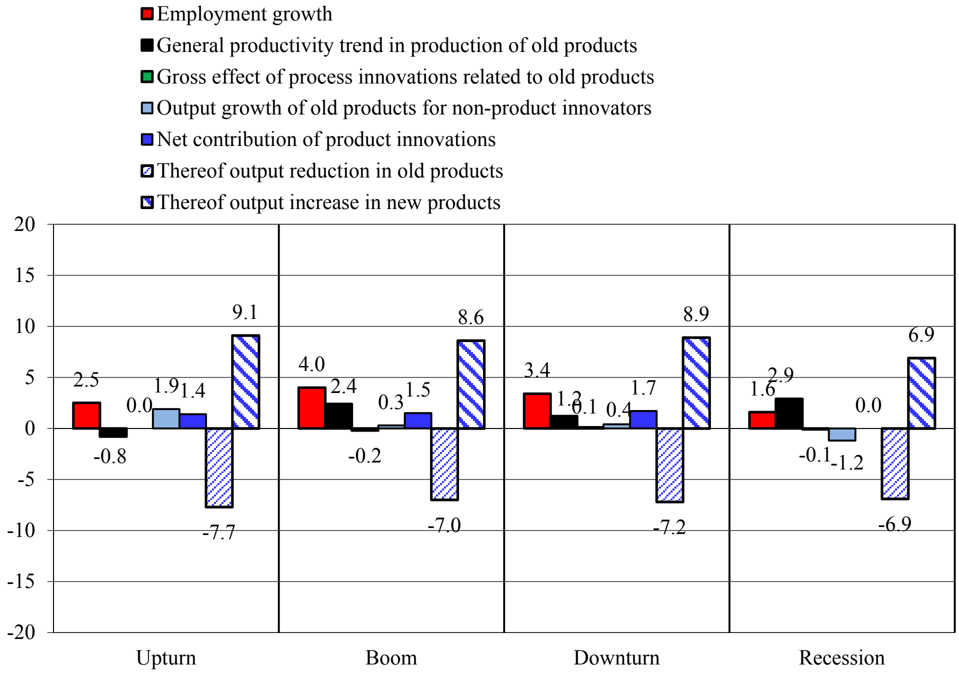

*Notes: Decomposition based on regression (4) of Table 9.3.*
*Source: Mannheim Innovation Panel; own calculation.*

For German manufacturing firms the output increase in new products is significantly higher in all business cycle phases compared to the EU average. However, this increase is accompanied by higher output reductions in old products for product innovators in Germany than in Europe, reflecting larger cannibalization effects. As a result the absolute net contribution of product innovations to employment growth is very similar for upturn and recession periods in Germany and Europe. In boom and downturn periods the net contribution of product innovations is even slightly lower than at the European level. Though the absolute net contribution of product innovation is similar, in relation to the other sources product innovation plays a much more important role for employment creation in Germany than in Europe on average. In upturn and boom phases we observe large general productivity increases that would have led to job losses of about 5%. The output growth due to old products for non-product innovators was not strong enough to compensate these losses. This implies that during both phases labour savings in the production of the old good are much more pronounced in Germany compared to the EU. The observed growth in employment in both phases can be thus traced back to the introduction of new products. Product innovations are the largest single contributor to employment growth in both phases.

In line with the findings at the European level, we find the net contribution of product innovation to be negative during the recession. But again, the employment losses of product innovators are smaller than for non-product innovators which experience a stronger decline in sales growth due to old products. The collapse in sales growth due to old products, however, was much smaller in Germany than in Europe, feeding to smaller job cuts in Germany.

Also in line with the European findings, the general productivity trend is negative in Germany during the recession which can be interpreted as a sign of labour hoarding. Surprisingly, the general productivity trend is already slightly positive in the downturn in Germany whereas it is negative in the EU. It seems that labour hoarding set in earlier in Germany.

**Figure 9.2: Contribution of innovation to employment growth in different phases of the business cycle in Germany, services 1994-2012**




*Notes: Decomposition based on regression (8) of Table 9.3.*
*Source: Mannheim Innovation Panel; own calculation.*

For services we find very similar results with respect to product innovation as for manufacturing. The output increase in new products is higher in German service firms compared to the EU average in all phases of the business cycle with the exception of the boom. Again this comes along with higher output reductions in old products for German product innovators. The net contribution of product innovation is positive and it is the largest contributor to employment growth in booms and downturns. In absolute values, however, it is smaller than in Europe.

Interestingly, the general productivity trend is positive in most of the business cycle phases. Its contribution is lower compared to the EU level and shows for most phases of the business cycle an opposite sign. The most striking difference to European service firms is however the low contribution of the output growth due to old products in Germany. There are several explanations for this finding. First, it may be that the demand for existing services is relatively stable over the course of the business cycle. Second, it may also be that non-product-innovating service firms in Germany tend to hold the number of employees constant and instead adapt the working hours to the demand changes.

To sum up, the German data reveal a slightly different pattern with respect to the sources of employment growth over the business cycle. In Europe we have found that in upturn, boom and downturn periods the main contribution to employment growth stems from output growth in old products for non-product innovators in both sectors. In Germany, product innovation plays a much more important role in creating employment growth. That is, in most cases the net contribution of product innovation exceeds the contribution of old products to employment growth. In line with the findings at the European level, we find that product innovations have an employment-preserving effect during recessions. The output decline for old products, however, was less severe during the recession in Germany. Furthermore displacement effects of process innovation play a minor role for employment growth in Germany.

# Chapter 10.
# INNOVATION AND PRODUCTIVITY GROWTH OVER THE BUSINESS CYCLE

As explained in section 2 and section 5, innovation and employment growth are closely related through productivity growth. Descriptive evidence on the evolution of firm-level productivity growth over the business cycle in general and for different types of innovators has already been presented in section 5.4.2. Furthermore, estimates on the effect of innovation on employment growth in Section 5.5 and Chapter 6 to Chapter 9 have already indirectly shown productivity effects of innovation. This section presents some further direct evidence on productivity effects of innovation over the business cycle. We will first shortly present the methodology in section10.1, followed by empirical evidence based on pooled estimates for European countries in section 10.2. Panel data evidence based on German data complements the results of this chapter in section 10.3.

### 10.1. METHODOLOGY

In order to analyze the impact of innovation on productivity, we use a well-known extended revenue-based production function approach as theoretical backbone (see Griliches 1979, Mairesse and Sassenou 1991 and Hall et al. 2010 for a survey). Most empirical studies have used a Cobb-Douglas production function:

$$(10.1)\quad Q_{it} = Ae^{\lambda_t}\, L_{it}^{\alpha}\, K_{it}^{\beta}\, M_{it}^{\delta}\, KC_{it}^{\gamma}\, e^{u_{it}}$$

where Q, M, and K denote output, material, and physical capital. L is the number of employees, λ is exogenous technological change, and u is the error term that captures unsystematic productivity shocks. In addition to the traditional input factors, the production function accounts for knowledge capital KC.

Taking logs and using small letters for log values, equation (10.1) can be written as:

$$(10.2)\quad q_{it} = a + \alpha\, l_{it} + \beta k_{it} + \delta m_{it} + \gamma_1 kc_{it} + \lambda_t + u_{it}$$

Defining the left hand side as output per employee and therefore as labour productivity, we get:

$$(10.3)\quad q_{it} - l_{it} = a + (\alpha+\beta+\delta+\gamma-1)l_{it} + \beta(k_{it}-l_{it}) + \delta(m_{it}-l_{it}) + \gamma_1(kc_{it}-l_{it}) + \lambda_t + u_{it}$$

Constant returns to scale would imply $\alpha+\beta+\delta+\gamma=1$. In addition, we can specify labour productivity growth by taking first differences:

$$(10.4)\quad \begin{aligned}\Delta(q_{it}-l_{it}) &= (\alpha+\beta+\delta+\gamma-1)\Delta l_{it} + \beta\Delta(k_{it}-l_{it}) + \delta\Delta(m_{it}-l_{it}) \\ &\quad + \gamma\ \Delta(kc_{it}-l_{it}) + \Delta\lambda_t + \Delta u_{it}\end{aligned}$$

Note that the equation in first differences also eliminates potential individual effects included in the error term $u$.

### 10.2. EVIDENCE FOR EUROPEAN COUNTRIES

This section investigates the impact of innovation on productivity in Europe. Evidence for European countries is again based on CIS data. The dependent variable is labour productivity, either measured in levels – defined as logarithm of firm sales over firm employees (LnLP) – or as growth rate (LPGR).

A flaw of CIS data is that it does not contain information on physical capital or physical investment for the whole period (only for CIS3) and on material. We can therefore only include different measures of knowledge capital. In specification (1) we focus on product innovation (PD) and process innovation (PC). The definitions of the innovation indicators are the same as in section 5.2.2. Additionally, we examine potential complementarity effects between product and process innovation. Complementarity exists if the productivity effect of performing product and process innovation simultaneously is larger than the sum of doing both activities separately. In order to test this hypothesis, we include three dummy variables for firms introducing only product innovation (PDONLY), only process innovation (PCONLY) and for those firms that simultaneously have product and process innovation (PC&PD) in specification (2). Specification (3) enriches the specification by taking account of organizational innovation (ORGA). Finally we investigate to what extent the degree of novelty matters for productivity effects of product innovation. In order to do so, we distinguish between market novelties (MN) and firm novelties (FN) in specification (3). In addition to innovation indicators, the specification includes industry, time, country, size and ownership dummies as control variables.

Results for European manufacturing are reported in Table 10.1 (labour productivity) and Table 10.2 (labour productivity growth).

The results in Table 10.1 highlight that there is a positive and significant association between innovation and firms' productivity level over all stages of the business cycle. The productivity level of innovators is roughly 10 to 25% larger than that of non-innovators. This finding holds for both product and process innovation. Furthermore, we find this pattern for all phases of the business cycle. It is particularly pronounced though in upturn, downturn and recession periods whereas it is smaller in boom periods. That is product and process innovators have less of an advantage in terms of higher productivity level than non-innovators in boom periods. In contrast, the lead to non-innovators is particularly large in recessions and for product innovators also in upturns. Comparing the productivity effect of product and process innovators, we interestingly find that the productivity lead compared to non-innovators is larger for product innovators than for process innovators in upturns and booms. In downturns it is the other way round whereas the gap is similar for product and process innovators in the recession.

The results further reveal that firms doing both product and process innovation simultaneously have a larger productivity lead compared to non-innovators than firms introducing either product or process innovation. However, the simultaneous effect is not larger than the sum of the two single effects and thus the complementarity hypothesis effect is not supported by the data.

Moreover, productivity levels are also significantly higher for organizational innovators. In all phases of the business cycle they turn out to have higher productivity than non-innovators. Organizational innovators benefit in particular in upturn and downturn periods. Again we find the smallest gap in boom periods. In general, the effect is smaller for organizational innovation than for process and product innovation in all phases of the business cycle.

Comparing different types of product innovations, we find that in general market novelties seem to be more important for productivity than new products that are new to the firm only. This finding holds for upturn and downturns. In recessions both types of product innovations are equally important.

Table 10.2 reports the impact of innovation on labour productivity growth. Indirect productivity impacts that we have inferred from the employment regressions are by and large confirmed. Note that we use the dummy variable for product innovation here instead of the sales growth rate due to new products. Despite this difference we by and large do not find an effect of product innovation on productivity growth. This coincides with the finding that the estimated elasticity in the employment model is one. We have interpreted a coefficient of one that product innovation does not have any effect on productivity growth. This is confirmed in Table 10.2.

We also confirm prior findings for process and organizational innovation across different phases of the business cycle. For process innovation the employment estimates have pointed towards significant increases in productivity – and hence to reductions in labour demand – in upturn and downturn periods. The same effect is found in Table 10.2. The magnitude of productivity effects is also nearly the same in both regressions. For instance, we estimate an increase in productivity growth of 1.9 percentage points due to the introduction of process innovations in upturns. In section 5.4 we have estimated a similar effect of 1.7 percentage points. Likewise employment growth estimates have pointed towards significant productivity effects of organizational innovations in upturn and downturn period. This finding is also corroborated by our productivity estimates. In boom periods the employment estimates did not reveal any productivity effects of organizational and process innovator. A finding that is also confirmed in Table 10.2.

Table 10.3 and Table 10.4 show corresponding results for service sector finds. Like in manufacturing we find innovators to have higher productivity levels than non-innovators. In contrast to manufacturing, process innovations matters more for productivity in services than product innovation, except for booms. Organizational innovations are particularly important in upturn and downturn phases where it shows the largest effect. In contrast the effect is smaller than the effect of process innovation is recession periods and not even significant in boom periods. In booms we only find product innovation to matter.

The results on labour productivity growth are again by and large confirmed.

**Table 10.1: Effect of innovation on labour productivity over the business cycle in Europe, manufacturing, 2000-2010**

| | Upturn | | | | Boom | | | | Downturn | | | | Recession | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (1) | (2) | (3) | (4) | (1) | (2) | (3) | (4) | (1) | (2) | (3) | (4) |
| PD | 0.157*** | | | | 0.126*** | | | | 0.128*** | | | | 0.144*** | | | |
| | (0.020) | | | | (0.023) | | | | (0.018) | | | | (0.024) | | | |
| PDONLY | | 0.228*** | 0.215*** | | | 0.144*** | 0.128*** | | | 0.218*** | 0.197*** | | | 0.167*** | 0.158*** | |
| | | (0.030) | (0.029) | | | (0.035) | (0.038) | | | (0.024) | (0.024) | | | (0.031) | (0.032) | |
| PD&PC | | 0.255*** | 0.224*** | | | 0.192*** | 0.159*** | | | 0.253*** | 0.190*** | | | 0.281*** | 0.243*** | |
| | | (0.024) | (0.023) | | | (0.032) | (0.034) | | | (0.018) | (0.019) | | | (0.027) | (0.028) | |
| PC | 0.122*** | | | 0.108*** | 0.073*** | | | 0.046 | 0.146*** | | | 0.115*** | 0.144*** | | | 0.120*** |
| | (0.018) | | | (0.019) | (0.027) | | | (0.030) | (0.017) | | | (0.019) | (0.024) | | | (0.024) |
| PCONLY | | 0.172*** | 0.150*** | | | 0.093** | 0.052 | | | 0.209*** | 0.171*** | | | 0.167*** | 0.144*** | |
| | | (0.026) | (0.026) | | | (0.040) | (0.046) | | | (0.025) | (0.026) | | | (0.034) | (0.034) | |
| ORGA | | | 0.102*** | 0.103*** | | | 0.047** | 0.049** | | | 0.122*** | 0.123*** | | | 0.075*** | 0.074*** |
| | | | (0.015) | (0.015) | | | (0.021) | (0.021) | | | (0.021) | (0.021) | | | (0.017) | (0.017) |
| PD_MN | | | | 0.121*** | | | | 0.057** | | | | 0.098*** | | | | 0.093*** |
| | | | | (0.018) | | | | (0.028) | | | | (0.024) | | | | (0.023) |
| PD_FN | | | | 0.063*** | | | | 0.086*** | | | | 0.031* | | | | 0.095*** |
| | | | | (0.016) | | | | (0.025) | | | | (0.018) | | | | (0.030) |
| MEDIUM | 0.160*** | 0.160*** | 0.153*** | 0.155*** | 0.046 | 0.046 | -0.000 | -0.000 | 0.142*** | 0.140*** | 0.133*** | 0.136*** | 0.172*** | 0.172*** | 0.165*** | 0.166*** |
| | (0.025) | (0.025) | (0.026) | (0.026) | (0.028) | (0.028) | (0.030) | (0.031) | (0.026) | (0.026) | (0.028) | (0.028) | (0.020) | (0.020) | (0.019) | (0.019) |
| LARGE | 0.151*** | 0.154*** | 0.147*** | 0.144*** | 0.194*** | 0.196*** | 0.175*** | 0.172*** | 0.136*** | 0.137*** | 0.120** | 0.119** | 0.228*** | 0.230*** | 0.214*** | 0.209*** |
| | (0.030) | (0.031) | (0.032) | (0.031) | (0.039) | (0.039) | (0.045) | (0.045) | (0.045) | (0.045) | (0.047) | (0.047) | (0.033) | (0.033) | (0.033) | (0.033) |
| DGP | 0.316*** | 0.316*** | 0.309*** | 0.310*** | 0.287*** | 0.286*** | 0.261*** | 0.263*** | 0.384*** | 0.385*** | 0.373*** | 0.372*** | 0.348*** | 0.348*** | 0.342*** | 0.342*** |
| | (0.019) | (0.019) | (0.020) | (0.020) | (0.034) | (0.034) | (0.035) | (0.035) | (0.030) | (0.030) | (0.030) | (0.030) | (0.028) | (0.028) | (0.027) | (0.027) |
| FGP | 0.604*** | 0.603*** | 0.585*** | 0.585*** | 0.560*** | 0.560*** | 0.541*** | 0.544*** | 0.648*** | 0.647*** | 0.623*** | 0.623*** | 0.642*** | 0.642*** | 0.635*** | 0.636*** |
| | (0.029) | (0.029) | (0.029) | (0.029) | (0.049) | (0.049) | (0.057) | (0.056) | (0.033) | (0.033) | (0.034) | (0.034) | (0.031) | (0.031) | (0.031) | (0.031) |
| Constant | -3.534*** | -3.540*** | -3.636*** | -3.632*** | -2.928*** | -2.929*** | -2.241*** | -2.228*** | -3.611*** | -3.622*** | -3.604*** | -3.592*** | -3.165*** | -3.168*** | -3.155*** | -3.152*** |
| | (0.083) | (0.083) | (0.085) | (0.086) | (0.064) | (0.064) | (0.116) | (0.115) | (0.068) | (0.068) | (0.071) | (0.071) | (0.081) | (0.081) | (0.074) | (0.073) |
| R2a | 0.544 | 0.544 | 0.543 | 0.542 | 0.304 | 0.304 | 0.287 | 0.287 | 0.581 | 0.581 | 0.593 | 0.592 | 0.937 | 0.937 | 0.934 | 0.934 |
| Observations | 70,632 | 70,632 | 67,682 | 67,682 | 33,778 | 33,778 | 18,295 | 18,295 | 72,749 | 72,749 | 67,371 | 67,360 | 52,495 | 52,495 | 52,326 | 52,131 |

*Notes: Weighted OLS regression. Additionally included but not reported: industry dummies, time dummies and country dummies.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

**Table 10.2: Effect of innovation on labour productivity growth over the business cycle in Europe, manufacturing, 2000-2010**

| | Upturn | | | | Boom | | | | Downturn | | | | Recession | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (1) | (2) | (3) | (4) | (1) | (2) | (3) | (4) | (1) | (2) | (3) | (4) |
| PD | -0.010 | | | | 0.005 | | | | -0.002 | | | | -0.000 | | | |
| | (0.007) | | | | (0.007) | | | | (0.005) | | | | (0.007) | | | |
| PDONLY | | -0.010 | -0.016* | | | 0.009 | 0.006 | | | 0.012* | 0.012* | | | -0.006 | -0.006 | |
| | | (0.009) | (0.010) | | | (0.010) | (0.010) | | | (0.007) | (0.007) | | | (0.008) | (0.007) | |
| PD&PC | | 0.008 | -0.010 | | | 0.002 | -0.002 | | | 0.003 | -0.004 | | | 0.012 | 0.009 | |
| | | (0.007) | (0.010) | | | (0.007) | (0.008) | | | (0.006) | (0.007) | | | (0.008) | (0.008) | |
| PC | 0.019*** | | | 0.008 | -0.002 | | | -0.007 | 0.008 | | | 0.004 | 0.011 | | | 0.008 |
| | (0.006) | | | (0.006) | (0.008) | | | (0.011) | (0.005) | | | (0.005) | (0.007) | | | (0.007) |
| PCONLY | | 0.019** | 0.009 | | | 0.001 | -0.002 | | | 0.017*** | 0.017** | | | 0.004 | 0.003 | |
| | | (0.008) | (0.008) | | | (0.008) | (0.012) | | | (0.007) | (0.007) | | | (0.010) | (0.010) | |
| ORGA | | | 0.044*** | 0.045*** | | | -0.003 | -0.003 | | | 0.009* | 0.009* | | | 0.009** | 0.009** |
| | | | (0.011) | (0.011) | | | (0.006) | (0.006) | | | (0.005) | (0.005) | | | (0.004) | (0.004) |
| PD_MN | | | | 0.007 | | | | -0.001 | | | | -0.004 | | | | -0.003 |
| | | | | (0.008) | | | | (0.007) | | | | (0.006) | | | | (0.006) |
| PD_FN | | | | -0.032*** | | | | 0.014 | | | | -0.001 | | | | 0.004 |
| | | | | (0.011) | | | | (0.009) | | | | (0.006) | | | | (0.007) |
| MEDIUM | 0.034*** | 0.034*** | 0.032*** | 0.032*** | 0.005 | 0.005 | 0.005 | 0.005 | 0.017*** | 0.016*** | 0.015*** | 0.016*** | 0.014** | 0.014** | 0.014** | 0.014** |
| | (0.007) | (0.007) | (0.007) | (0.007) | (0.006) | (0.006) | (0.008) | (0.008) | (0.005) | (0.005) | (0.005) | (0.005) | (0.006) | (0.006) | (0.005) | (0.005) |
| LARGE | 0.068*** | 0.068*** | 0.063*** | 0.063*** | 0.028*** | 0.028*** | 0.034*** | 0.033*** | 0.026*** | 0.026*** | 0.022*** | 0.022*** | 0.034*** | 0.033*** | 0.032*** | 0.032*** |
| | (0.011) | (0.011) | (0.010) | (0.010) | (0.009) | (0.009) | (0.010) | (0.011) | (0.007) | (0.007) | (0.007) | (0.007) | (0.007) | (0.008) | (0.007) | (0.007) |
| DGP | 0.016** | 0.016** | 0.010 | 0.010 | -0.020** | -0.020** | -0.024** | -0.024** | -0.005 | -0.005 | -0.006 | -0.006 | -0.011* | -0.011* | -0.012* | -0.012* |
| | (0.008) | (0.008) | (0.008) | (0.008) | (0.008) | (0.008) | (0.010) | (0.010) | (0.005) | (0.005) | (0.006) | (0.006) | (0.007) | (0.007) | (0.007) | (0.007) |
| FGP | 0.006 | 0.006 | 0.000 | 0.000 | -0.008 | -0.009 | -0.007 | -0.007 | -0.002 | -0.002 | -0.005 | -0.004 | 0.023*** | 0.023*** | 0.022*** | 0.022*** |
| | (0.008) | (0.008) | (0.008) | (0.008) | (0.008) | (0.008) | (0.010) | (0.010) | (0.006) | (0.006) | (0.006) | (0.006) | (0.007) | (0.007) | (0.007) | (0.007) |
| Constant | 0.200*** | 0.200*** | 0.322*** | 0.321*** | 0.140*** | 0.140*** | 0.054*** | 0.055*** | 0.237*** | 0.236*** | 0.229*** | 0.231*** | 0.096*** | 0.097*** | 0.096*** | 0.095*** |
| | (0.033) | (0.033) | (0.048) | (0.048) | (0.018) | (0.018) | (0.019) | (0.019) | (0.019) | (0.019) | (0.019) | (0.019) | (0.021) | (0.021) | (0.021) | (0.021) |
| R2a | 0.185 | 0.185 | 0.191 | 0.192 | 0.052 | 0.052 | 0.052 | 0.053 | 0.072 | 0.072 | 0.082 | 0.082 | 0.078 | 0.078 | 0.079 | 0.079 |
| Observations | 70,632 | 70,632 | 67,682 | 67,682 | 33,778 | 33,778 | 18,295 | 18,295 | 72,749 | 72,749 | 67,371 | 67,360 | 52,495 | 52,495 | 52,326 | 52,131 |

*Notes: Weighted OLS regression. Additionally included but not reported: industry dummies, time dummies and country dummies.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

## Table 10.3: Effect of innovation on labour productivity over the business cycle in Europe, services, 2000-2010

| | Upturn | | | | Boom | | | | Downturn | | | | Recession | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (1) | (2) | (3) | (4) | (1) | (2) | (3) | (4) | (1) | (2) | (3) | (4) |
| PD | 0.078*** | | | | 0.074 | | | | 0.012 | | | | 0.002 | | | |
| | (0.030) | | | | (0.047) | | | | (0.028) | | | | (0.031) | | | |
| PDONLY | | 0.087** | 0.085** | | | 0.077** | 0.067** | | | 0.060** | 0.037 | | | 0.045 | 0.042 | |
| | | (0.036) | (0.034) | | | (0.030) | (0.031) | | | (0.030) | (0.030) | | | (0.031) | (0.033) | |
| PD&PC | | 0.187*** | 0.131*** | | | 0.161*** | 0.153** | | | 0.072** | 0.024 | | | 0.070 | 0.047 | |
| | | (0.027) | (0.029) | | | (0.052) | (0.061) | | | (0.034) | (0.034) | | | (0.048) | (0.054) | |
| PC | 0.114*** | | | 0.063*** | 0.088** | | | 0.051 | 0.081*** | | | 0.043** | 0.087** | | | 0.063 |
| | (0.024) | | | (0.022) | (0.043) | | | (0.057) | (0.021) | | | (0.020) | (0.042) | | | (0.053) |
| PCONLY | | 0.120*** | 0.064** | | | 0.091 | 0.045 | | | 0.113*** | 0.071** | | | 0.120*** | 0.095* | |
| | | (0.033) | (0.031) | | | (0.074) | (0.110) | | | (0.031) | (0.032) | | | (0.046) | (0.054) | |
| ORGA | | | 0.115*** | 0.116*** | | | 0.045 | 0.047 | | | 0.090*** | 0.091*** | | | 0.058* | 0.056* |
| | | | (0.024) | (0.024) | | | (0.034) | (0.035) | | | (0.019) | (0.019) | | | (0.033) | (0.032) |
| PD_MN | | | | 0.064** | | | | 0.144** | | | | 0.026 | | | | 0.057 |
| | | | | (0.032) | | | | (0.067) | | | | (0.027) | | | | (0.063) |
| PD_FN | | | | 0.032 | | | | 0.013 | | | | -0.023 | | | | -0.038 |
| | | | | (0.030) | | | | (0.038) | | | | (0.026) | | | | (0.040) |
| MEDIUM | -0.080** | -0.080** | -0.089** | -0.088** | -0.096 | -0.096 | -0.117 | -0.114 | -0.025 | -0.026 | -0.027 | -0.027 | -0.065 | -0.065 | -0.069 | -0.068 |
| | (0.039) | (0.039) | (0.041) | (0.041) | (0.062) | (0.062) | (0.084) | (0.085) | (0.034) | (0.034) | (0.036) | (0.036) | (0.045) | (0.045) | (0.044) | (0.044) |
| LARGE | -0.219*** | -0.218*** | -0.226*** | -0.226*** | -0.011 | -0.011 | 0.037 | 0.037 | -0.248* | -0.247* | -0.241* | -0.243* | -0.190*** | -0.190*** | -0.204*** | -0.205*** |
| | (0.065) | (0.065) | (0.068) | (0.068) | (0.090) | (0.087) | (0.093) | (0.098) | (0.131) | (0.131) | (0.139) | (0.139) | (0.073) | (0.073) | (0.072) | (0.073) |
| DGP | 0.361*** | 0.361*** | 0.350*** | 0.350*** | 0.346*** | 0.346*** | 0.311*** | 0.309*** | 0.364*** | 0.364*** | 0.349*** | 0.349*** | 0.416*** | 0.416*** | 0.411*** | 0.410*** |
| | (0.035) | (0.034) | (0.034) | (0.034) | (0.056) | (0.055) | (0.065) | (0.065) | (0.034) | (0.033) | (0.033) | (0.033) | (0.051) | (0.051) | (0.051) | (0.051) |
| FGP | 0.662*** | 0.662*** | 0.651*** | 0.651*** | 0.642*** | 0.642*** | 0.614*** | 0.609*** | 0.751*** | 0.750*** | 0.728*** | 0.728*** | 0.741*** | 0.740*** | 0.735*** | 0.733*** |
| | (0.052) | (0.052) | (0.054) | (0.054) | (0.073) | (0.072) | (0.081) | (0.084) | (0.060) | (0.060) | (0.060) | (0.060) | (0.059) | (0.059) | (0.059) | (0.058) |
| Constant | -2.231*** | -2.231*** | -2.258*** | -2.259*** | -2.188*** | -2.188*** | -1.221*** | -1.224*** | -2.647*** | -2.653*** | -2.624*** | -2.620*** | -2.013*** | -2.017*** | -2.021*** | -2.017*** |
| | (0.074) | (0.075) | (0.103) | (0.103) | (0.065) | (0.065) | (0.141) | (0.142) | (0.132) | (0.131) | (0.149) | (0.150) | (0.034) | (0.034) | (0.035) | (0.035) |
| R2a | 0.450 | 0.450 | 0.450 | 0.450 | 0.410 | 0.410 | 0.328 | 0.329 | 0.404 | 0.404 | 0.413 | 0.413 | 0.932 | 0.932 | 0.931 | 0.931 |
| Observations | 49,179 | 49,179 | 46,689 | 46,689 | 21,430 | 21,430 | 10,398 | 10,398 | 57,511 | 57,511 | 53,561 | 53,558 | 47,969 | 47,969 | 47,841 | 47,778 |

*Notes: Weighted OLS regression. Additionally included but not reported: industry dummies, time dummies and country dummies.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

**Table 10.4: Effect of innovation on labour productivity growth over the business cycle in Europe, services, 2000-2010**

| | Upturn | | | | Boom | | | | Downturn | | | | Recession | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (1) | (2) | (3) | (4) | (1) | (2) | (3) | (4) | (1) | (2) | (3) | (4) |
| PD | 0.005 | | | | 0.011 | | | | 0.015* | | | | 0.003 | | | |
| | (0.009) | | | | (0.015) | | | | (0.008) | | | | (0.007) | | | |
| PDONLY | | 0.009 | 0.009 | | | 0.010 | 0.017 | | | 0.015* | 0.013 | | | -0.001 | 0.004 | |
| | | (0.016) | (0.017) | | | (0.018) | (0.022) | | | (0.009) | (0.009) | | | (0.008) | (0.007) | |
| PD&PC | | 0.012 | 0.001 | | | 0.007 | 0.009 | | | 0.011 | 0.008 | | | 0.015 | 0.019* | |
| | | (0.010) | (0.015) | | | (0.008) | (0.009) | | | (0.008) | (0.009) | | | (0.010) | (0.011) | |
| PC | 0.009 | | | -0.001 | -0.004 | | | 0.003 | -0.003 | | | -0.005 | 0.010 | | | 0.011* |
| | (0.009) | | | (0.010) | (0.014) | | | (0.016) | (0.006) | | | (0.006) | (0.006) | | | (0.007) |
| PCONLY | | 0.012 | 0.004 | | | -0.005 | 0.002 | | | -0.003 | -0.006 | | | 0.006 | 0.010 | |
| | | (0.012) | (0.011) | | | (0.013) | (0.021) | | | (0.007) | (0.008) | | | (0.008) | (0.008) | |
| ORGA | | | 0.027* | 0.026 | | | -0.007 | -0.005 | | | 0.007* | 0.007* | | | -0.007 | -0.006 |
| | | | (0.016) | (0.016) | | | (0.015) | (0.014) | | | (0.004) | (0.004) | | | (0.006) | (0.006) |
| PD_MN | | | | 0.034*** | | | | -0.018 | | | | -0.008 | | | | -0.011 |
| | | | | (0.009) | | | | (0.018) | | | | (0.010) | | | | (0.012) |
| PD_FN | | | | -0.018 | | | | 0.013 | | | | 0.020** | | | | 0.014 |
| | | | | (0.014) | | | | (0.026) | | | | (0.009) | | | | (0.011) |
| MEDIUM | 0.045*** | 0.045*** | 0.043*** | 0.043*** | 0.019* | 0.019* | 0.015 | 0.015 | 0.032*** | 0.032*** | 0.032*** | 0.032*** | 0.037*** | 0.037*** | 0.037*** | 0.037*** |
| | (0.010) | (0.010) | (0.010) | (0.010) | (0.011) | (0.011) | (0.014) | (0.014) | (0.005) | (0.005) | (0.006) | (0.006) | (0.006) | (0.006) | (0.006) | (0.006) |
| LARGE | 0.038*** | 0.039*** | 0.036** | 0.035** | 0.035** | 0.035** | 0.045** | 0.045** | 0.051*** | 0.051*** | 0.051*** | 0.052*** | 0.035*** | 0.035*** | 0.036*** | 0.037*** |
| | (0.015) | (0.015) | (0.015) | (0.015) | (0.016) | (0.016) | (0.019) | (0.019) | (0.010) | (0.010) | (0.010) | (0.010) | (0.011) | (0.011) | (0.011) | (0.011) |
| DGP | 0.013 | 0.012 | 0.014* | 0.014* | -0.006 | -0.006 | -0.012 | -0.011 | -0.001 | -0.001 | -0.002 | -0.002 | -0.000 | -0.000 | -0.001 | -0.000 |
| | (0.009) | (0.009) | (0.008) | (0.008) | (0.008) | (0.008) | (0.009) | (0.009) | (0.005) | (0.005) | (0.005) | (0.005) | (0.006) | (0.006) | (0.006) | (0.006) |
| FGP | 0.043*** | 0.043*** | 0.042*** | 0.041*** | 0.016 | 0.016 | 0.008 | 0.010 | -0.002 | -0.002 | -0.006 | -0.005 | -0.011 | -0.011 | -0.009 | -0.009 |
| | (0.012) | (0.012) | (0.012) | (0.012) | (0.012) | (0.012) | (0.014) | (0.015) | (0.007) | (0.007) | (0.008) | (0.008) | (0.010) | (0.010) | (0.010) | (0.009) |
| Constant | 0.247*** | 0.247*** | 0.229** | 0.228** | 0.130*** | 0.130*** | 0.101** | 0.104** | 0.125*** | 0.125*** | 0.133*** | 0.133*** | -0.105*** | -0.105*** | -0.106*** | -0.107*** |
| | (0.066) | (0.066) | (0.095) | (0.095) | (0.013) | (0.013) | (0.045) | (0.045) | (0.018) | (0.018) | (0.019) | (0.019) | (0.013) | (0.013) | (0.013) | (0.013) |
| R2a | 0.059 | 0.059 | 0.060 | 0.061 | 0.036 | 0.036 | 0.043 | 0.043 | 0.066 | 0.066 | 0.070 | 0.070 | 0.037 | 0.037 | 0.037 | 0.037 |
| Observations | 49,179 | 49,179 | 46,689 | 46,689 | 21,430 | 21,430 | 10,398 | 10,398 | 57,511 | 57,511 | 53,561 | 53,558 | 47,969 | 47,969 | 47,841 | 47,778 |

*Notes: Weighted OLS regression. Additionally included but not reported: industry dummies, time dummies and country dummies.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

## 10.3. EVIDENCE FOR GERMANY

CIS data do not allow us to estimate more sophisticated productivity models, in particular we cannot control for capital and material input which might bias the result and we cannot trace firms over time. In order to take this in account, we use data from the Mannheim Innovation Panel (MIP). In particular, we put emphasis on the question and test whether the effect of innovation on productivity growth is constant over the business cycle or to what extent the business cycle moderates this effect. We exploit the availability of a longer time period and use the period 1992-2012.

Table 11.28 shows pooled OLS productivity estimations. The dependent variable is again LnLP. Material input LnMAT is measured as the logarithm of expenditures for material, intermediate consumption and energy per employee. Further, capital LnCAP is defined as logarithm of investment in tangible assets (buildings, machines, etc.) per employee. The innovation indicators are the same as in section 5.2.2. The business cycle indicator, GDPGR, is defined as the annual (real) GDP growth rate in Germany. As additional control variables we include firm size measured as logarithm of number of employees (LnL) and a dummy variable that indicates whether a firm is located in the Eastern or in the Western part of Germany (EAST). The specification further contains an export dummy (EXPORT), firm age (LnAGE) and two dummy variables that indicate whether a firm is part of a domestic group (DGP) or foreign group (FGP).

We have estimated the productivity equation using pooled OLS and FE estimators. OLS results can be found in Tables 13-11 to 13-13 and FE results are represented in Tables 13-14 to 13-16. For both estimators, the first table presents results when we distinguish between product and process innovation (Table 13-11 and Table 13-14). Table 13-12 and Table 13-15 explore to what extent the degree of novelty matters for productivity effects of product innovation. Additionally, we examine potential productivity-enhancing effects of pure product and pure process innovators as well as for firms who have simultaneously implemented product and process innovations in Table 13-13 and Table 13-16.

The estimates disclose strong capital and tangible assets effects across all three specifications. In the pooled estimates, the output elasticity of material amounts to 0.37, the elasticity of the tangible assets is about 0.053. This relatively low value indicates that we are likely to be confronted with an endogeneity problem due to simultaneity. In the OLS estimates, product innovating firms seem to not have gained from their innovations in terms of labour productivity as all coefficients are insignificant. In contrast, the introduction of process innovation is associated with larger labour productivity, on average. That applies to the baseline specification, *Baseline*, to the specification including a business cycle indicator, *BC* as well as to the specification that includes interaction terms between the business cycle and the innovation indicators, *BC-Interactions*. The business cycle indicator also has a productivity-enhancing effect. The larger the GDP growth the larger is the labour productivity, on average. This indicator is, however, not significant in the interaction specification. The same applies to the interaction terms. Thus, the home economy's GDP growth rate might not matter for the decision on the introduction of innovations.

We gain further insights into the role of product innovation on productivity when we split product innovations into market novelties, *MAR_NOV*, and firm novelties, *FIRM_NOV*. Table 11.29 presents productivity estimations where product innovations are differentiated by their degree of novelty. It turns out that on average market novelties significantly impact productivity. Firm novelties (imitations) however do not spur productivity. The interaction terms, again, do not show any significant effect. The introduction of innovations seems to be rather business cycle independent.

In Table 11.30, the innovation indicators describe whether a firm has been a pure product innovator, a pure process innovator or whether a firm has simultaneously implemented product as well as process innovations. Surprisingly, pure innovators do not show a higher labour productivity, on average, than others. The coefficients of *PDONLY*, *PCONLY* as well as of *PCAPD* are insignificant. Since this sample covers a period of 20 years, that could mean that innovations are only successful in terms of labour productivity when the complementarity character of different kinds of product and process innovations is exploited, in the long-term. However, that would not explain the insignificant coefficient of *PCAPD*. Successfully implementing product innovations on competing markets requires a different set of resources than is required for process innovations. Innovations are mainly financed internally. A firm who conducts process and product innovation activities at the same time might inefficiently allocate its financial means. Thus, it could be more efficient for a firm to really put the effort to the successful implementation of new products or of new processes unless the firm has a large financial scope. That could explain the significantly positive coefficient of the respective interaction term. Simultaneous innovators have gained from their innovations only in periods of rather stable, certain and high demand (upturn or boom periods).

One of the problems with pooled OLS is that it does not consider individual heterogeneity. For that reason we also estimated Fixed-Effects regressions (FE) for the productivity effects. FE regressions correct for firm individual heterogeneity by subtracting each variable's firm specific mean from the value of the respective variable.

Table 11.31 to Table 13-16 present the results of FE regressions for the specifications we have just described. As it is often observed in FE regressions, the estimated output elasticities of material and capital are unreasonable low. When we compare results with OLS we do find a significantly positive effect of product innovations on labour productivity. In contrast, the significant effect of process innovations has vanished. GDP growth has an even larger effect on labour productivity than before and this effect is still significant in the interactions specification. The interaction term between GDP growth and product innovations is positively significant, although this effect is weak. Thus, product innovations do have an even larger impact on labour productivity when introduced during economic upswing (or boom) periods, on average.

OLS results are confirmed in FE regressions when we split product innovations into market novelties and firm novelties in Table 11.32. Firms that have introduced products that were new to the market reveal larger labour productivity than other firms. However, this positive effect is not enhanced when the particular innovation has been implemented during economic upswings (or booms). In contrast, imitators have gained from upturn periods when they have implemented their particular innovation during a period of flourishing sales, even though this effect is small.

Table 11.33 presents the FE regression results of the pure innovators model. In contrast to Table 11.30, firms who have simultaneously implemented product as well as process innovations could increase their labour productivity compared to other firms, on average. This positive effect holds across all three specifications. Moreover, the interaction term is also significantly positive. These firms could also gain from periods of stable and high demand.

In a nutshell, this section has examined productivity effects of innovation activities over the business cycle in Germany covering the period 1992 to 2012. We have presented results of pooled OLS regressions and of Fixed-Effects regressions which correct for individual heterogeneity. A main finding is that market novelties spur productivity independently of whether using OLS or FE. FE results show that this positive effect is independently of whether they have been implemented during economic upswings or downturns. The effects of firm novelties is innovation on productivity turns out to be positive in the FE regression and the effect increases with the size of GDP growth.

# Chapter 11. SUMMARY

European policy regards innovation as an engine for growth. Measures to encourage the development and diffusion of new technologies are seen as a suitable instrument to promote employment in Europe.

This chapter studied the relationship between employment growth and innovation with a large sample of European firms. In particular, the chapter investigated how the relationship between innovation and employment changes in various phases of the business cycle in general and in particular for different types of firms depending on their technological intensity, business cycle sensitivity, size, ownership structure or geographical location. Understanding how this mechanism works at the firm-level is central for the design of innovation policy.

The results show that **employment creation is larger in innovative firms than in non-innovative firms in all phases of the business cycle.** The number of employees in innovating firms grows faster than in non-innovating firms. This pattern can be observed in all phases of the business cycle but it is particularly pronounced in downturn and recession periods where the gap between innovating and non-innovating firms is particularly large. So, innovation is positively correlated with employment growth.

The results also confirm that **productivity** grows **pro-cyclical**; it shrinks during recessions, and grows fastest during periods of high economic growth rates and in the following downturn. Innovators reveal a higher productivity growth in all stages of the business cycle compared to non-innovators. The **productivity gap between innovators and non-innovators** is particularly large in a recession but still around 1 percentage points in up- and downturns. Interestingly, however, there is hardly any difference in productivity growth among innovators and non-innovators in manufacturing in an economic boom. This may indicate that innovators do not utilize all opportunities for productivity growth in this stage of the business cycle due to the favourable economic climate.

In a firm perspective, the relationship between employment and innovation is a race between **jobs creation** due to additional demand for new products and **jobs destruction** due to productivity effects and lower demand for old products. **Product innovators** generate more employment growth than non-innovators because they create more employment with higher sales of new products than they lose due to decreasing sales of old products. This effect is particularly strong in an economic upturn and during boom periods, when product innovators create much more new sales than they destroy due to higher productivity and substitution effects between old and new products.

Particularly important is product innovation during a **recession**, where it has an employment-preserving effect. Employment losses for product innovators are much smaller than for non-product innovators in manufacturing, because output from new products partly compensates losses in sales of old products. In services, the net contribution of product innovation to employment growth turns out to be positive even in the recession whereas firms which do not introduce any new products suffer from a large decline in demand for old products. Another factor that dampens employment losses during recessions is **labour hoarding**; firms are willing to accept productivity losses during recessions to avoid laying off employees. Otherwise, employment would have dipped much stronger during the past recession.

The effects of **process and organisational innovation** on employment growth are smaller than the effects of product innovation in all phases of the business cycle. In manufacturing, employment estimates have pointed towards significant increases in productivity – and hence to reductions in labour demand – in upturn and downturn periods due to both process innovation and organizational innovation. In services, we find the same pattern for organizational innovation but no effect of process innovation. In boom periods and recessions, however, the employment estimates did not reveal any productivity effects of both types of innovation. Overall, their contributions to employment growth are rather small and do not vary much over the business cycle.

**Firm size** and the **sector of the firm** are important determinants of the strength of the aforementioned effects of innovation. Product innovation has a much more profound effect on employment growth in high-technology and knowledge-intensive sectors than in low-technology and less knowledge-intensive sectors. Product innovation is also responsible that employment fluctuations related to innovation over the business cycle are stronger in these sectors. Moreover, the results point to the pivotal role of small and medium sized firms for employment creation in upturns and booms. Large firms are the only group in the analysis which lose employment in all stages of the business cycle except booms. Large firms lose more employment from higher productivity than they gain from product innovation, leading to mostly jobless growth. In times of a recession, however, SMEs lose proportionately more employment than large firms, which have much higher gains in sales from new products and fewer losses from old products.

Our results further show that employment growth is more volatile in **foreign-owned firms** than in domestic firms. On the one hand foreign-owned firms grow less in upturn, boom and downturn periods and on the other hand they cut more jobs during recessions. The main source of this finding can be traced back to the impact of product innovation. Foreign-owned firms create more employment due to more product innovation and a stronger demand effect in upturn, boom and downturn periods (overcompensating stronger productivity effects of product innovation). At the same time, they lost more jobs due to product innovation during the recent crisis which affected export-oriented firms more strongly and foreign-owned firms show a higher export orientation. Overall, the larger volatility in product innovation impacts in foreign-owned firms has contributed to larger employment volatility in foreign-owned firms over the business cycle. In upturn, boom and downturn phases of the business cycle, the positive effect of product innovation is somewhat dampened by the larger general productivity gains in foreign-owned firms due to benefits from internal technology transfer and learning effects. In the recession, however, the general productivity trend and less labour hoarding reinforces the employment growth disadvantage of foreign-owned firms in manufacturing.

Overall, this study has shown that (i) different types of innovation affect productivity and employment growth differently, (ii) the absolute and relative size of these effects furthermore vary over the business cycle and (iii) the effects are moderated by different firm characteristics and industry characteristics. Regarding employment growth, product innovation turns out to be the most important type of innovation. Product innovation stimulates employment growth in all phases of the business cycle, the absolute effect being particularly strong in boom periods which are characterized by high demand. In recessions our results indicate an employment-preserving effect of product innovation.

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# TABLE APPENDIX

**Table 11.1 Classification of industries based on their technology intensity**

| Sector | Subsector | Nace 2.0 | Nace Rev. 1.1. | Basic decription |
|---|---|---|---|---|
| HIGH | High-tech manuf. | 21 | 24.4 | Pharmaceutical products and preparations |
| | | 26 | 30-32 | Computer, electronic and optical products |
| | | 30.3 | 35.3 | Air and spacecraft and related machinery |
| | Medium-high-tech manuf. | 20 | 24 exc. 24.4 | Chemicals |
| | | 25.4 | | Weapons and ammunition |
| | | 27 | 31 | Electrical equipment, electrical machinery |
| | | 28 | 29 | Machinery and equipment n.e.c., |
| | | 29 | 34 | Motor vehicles, trailers and semi-trailers |
| | | 30 excl. 30.1/30.3 | 35 excl. 35.1/35.3 | Other transport equipment excluding ships and air and spacecraft and related machinery |
| | | 32.5 | | medical and dental instruments and supplies |
| LOW | Medium-low-tech manuf. | 18.2 | | Reproduction of recorded media |
| | | 19 | 23 | Coke and refined petroleum products |
| | | 22-24 | 25-27 | Rubber and plastic products, other non-metallic mineral products, basic metals |
| | | 25, excl. 25.4 | 28 | Fabricated metal products, excluding weapons and ammunition |
| | | 30.1 | 35.1 | Building of ships and boats |
| | | 33 | | Repair and installation of machinery and equipment |
| | Low-tech manuf. | 10-17 | 15 to 21 | Food products, beverages, tobacco products, textiles, wearing apparel, leather and related products, wood and of products of wood, paper and paper products |
| | | 18, excl. 18.2 | 22 | Printing and reproduction of recorded media excluding reproduction of recorded media |
| | | 31 | 36 | Furniture |
| | | 32, excl. 32.5 | 37 | Other manufacturing, excluding medical and dental instruments and supplies |
| KIS | | 50-51 | 61-62 | Water transport, air transport |
| | | 58 to 63 | 64, 72.3, 72.4, 92.2, 92.3 | Publishing activities, Motion picture, video and television programme production, sound recording and music publishing activities; Programming and broadcasting activities;, telecommunications; computer programming; consultancy and related activities; information service activities |
| | | 64 to 66 | 65-67 | Financial and insurance activities |
| | | 69 to 75, 78, 80 | 72-74, excl. 72.3, 72.4, 74.7 | Legal and accounting activities; activities of head offices; management consultancy activities; architectural and engineering activities; technical testing and analysis; scientific research and development; advertising and market research, other professional, scientific and technical activities, veterinary activities, employment activities, security and investigation activities |
| LKIS | | 45 to 47 | 50-52 | Wholesale and retail trade; repair of motor vehicles and motorcycles |
| | | 49 | 60 | Land transport and transport via pipelines |
| | | 52 to 53 | 63 | Warehousing and support activities for transportation, postal and courier activities |
| | | 68 | 70 | Real estate activities |
| | | 77 | 71 | Rental and leasing activities |
| | | 79 | | Travel agency, tour operator reservation service and related activities |
| | | 81 | 74.7, 70.3 | Services to buildings and landscape activities |
| | | 82 | | Office administrative, office support and other business support activities |

*Source: Eurostat.*

**Table 11.2: Impact of innovation on employment growth in economic downturns and upturns, manufacturing, 1998-2010**

| **Dep var:** | **Upturn** | **Downturn** | **Upturn** | **Downturn** |
|---|---|---|---|---|
| $EMP = l - (g_i - \hat{\pi}_i)$ | **(1)** | **(2)** | **(3)** | **(4)** |
| SGR_NEWPD | 0.966*** | 0.987*** | 1.045*** | 0.993*** |
| | (0.021) | (0.022) | (0.041) | (0.022) |
| PCONLY | -1.558** | -1.295* | 0.399 | -1.070 |
| | (0.724) | (0.746) | (1.309) | (0.733) |
| ORGA | -1.669*** | -0.835** | -5.069*** | -0.800** |
| | (0.460) | (0.401) | (0.772) | (0.397) |
| GDPGR | 3.673*** | -0.598*** | 3.609*** | -0.549*** |
| | (0.562) | (0.138) | (0.571) | (0.143) |
| SGR_NEWPD | | | -0.013*** | -0.005* |
| x GDPGR | | | (0.005) | (0.003) |
| PC | | | -0.363** | -0.269** |
| x GDPGR | | | (0.179) | (0.137) |
| ORGA | | | 0.606*** | -0.002 |
| x GDPGR | | | (0.115) | (0.067) |
| MEDIUM | -1.867*** | -1.535*** | -1.884*** | -1.547*** |
| | (0.451) | (0.438) | (0.449) | (0.436) |
| LARGE | -3.939*** | -2.420*** | -4.023*** | -2.394*** |
| | (0.637) | (0.543) | (0.638) | (0.534) |
| DGP | 0.549 | 0.950* | 0.502 | 0.949* |
| | (0.722) | (0.509) | (0.736) | (0.506) |
| FGP | -0.123 | -0.728 | -0.173 | -0.724 |
| | (0.662) | (0.501) | (0.659) | (0.497) |
| Constant | -63.590*** | -11.981*** | -63.084*** | -11.946*** |
| | (7.397) | (2.414) | (7.440) | (2.397) |
| *Joint sign. (p-value)* | | | | |
| W_industry | 0.000*** | 0.000*** | 0.000*** | 0.000*** |
| W_country | 0.000*** | 0.000*** | 0.000*** | 0.000*** |
| W_time | 0.000*** | 0.000*** | 0.000*** | 0.000*** |
| R2a | 0.398 | 0.411 | 0.398 | 0.412 |
| RMSE | 28.496 | 25.846 | 28.494 | 25.835 |
| Wald-Test: β=1 | 0.105 | 0.536 | 0.268 | 0.757 |
| *Tests on Exogeneity* | | | | |
| SGR_NEWPD | 0.000*** | 0.000*** | 0.000*** | 0.000*** |
| *Tests on instr. validity* | | | | |
| Sargan/Hansen J-Test | 0.654 | 0.518 | 0.817 | 0.525 |
| *First stage results* | | | | |
| RANGE | 23.734*** | 22.764*** | 19.351*** | 13.191*** |
| | (0.656) | (0.642) | (1.256) | (2.851) |
| COOP | 7.310*** | 5.422*** | 5.071*** | 6.515*** |
| | (0.812) | (0.614) | (1.473) | (2.081) |
| RANGE x GDPGR | | | 0.744*** | 31.032*** |
| | | | (0.161) | (1.229) |
| COOP x GDPGR | | | 0.326 | 4.772*** |
| | | | (0.218) | (0.930) |
| F test on excl. Instr. | 700.39*** | 740.69*** | 373.26*** | 262.32*** |
| *Tests on underident.* | | | | |
| Kleibergen-Paap LM test | 266.525*** | 1826.441*** | 224.923*** | 1342.605*** |
| *Test on weak instr.* | | | | |
| Cragg-Donald F test | 9895.000*** | 14581.822*** | 4725.940*** | 7353.460*** |
| Kleibergen-Paap F test | 1134.609*** | 1464.345*** | 380.470*** | 490.028*** |
| *Weak instr. rob. inf.* | | | | |
| Anderson-R. Wald test | 1125.380*** | 643.634*** | 1139.855*** | 826.718*** |
| Stock-Wright LM test | 83.679*** | 70.903*** | 105.677*** | 107.102*** |
| Obs | 85,718 | 118,395 | 85,718 | 118,395 |

*Notes: Method: Instrumental variables estimation. ***, ** and * indicate significance at the 1%, 5% and 10% level. Clustered standard errors are reported, clustered by industry (2-digit NACE level) and country. Industry, country and time dummies are included in each regression. For each set of dummies the p-value of a test on joint significance is reported. Instruments for sales growth due to new products (SGR_NEWPD): RANGE and COOP in manufacturing. J-Test reports the p-value of the Sargan-Hansen test on overidentifying restrictions. Under H0 (overall set of instruments is valid) J follows a X2(m) distribution with m as the number of overidentifying restrictions. A difference-in-Sargan/Hansen test statistic is used for the test on the exogeneity of SGR_NEWPD. The test statistic is robust to violations of conditional homoskedasticity. If conditional homoskedasticity holds, it is* *numerically equal to a Hausman-Durbin-Wu test statistic. First stage statistics: Reported are only coefficients and standard errors of the instruments, results for the other exogenous variables in the first stage are available upon request. F reports the test statistic of an F-Test on the joint significance of the (excluded) instruments in the first stage. The test on underidentification tests whether the instrument matrix has full rank in the first stage. Rejection of the null hypothesis implies that the equation is identified, i.e., that the excluded instruments are relevant meaning correlated with the endogenous regressors. Reported is the heteroskedasticity-robust Kleibergen-Paap rk LM statistic (Kleibergen and Paap 2006) which follows a X2(m+1)-distribution. Weak instruments can lead to a large relative bias of IV compared to the bias of OLS. The Cragg-Donald F statistic and Kleibergen-Paap Wald F statistic both test the null hypothesis that the instruments are weak, more precisely that the maximal IV size is larger than p%. Here p is chosen to be 10%, 15%, 20%, and 25%. Cragg-Donald F statistic is for i.i.d. errors whereas Kleibergen and Paap statistic is heteroskedasticity-robust. For K=1 endogenous regressor and L=2 instruments the critical values are 19.93 (p=10%,***), 11.59 (p=15%, **), 8.75 (p=20%, *) and 7.25 (p=25%, #). For K=2 endogenous regressor and L=4 instruments the critical values are 16.87 (p=10%,***), 9.93 (p=15%, **), 7.54 (p=20%, *) and 6.28 (p=25%, #).Note that these critical values are for i.i.d. errors; see Baum et al. 2007, Cragg and Donald 1993, Stock and Yogo 2005)*

*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

**Table 11.3: Impact of innovation on employment growth in economic downturns and upturns, services, 1998-2010**

| | Upturn (1) | Downturn (2) | Upturn (3) | Downturn (4) |
|---|---|---|---|---|
| SGR_NEWPD | 0.937*** | 1.034*** | 0.931*** | 1.041*** |
| | (0.049) | (0.031) | (0.088) | (0.032) |
| PCONLY | -1.095 | 0.288 | -0.436 | 0.264 |
| | (1.481) | (0.824) | (2.365) | (0.807) |
| ORGA | -0.789 | -0.263 | -3.344** | -0.220 |
| | (0.765) | (0.451) | (1.401) | (0.453) |
| GDPGR | 1.897 | -1.092*** | 1.722 | -1.064*** |
| | (1.831) | (0.150) | (1.877) | (0.151) |
| SGR_NEWPD x GDPGR | | | 0.001 | -0.006 |
| | | | (0.010) | (0.005) |
| PCONLY x GDPGR | | | -0.115 | -0.001 |
| | | | (0.282) | (0.124) |
| ORGA x GDPGR | | | 0.439** | 0.006 |
| | | | (0.178) | (0.087) |
| MEDIUM | -3.223*** | -3.960*** | -3.248*** | -3.948*** |
| | (0.883) | (0.431) | (0.888) | (0.430) |
| LARGE | -4.418*** | -5.494*** | -4.433*** | -5.490*** |
| | (1.063) | (0.725) | (1.066) | (0.720) |
| DGP | -0.377 | 0.363 | -0.378 | 0.365 |
| | (0.852) | (0.453) | (0.853) | (0.453) |
| FGP | -3.771*** | 0.714 | -3.816*** | 0.693 |
| | (1.184) | (0.538) | (1.187) | (0.542) |
| Constant | -32.560 | 1.944 | -31.246 | 1.941 |
| | (23.997) | (2.917) | (24.225) | (2.938) |
| *Joint sign. (p-value)* | | | | |
| W_industry | 0.218 | 0.000*** | 0.229 | 0.415 |
| W_country | 0.000*** | 0.000*** | 0.000*** | 0.000*** |
| W_time | 0.000*** | 0.430 | 0.000*** | 0.000*** |
| R2a | 0.263 | 0.302 | 0.263 | 0.303 |
| RMSE | 35.934 | 29.714 | 35.927 | 29.690 |
| Wald-Test: β=1 | 0.197 | 0.273 | 0.435 | 0.203 |
| *Tests on Exogeneity* | | | | |
| SGR_NEWPD | 0.055* | 0.000*** | 0.057* | 0.000*** |
| *Tests on instr. validity* | | | | |
| Sargan/Hansen J-Test | 0.581 | 0.843 | 0.645 | 0.223 |
| *First stage results* | | | | |
| RD | 21.175*** | 18.659*** | 21.835*** | 18.597*** |
| | (1.816) | (1.149) | (2.776) | (1.138) |
| COOP | 14.723*** | 13.430*** | 11.187*** | 13.087*** |
| | (0.969) | (0.723) | (1.570) | (0.702) |
| RD x GDPGR | | | -0.113 | 0.349 |
| | | | (0.270) | (0.241) |
| COOP x GDPGR | | | 0.599** | 0.465*** |
| | | | (0.233) | (0.132) |
| F test on excl. Instr. | 217.21*** | 336.10*** | 115.71*** | 170.25*** |
| *Tests on underident.* | | | | |
| Kleibergen-Paap LM test | 129.274*** | 912.813*** | 168.256*** | 512.026*** |
| *Test on weak instr.* | | | | |
| Cragg-Donald F test | 3227.663*** | 5389.005*** | 1565.764*** | 2501.414*** |
| Kleibergen-Paap F test | 308.479*** | 503.397*** | 146.009*** | 125.780*** |
| *Weak instr. rob. inf.* | | | | |
| Anderson-R. Wald test | 212.804*** | 567.201*** | 221.927*** | 574.760*** |
| Stock-Wright LM test | 49.829*** | 64.215*** | 52.544*** | 66.450*** |
| Obs | 56,964 | 100,788 | 56,964 | 100,788 |

*Notes: See Table 11.2.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

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**Table 11.4: Impact of innovation on employment growth in different phases of the business cycle, manufacturing, 1998-2010**

| Dep var: | Upturn | Boom | Downturn | Recession |
|---|---|---|---|---|
| $EMP = l - (g_i - \hat{\pi}_i)$ | (1) | (2) | (3) | (4) |
| SGR_NEWPD | 0.984*** | 0.965*** | 1.002*** | 0.976*** |
| | (0.024) | (0.029) | (0.025) | (0.026) |
| PCONLY | -1.747** | -0.268 | -1.835* | -0.367 |
| | (0.853) | (1.391) | (0.941) | (1.027) |
| ORGA | -2.207*** | 0.601 | -1.373** | -0.567 |
| | (0.467) | (0.738) | (0.617) | (0.490) |
| GDPGR | 3.641*** | 2.816 | -0.600*** | -0.017 |
| | (0.556) | (1.811) | (0.175) | (0.278) |
| MEDIUM | -3.080*** | -0.006 | -1.255** | -2.019*** |
| | (0.460) | (0.865) | (0.596) | (0.496) |
| LARGE | -4.718*** | -3.542*** | -1.351* | -3.979*** |
| | (0.609) | (1.284) | (0.787) | (0.659) |
| DGP | -1.472* | 3.213*** | 0.567 | 1.290* |
| | (0.791) | (1.163) | (0.648) | (0.661) |
| FGP | -1.130 | 1.034 | 0.124 | -1.805*** |
| | (0.804) | (1.147) | (0.659) | (0.631) |
| Constant | -67.186*** | -33.372** | -15.091*** | 3.049* |
| | (7.291) | (15.808) | (2.647) | (1.654) |
| *Joint sign. (p-value)* | | | | |
| W_industry | 0.000*** | 0.000*** | 0.000*** | 0.000*** |
| W_country | 0.000*** | 0.000*** | 0.000*** | 0.000*** |
| W_time | 0.000*** | - | 0.000*** | - |
| R2a | 0.378 | 0.493 | 0.387 | 0.465 |
| RMSE | 29.790 | 23.581 | 28.917 | 21.062 |
| Wald-Test: β=1 | 0.500 | 0.229 | 0.950 | 0.350 |
| *Tests on Exogeneity* | | | | |
| SGR_NEWPD | 0.000*** | 0.004*** | 0.000*** | 0.009*** |
| *Tests on instr. validity* | | | | |
| Sargan/Hansen J-Test | 0.904 | 0.197 | 0.058* | 0.483 |
| *First stage results* | | | | |
| RANGE | 24.216*** | 22.627*** | 24.494*** | 20.830*** |
| | (0.769) | (1.076) | (0.866) | (1.018) |
| COOP | 7.159*** | 6.642*** | 6.643*** | 4.191*** |
| | (0.845) | (1690) | (0.723) | (0.898) |
| F test on excl. Instr. | 588.93*** | 232.74 | 436.73*** | 334.75*** |
| *Tests on underident.* | | | | |
| Kleibergen-Paap LM test | 278.305*** | 47.723*** | 1320.026*** | 650.675*** |
| *Test on weak instr.* | | | | |
| Cragg-Donald F test | 7521.560*** | 1904.171*** | 8392.591*** | 6296.530*** |
| Kleibergen-Paap F test | 830.146*** | 323.097*** | 1210.113*** | 462.008*** |
| *Weak instr. rob. inf.* | | | | |
| Anderson-R. Wald test | 810.060*** | 407.550*** | 783.385*** | 328.914*** |
| Stock-Wright LM test | 59.581*** | 44.579*** | 85.623*** | 48.630*** |
| Obs | 67,521 | 15,863 | 67,200 | 51,195 |

*Notes: See Table 11.2. The Netherlands have been excluded from boom periods.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

**Table 11.5: Impact of innovation on employment growth in different phases of the business cycle, services, 1998-2010**

| **Dep var:** | **Upturn** | **Boom** | **Downturn** | **Recession** |
|---|---|---|---|---|
| $EMP = l - (g_1 - \hat{\pi}_1)$ | **(1)** | **(2)** | **(3)** | **(4)** |
| SGR_NEWPD | 0.988*** | 0.845*** | 1.036*** | 1.026*** |
| | (0.051) | (0.119) | (0.046) | (0.036) |
| PCONLY | -0.524 | -1.831 | 1.224 | -0.255 |
| | (1.463) | (4.295) | (1.097) | (0.882) |
| ORGA | -2.034** | 1.501 | -1.390* | 0.338 |
| | (0.793) | (1.970) | (0.825) | (0.565) |
| GDPGR | 1.694 | -3.500* | -0.631*** | 0.846*** |
| | (2.084) | (2.008) | (0.220) | (0.256) |
| MEDIUM | -4.640*** | -1.045 | -3.376*** | -4.197*** |
| | (0.942) | (1.720) | (0.646) | (0.581) |
| LARGE | -4.890*** | -4.085** | -5.868*** | -4.922*** |
| | (1.531) | (1.914) | (1.174) | (1.058) |
| DGP | -1.169 | 0.346 | 0.119 | 0.380 |
| | (1.094) | (1.578) | (0.631) | (0.609) |
| FGP | -5.169*** | -1.844 | 0.118 | 0.462 |
| | (1.359) | (2.202) | (0.801) | (0.830) |
| Constant | -32.862 | 18.939 | -6.139* | 15.404*** |
| | (25.674) | (17.056) | (3.585) | (1.221) |
| *Joint sign. (p-value)* | | | | |
| W_industry | 0.210 | 0.041** | 0.000*** | 0.000*** |
| W_country | 0.000*** | 0.000*** | 0.000*** | 0.000*** |
| W_time | 0.022** | - | 0.887 | - |
| R2a | 0.226 | 0.352 | 0.271 | 0.361 |
| RMSE | 37.225 | 32.635 | 35.065 | 23.530 |
| Wald-Test: β=1 | 0.807 | 0.192 | 0.442 | 0.468 |
| *Tests on Exogeneity* | | | | |
| SGR_NEWPD | 0.001*** | 0.966 | 0.000*** | 0.005*** |
| *Tests on instr. validity* | | | | |
| Sargan/Hansen J-Test | 0.396 | 0.815 | 0.069* | 0.291 |
| *First stage results* | | | | |
| RD | 21.490*** | 19.908*** | 20.101*** | 17.685*** |
| | (2.102) | (3.0912) | (1.542) | (1.411) |
| COOP | 15.304*** | 13.651*** | 14.836*** | 11.793*** |
| | (0.927) | (2.184) | (1.014) | (0.915) |
| F test on excl. Instr. | 193.83*** | 49.44*** | 175.78*** | 186.36*** |
| *Tests on underident.* | | | | |
| Kleibergen-Paap LM test | 316.040*** | 14.346*** | 742.208*** | 332.625*** |
| *Test on weak instr.* | | | | |
| Cragg-Donald F test | 2981.098*** | 351.421*** | 2543.962*** | 2972.838*** |
| Kleibergen-Paap F test | 328.943*** | 55.257*** | 295.541*** | 224.895*** |
| *Weak instr. rob. inf.* | | | | |
| Anderson-R. Wald test | 270.803*** | 46.456*** | 349.980*** | 342.688*** |
| Stock-Wright LM test | 42.257*** | 14.293*** | 52.252*** | 55.507*** |
| Obs | 46,566 | 8,241 | 53,510 | 47,278 |

*Notes: See Table 11.2. The Netherlands have been excluded from boom periods.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

**Table 11.6: Impact of innovation on employment growth in phases of negative, low and high economic growth, 1998-2010**

| | Manufacturing | | | Services | | |
|---|---|---|---|---|---|---|
| | Negative | Low pos. | High pos. | Negative | Low pos. | High pos. |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| SGR_NEWPD | 0.976*** | 1.042*** | 0.943*** | 1.026*** | 0.986*** | 0.965*** |
| | (0.026) | (0.031) | (0.016) | (0.036) | (0.053) | (0.047) |
| PCONLY | -0.367 | -1.386* | -2.230*** | -0.255 | -0.089 | -1.011 |
| | (1.027) | (0.777) | (0.715) | (0.882) | (1.269) | (1.436) |
| ORGA | -0.567 | -2.112*** | 0.011 | 0.338 | -1.408 | -0.263 |
| | (0.490) | (0.598) | (0.422) | (0.565) | (0.938) | (0.816) |
| GDPGR | -0.017 | 1.391*** | -0.379 | 0.846*** | 3.031*** | -0.721** |
| | (0.278) | (0.509) | (0.237) | (0.256) | (0.655) | (0.315) |
| MEDIUM | -2.019*** | -3.989*** | -0.764 | -4.197*** | -5.612*** | -2.283*** |
| | (0.496) | (0.613) | (0.488) | (0.581) | (0.865) | (0.804) |
| LARGE | -3.979*** | -4.859*** | -2.592*** | -4.922*** | -6.930*** | -3.902*** |
| | (0.659) | (0.843) | (0.709) | (1.058) | (1.809) | (1.020) |
| DGP | 1.290* | -0.750 | 1.469** | 0.380 | -0.657 | 0.685 |
| | (0.661) | (0.845) | (0.647) | (0.609) | (0.942) | (0.754) |
| FGP | -1.805*** | -0.270 | -0.071 | 0.462 | -1.847 | -2.443** |
| | (0.631) | (0.814) | (0.600) | (0.830) | (1.534) | (1.059) |
| Constant | 3.049* | -15.214*** | -14.253*** | 15.404*** | -13.285*** | 1.108 |
| | (1.654) | (2.929) | (3.764) | (1.221) | (2.653) | (5.219) |
| *Joint sign. (p-value)* | | | | | | |
| W_industry | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.019** | 0.000*** |
| W_country | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** |
| W_time | - | 0.005*** | 0.000*** | - | - | 0.357 |
| R2a | 0.465 | 0.396 | 0.401 | 0.361 | 0.237 | 0.273 |
| RMSE | 21.062 | 27.191 | 29.325 | 23.530 | 34.114 | 36.714 |
| Wald-Test: β=1 | 0.350 | 0.168 | 0.001*** | 0.468 | 0.798 | 0.447 |
| *Tests on Exog.* | | | | | | |
| SGR_NEWPD | 0.009*** | 0.000*** | 0.000*** | 0.005*** | 0.019** | 0.000*** |
| *Tests on instr. val.* | | | | | | |
| Sargan/Hansen J-Test | 0.483 | 0.329 | 0.327 | 0.291 | 0.269 | 0.889 |
| *First stage results* | | | | | | |
| RANGE (m) / | 20.830*** | 20.985*** | 20.830*** | 17.685*** | 20.094*** | 21.412*** |
| RD (s) | (1.018) | (0.743) | (1.018) | (1.411) | (1.531) | (1.822) |
| COOP | 4.191*** | 5.052*** | 4.191*** | 11.793*** | 13.867*** | 15.514*** |
| | (0.898) | (0.693) | (0.898) | (0.915) | (1.034) | (1.111) |
| F test on excl. Instr. | 334.75*** | 441.40*** | 334.75*** | 186.36*** | 157.53*** | 210.00*** |
| *Tests on underid..* | | | | | | |
| Kleibergen-Paap LM test | 650.675*** | 1043.48*** | 265.909*** | 332.625*** | 432.520*** | 120.665*** |
| *Test on weak instr.* | | | | | | |
| Cragg-Donald F | 6296.53*** | 5242.24*** | 13394.3*** | 2972.84*** | 2523.92*** | 3517.53*** |
| Kleibergen-Paap F | 462.008*** | 769.477*** | 1319.17*** | 224.895*** | 292.321*** | 271.421*** |
| *Weak instr. rob. inf.* | | | | | | |
| Anderson-R. Wald | 328.914*** | 503.101*** | 1222.31*** | 342.688*** | 218.501*** | 230.867*** |
| Stock-Wright LM | 48.630*** | 29.735*** | 112.232*** | 55.507*** | 23.922*** | 51.642*** |
| Obs | 51,195 | 43,032 | 109,886 | 47,278 | 34,309 | 76,165 |

*Notes: See Table 11.2.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

**Table 11.7: Impact of innovation on employment growth over the business cycle, high-tech manufacturing, 1998-2010**

| **Dep var:** | **Upturn** | **Boom** | **Downturn** | **Recession** |
|---|---|---|---|---|
| $EMP = l - (g_1 - \hat{\pi}_1)$ | **(1)** | **(2)** | **(3)** | **(4)** |
| SGR_NEWPD | 0.995*** | 0.964*** | 1.021*** | 0.993*** |
| | (0.034) | (0.056) | (0.055) | (0.058) |
| PCONLY | -2.813* | 1.522 | -1.408 | 0.568 |
| | (1.559) | (2.121) | (1.649) | (2.478) |
| ORGA | -2.187** | -0.430 | -0.661 | 0.390 |
| | (1.002) | (1.684) | (0.753) | (1.294) |
| GDPGR | 2.351** | -0.160 | -0.171 | 0.173 |
| | (0.979) | (0.406) | (0.248) | (0.523) |
| MEDIUM | -3.908*** | 1.022 | -2.283 | -3.285*** |
| | (1.007) | (2.161) | (1.466) | (0.762) |
| LARGE | -5.639*** | -2.986 | -2.671 | -5.526*** |
| | (1.018) | (2.407) | (1.802) | (1.061) |
| DGP | -1.838** | 4.824*** | -0.386 | 3.543*** |
| | (0.919) | (1.623) | (1.711) | (1.134) |
| FGP | -0.007 | 2.216 | -0.448 | -1.152 |
| | (1.275) | (1.716) | (1.306) | (0.949) |
| Constant | -53.550*** | -9.650** | -20.328*** | -0.632 |
| | (12.328) | (4.889) | (4.045) | (2.673) |
| *Joint sign. (p-value)* | | | | |
| W_industry | 0.000*** | 0.538 | 0.000*** | 0.000*** |
| W_country | 0.000*** | 0.000*** | 0.000*** | 0.000*** |
| W_time | 0.000*** | 0.003*** | 0.001*** | - |
| R2a | 0.436 | 0.534 | 0.458 | 0.582 |
| RMSE | 29.759 | 25.048 | 28.290 | 21.308 |
| Wald-Test: β=1 | 0.892 | 0.527 | 0.709 | 0.908 |
| *Tests on Exogeneity* | | | | |
| SGR_NEWPD | 0.005*** | 0.330 | 0.015** | 0.111 |
| *Tests on instr. validity* | | | | |
| Sargan/Hansen J-Test | 0.216 | 0.157 | 0.613 | 0.325 |
| *First stage results* | | | | |
| RANGE | 25.821*** | 24.914*** | 22.689*** | 20.919*** |
| | (1.564) | (1.574) | ( 1.218) | (2.200) |
| COOP | 6.780*** | 8.281*** | 7.694*** | 5.359*** |
| | (1.478) | (2.763) | (0.932) | (1.619) |
| F test on excl. Instr. | 218.00*** | 177.45 | 373.32*** | 114.21*** |
| *Tests on underident.* | | | | |
| Kleibergen-Paap LM test | 105.508*** | 14.482*** | 321.757*** | 119.556*** |
| *Test on weak instr.* | | | | |
| Cragg-Donald F test | 2198.649*** | 671.860*** | 1921.677*** | 1193.139*** |
| Kleibergen-Paap F test | 373.042*** | 255.525*** | 268.397*** | 82.356*** |
| *Weak instr. rob. inf.* | | | | |
| Anderson-R. Wald test | 309.586*** | 211.052*** | 262.383*** | 101.164*** |
| Stock-Wright LM test | 23.560*** | 14.055*** | 21.926*** | 12.432*** |
| Obs | 18,407 | 5,097 | 15489 | 12,632 |

*Notes: See Table 11.2. The Netherlands have been excluded from boom periods. In regression (3) CLIENT has been used as instrument instead of COOP in order to ensure instrument validity. CLIENT is a binary variable that equals 1 if clients have been a high-to-medium important information source for innovation.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

**Table 11.8: Impact of innovation on employment growth over the business cycle, low-tech manufacturing, 1998-2010**

| **Dep var:** | **Upturn** | **Boom** | **Downturn** | **Recession** |
|---|---|---|---|---|
| $EMP = l - (g_1 - \hat{\pi}_1)$ | **(1)** | **(2)** | **(3)** | **(4)** |
| SGR_NEWPD | 0.972*** | 0.970*** | 0.997*** | 0.955*** |
| | (0.027) | (0.040) | (0.027) | (0.023) |
| PCONLY | -1.613* | -0.573 | -1.921* | -0.634 |
| | (0.930) | (1.382) | (1.060) | (1.100) |
| ORGA | -2.131*** | 1.007 | -1.553** | -0.822** |
| | (0.639) | (0.930) | (0.743) | (0.413) |
| GDPGR | 3.849*** | 3.533** | -0.722*** | -0.045 |
| | (0.117) | (1.689) | (0.200) | (0.314) |
| MEDIUM | -2.836*** | -0.398 | -1.037 | -1.721*** |
| | (0.468) | (0.884) | (0.639) | (0.561) |
| LARGE | -4.247*** | -3.813*** | -1.079 | -3.490*** |
| | (0.637) | (1.139) | (0.883) | (0.762) |
| DGP | -1.243 | 2.559** | 0.836 | 0.340 |
| | (0.828) | (1.163) | (0.707) | (0.640) |
| FGP | -1.736 | 0.474 | 0.550 | -2.007** |
| | (1.077) | (1.261) | (0.836) | (0.817) |
| Constant | -69.290*** | -39.935*** | -14.044*** | 3.554* |
| | (2.005) | (15.156) | (3.063) | (1.875) |
| *Joint sign. (p-value)* | | | | |
| W_industry | 0.000*** | 0.000*** | 0.000*** | 0.000*** |
| W_country | 0.000*** | 0.000*** | 0.000*** | 0.000*** |
| W_time | 0.000*** | - | 0.000*** | - |
| R2a | 0.359 | 0.466 | 0.369 | 0.406 |
| RMSE | 29.740 | 23.027 | 29.002 | 20.890 |
| Wald-Test: β=1 | 0.293 | 0.446 | 0.914 | 0.054* |
| *Tests on Exogeneity* | | | | |
| SGR_NEWPD | 0.000*** | 0.011** | 0.000*** | 0.058* |
| *Tests on instr. validity* | | | | |
| Sargan/Hansen J-Test | 0.511 | 0.555 | 0.166 | 0.693 |
| *First stage results* | | | | |
| RANGE | 23.436*** | 21.675*** | 24.034*** | 20.446*** |
| | (0.856) | (1.031) | (1.047) | (1.037) |
| COOP | 7.226*** | 5.244*** | 6.643*** | 3.324*** |
| | ('1.052) | (1.956) | (0.883) | (0.881) |
| F test on excl. Instr. | 589.95*** | 231.98*** | 290.3*** | 282.51*** |
| *Tests on underident.* | | | | |
| Kleibergen-Paap LM test | 807.923*** | 358.007*** | 964.577*** | 726.334*** |
| *Test on weak instr.* | | | | |
| Cragg-Donald F test | 5213.534*** | 1222.686*** | 6472.240*** | 5276.926*** |
| Kleibergen-Paap F test | 589.953*** | 231.983*** | 943.380*** | 521.092*** |
| *Weak instr. rob. inf.* | | | | |
| Anderson-R. Wald test | 743.596*** | 301.041*** | 626.487*** | 408.909*** |
| Stock-Wright LM test | 574.908*** | 246.402*** | 69.726*** | 51.755*** |
| Obs | 49,163 | 10,771 | 52,243 | 39,208 |

*Notes: See Table 11.2. The Netherlands have been excluded from boom periods. Due to a singleton dummy problem, standard errors are not clustered but heteroskedasticity-robust in regressions (1) and (2).*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

**Table 11.9: Impact of innovation on employment growth over the business cycle, knowledge-intensive services, 1998-2010**

| **Dep var:** | Upturn | Boom | Downturn | Recession |
|---|---|---|---|---|
| $EMP = l - (g_1 - \hat{\pi}_1)$ | (1) | (2) | (3) | (4) |
| SGR_NEWPD | 0.956*** | 0.996*** | 0.965*** | 1.001*** |
| | (0.051) | (0.086) | (0.041) | (0.037) |
| PCONLY | -2.454 | 7.958 | 0.573 | -1.992 |
| | (2.324) | (7.408) | (1.309) | (1.471) |
| ORGA | -1.903 | -4.599** | -1.826** | 2.642*** |
| | (1.320) | (1.975) | (0.916) | (0.824) |
| GDPGR | 3.285*** | -9.420** | -0.334 | 0.902 |
| | (1.197) | (3.988) | (0.387) | (0.566) |
| MEDIUM | -6.298*** | 2.204 | -4.333*** | -3.208*** |
| | (1.272) | (3.901) | (1.049) | (0.901) |
| LARGE | -6.778*** | 0.687 | -7.541*** | -2.978* |
| | (2.152) | (2.747) | (1.990) | (1.740) |
| DGP | -1.828 | 1.150 | -1.135 | -0.110 |
| | (1.779) | (1.790) | (0.907) | (1.172) |
| FGP | -4.632** | 0.490 | 0.987 | 0.032 |
| | (2.278) | (2.707) | (1.332) | (1.383) |
| Constant | -53.700*** | 59.986* | -14.326** | 16.192*** |
| | (16.929) | (32.270) | (5.708) | (3.266) |
| *Joint sign. (p-value)* | | | | |
| W_industry | 0.189 | 0.515 | 0.007*** | 0.307 |
| W_country | 0.000*** | 0.000*** | 0.000*** | 0.000*** |
| W_time | 0.004*** | - | 0.334 | - |
| R2a | 0.294 | 0.412 | 0.338 | 0.438 |
| RMSE | 37.127 | 36.549 | 36.452 | 24.652 |
| Wald-Test: β=1 | 0.387 | 0.962 | 0.392 | 0.984 |
| *Tests on Exogeneity* | | | | |
| SGR_NEWPD | 0.001*** | 0.451 | 0.000*** | 0.072* |
| *Tests on instr. validity* | | | | |
| Sargan/Hansen J-Test | 0.656 | 0.230 | 0.898 | 0.236 |
| *First stage results* | | | | |
| RD | 24.178*** | 23.038*** | 19.424*** | 18.534*** |
| | (2.523) | (4.364) | (1.450) | (1.476) |
| COOP | 15.728*** | 14.493*** | 22.414*** | 12.227*** |
| | (1.048) | (3.543) | (1.458) | (1.111) |
| F test on excl. Instr. | 218.94*** | 70.60*** | 241.48*** | 221.65*** |
| *Tests on underident.* | | | | |
| Kleibergen-Paap LM test | 209.904*** | 7.254** | 732.282*** | 261.277*** |
| *Test on weak instr.* | | | | |
| Cragg-Donald F test | 1681.264*** | 226.664*** | 2120.737*** | 1929.478*** |
| Kleibergen-Paap F test | 228.924*** | 81.590*** | 548.304*** | 177.575*** |
| *Weak instr. rob. inf.* | | | | |
| Anderson-R. Wald test | 183.938*** | 74.295*** | 343.776*** | 268.618*** |
| Stock-Wright LM test | 29.789*** | 7.719** | 49.271*** | 34.162*** |
| Obs | 20,518 | 4,226 | 20,424 | 21,157 |

*Notes: See Table 11.2. The Netherlands have been excluded from boom periods. In regression (3) CLIENT has been used as instrument instead of COOP in order to ensure instrument validity. For a definition of CLIENT see Table 11.7.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

**Table 11.10: Impact of innovation on employment growth over the business cycle, less knowledge-intensive services, 1998-2010**

| **Dep var:** | Upturn | Boom | Downturn | Recession |
|---|---|---|---|---|
| $EMP = l - (g_1 - \hat{\pi}_1)$ | (1) | (2) | (3) | (4) |
| SGR_NEWPD | 1.037*** | 0.867*** | 1.104*** | 1.060*** |
| | (0.101) | (0.093) | (0.100) | (0.084) |
| PCONLY | 0.774 | -4.282 | 1.587 | 1.021 |
| | (2.126) | (3.685) | (1.709) | (1.085) |
| ORGA | -2.283** | 2.555 | -1.358 | -1.353** |
| | (0.956) | (2.132) | (1.487) | (0.557) |
| GDPGR | 1.297 | -0.518 | -0.668*** | 0.932*** |
| | (2.827) | (2.401) | (0.258) | (0.220) |
| MEDIUM | -3.298*** | -1.650 | -2.784*** | -4.903*** |
| | (1.207) | (1.877) | (0.800) | (0.745) |
| LARGE | -2.034 | -5.710** | -4.228*** | -6.929*** |
| | (1.921) | (2.810) | (1.080) | (1.199) |
| DGP | -0.347 | -0.126 | 0.743 | 0.735 |
| | (1.274) | (2.575) | (0.862) | (0.694) |
| FGP | -5.287*** | -3.215 | -0.371 | 0.336 |
| | (1.676) | (3.304) | (1.071) | (1.187) |
| Constant | -25.715 | -6.706 | -5.479 | 15.024*** |
| | (34.288) | (20.136) | (4.384) | (1.488) |
| *Joint sign. (p-value)* | | | | |
| W_industry | 0.311 | 0.247 | 0.000*** | 0.001*** |
| W_country | 0.000*** | 0.000*** | 0.000*** | 0.000*** |
| W_time | 0.086* | - | 0.605 | - |
| R2a | 0.185 | 0.306 | 0.233 | 0.295 |
| RMSE | 37.175 | 29.477 | 34.363 | 22.823 |
| Wald-Test: β=1 | 0.712 | 0.154 | 0.297 | 0.477 |
| *Tests on Exogeneity* | | | | |
| SGR_NEWPD | 0.056* | 0.805 | 0.023** | 0.038** |
| *Tests on instr. validity* | | | | |
| Sargan/Hansen J-Test | 0.256 | 0.675 | 0.477 | 0.574 |
| *First stage results* | | | | |
| RD | 17.234*** | 25.871*** | 15.298*** | 14.995*** |
| | (2.950) | (2.332) | (2.499) | (2.584) |
| COOP | 14.610*** | 4.468 | 13.262*** | 10.948*** |
| | (1.630) | (3.195) | (1.412) | (1.500) |
| F test on excl. Instr. | 58.79*** | 83.54*** | 53.48*** | 41.66*** |
| *Tests on underident.* | | | | |
| Kleibergen-Paap LM test | 106.586*** | 115.675*** | 178.346*** | 87.228*** |
| *Test on weak instr.* | | | | |
| Cragg-Donald F test | 1072.062*** | 644.318*** | 841.133*** | 839.654*** |
| Kleibergen-Paap F test | 102.157*** | 83.545*** | 66.120*** | 60.075*** |
| *Weak instr. rob. inf.* | | | | |
| Anderson-R. Wald test | 162.469*** | 54.017*** | 122.434*** | 250.144*** |
| Stock-Wright LM test | 14.082*** | 48.392*** | 16.766*** | 21.078*** |
| Obs | 24,833 | 3,741 | 32,738 | 26,121 |

*Notes: See Table 11.2. The Netherlands have been excluded in boom periods. In regression (2) RANGE has been used as instrument instead of RD in order to ensure instrument validity.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

**Table 11.11: Impact of innovation on employment growth in industries of high, medium and low business cycle sensitivity, 1998-2010**

| | **Manufacturing** | | | **Services** | | |
|---|---|---|---|---|---|---|
| | **Low** | **Medium** | **High** | **Low** | **Medium** | **High** |
| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** |
| SGR_NEWPD | 0.995*** | 0.998*** | 1.028*** | 1.037*** | 1.027*** | 0.902*** |
| | (0.033) | (0.029) | (0.043) | (0.083) | (0.035) | (0.042) |
| PCONLY | -0.567 | -0.458 | -0.259 | -0.346 | -0.106 | -0.843 |
| | (1.065) | (0.618) | (1.319) | (1.623) | (0.699) | (1.639) |
| ORGA | -3.087*** | -3.221*** | -2.022*** | 0.782 | -1.765 | -0.697 |
| | (0.782) | (1.132) | (0.725) | (1.686) | (1.120) | (1.085) |
| GDPGR | 0.192 | 0.730 | -0.206 | -0.978*** | 0.110 | -0.906*** |
| | (0.405) | (0.532) | (0.327) | (0.324) | (0.459) | (0.351) |
| SGR_NEWPD | -0.007** | -0.003 | -0.005 | -0.010 | -0.011* | 0.012** |
| x GDPGR | (0.003) | (0.004) | (0.005) | (0.010) | (0.006) | (0.006) |
| PCONLY | -0.288* | -0.339*** | -0.046 | -0.025 | -0.255* | 0.114 |
| x GDPGR | (0.150) | (0.129) | (0.209) | (0.209) | (0.148) | (0.344) |
| ORGA | 0.389*** | 0.229 | 0.169 | 0.106 | 0.204* | -0.376** |
| x GDPGR | (0.099) | (0.142) | (0.107) | (0.237) | (0.122) | (0.160) |
| MEDIUM | -1.571*** | -2.036*** | -1.532** | -4.025*** | -3.092*** | -4.254*** |
| | (0.543) | (0.491) | (0.667) | (0.623) | (0.630) | (1.227) |
| LARGE | -3.037*** | -4.290*** | -3.501*** | -5.527*** | -4.243*** | -5.666*** |
| | (0.767) | (0.532) | (0.942) | (1.171) | (0.927) | (1.167) |
| DGP | 1.291 | 1.078 | 1.073* | 0.511 | 0.543 | -0.244 |
| | (0.986) | (0.741) | (0.610) | (0.880) | (0.813) | (1.091) |
| FGP | 0.561 | -1.215 | -0.068 | 0.002 | -2.348** | -0.438 |
| | (0.788) | (0.826) | (0.656) | (1.303) | (0.917) | (1.416) |
| Constant | -20.665*** | -31.949*** | -17.336*** | 0.815 | -10.345 | -14.354** |
| | (5.554) | (7.330) | (4.710) | (6.113) | (6.842) | (6.299) |
| *Joint sign. (p-val)* | | | | | | |
| W_industry | 0.000*** | 0.000*** | 0.000*** | 0.004** | 0.000*** | 0.255 |
| W_country | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** |
| W_time | 0.005*** | 0.000*** | 0.000*** | 0.000*** | 0.018** | 0.004*** |
| R2a | 0.349 | 0.349 | 0.452 | 0.250 | 0.291 | 0.249 |
| RMSE | 27.425 | 28.557 | 27.320 | 33.085 | 33.103 | 32.006 |
| Wald-Test: β=1 | 0.880 | 0.954 | 0.518 | 0.656 | 0.435 | 0.019** |
| *Tests on Exog.* | | | | | | |
| SGR_NEWPD | 0.012** | 0.000*** | 0.001*** | 0.014** | 0.001*** | 0.181 |
| *Tests on instr. val.* | | | | | | |
| Sargan/Hansen J | 0.575 | 0.845 | 0.965 | 0.320 | 0.594 | 0.277 |
| *First stage results* | | | | | | |
| RANGE / RD | 20.320*** | 21.956*** | 21.667*** | 15.007*** | 20.147*** | 16.852*** |
| | (0.949) | (0.904) | (1.402) | (1.717) | (1.693) | (1.186) |
| COOP | 4.247*** | 4.511*** | 6.610*** | 13.726*** | 10.823*** | 15.581*** |
| | (0.628) | (1.078) | -0.969 | (1.573) | (0.562) | (1.068) |
| RANGE / RD | 0.547*** | 0.554*** | 0.656*** | 0.359 | 0.394** | 0.366 |
| x GDPGR | (0.120) | (0.147) | -0.201 | (0.247) | (0.177) | (0.310) |
| COOP | 0.344*** | 0.277 | 0.23 | 0.420* | 0.458*** | 0.421* |
| x GDPGR | (0.128) | (0.216) | (0.122) | (0.238) | (0.131) | (0.244) |
| F test on excl. Instr. | 180.79*** | 228.32*** | 239.18*** | 53.58*** | 132.47*** | 177.58*** |
| *Tests on underid.* | | | | | | |
| Kleibergen-Paap LM | 358.956*** | 601.807*** | 326.680*** | 180.042*** | 209.855*** | 102.674*** |
| *Test on weak instr.* | | | | | | |
| Cragg-Donald F | 4652.314*** | 3958.034*** | 3553.834*** | 832.866*** | 2015.974*** | 1188.986*** |
| Kleibergen-Paap F | 367.067*** | 529.641*** | 208.253*** | 74.039*** | 115.346*** | 134.813*** |
| *Weak instr. rob. inf.* | | | | | | |
| Anderson-R. Wald | 598.810*** | 797.114*** | 808.583*** | 154.107*** | 466.658*** | 278.936*** |
| Stock-Wright LM | 32.629*** | 70.005*** | 45.418*** | 36.093*** | 26.870*** | 21.228*** |
| Obs | 75,865 | 66,884 | 61,364 | 46,822 | 76,859 | 34,071 |

*Notes: See Table 11.2.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

**Table 11.12: Impact of innovation on employment growth over the business cycle in SME and large enterprises in manufacturing, 1998-2010**

| | **Manufacturing,10-249** | | | | **Manufacturing, 250+** | | | |
|---|---|---|---|---|---|---|---|---|
| | **Upturn** | **Boom** | **Downturn** | **Recession** | **Upturn** | **Boom** | **Downturn** | **Recession** |
| SGR_NEWPD | 0.989*** | 0.965*** | 1.010*** | 0.971*** | 0.953*** | 1.015*** | 1.025*** | 0.994*** |
| | (0.026) | (0.029) | (0.026) | (0.027) | (0.031) | (0.054) | (0.041) | (0.046) |
| PCONLY | -1.278 | -0.453 | -1.727* | -0.547 | -2.999*** | -0.130 | 0.427 | 0.696 |
| | (0.821) | (1.483) | (0.981) | (1.071) | (1.107) | (2.266) | (1.177) | (1.275) |
| ORGA | -2.012*** | 0.639 | -1.629** | -0.674 | -2.871*** | -1.710 | -0.743 | -1.022* |
| | (0.449) | (0.703) | (0.655) | (0.509) | (0.695) | (1.049) | (0.730) | (0.560) |
| GDPGR | 3.774*** | 2.466 | -0.655*** | 0.169 | 6.020*** | 1.134 | -0.950*** | 0.332 |
| | (0.532) | (1.915) | (0.188) | (0.290) | (0.556) | (2.726) | (0.206) | (0.420) |
| DGP | -1.559* | 3.178** | 0.647 | 0.812 | -3.393*** | 2.094* | -1.717* | -1.023 |
| | (0.835) | (1.249) | (0.674) | (0.676) | (0.963) | (1.159) | (0.935) | (0.777) |
| FGP | -1.559 | 1.059 | -0.119 | -2.364*** | -3.209*** | -0.289 | -0.402 | -3.480*** |
| | (0.970) | (1.190) | (0.780) | (0.648) | (0.995) | (1.425) | (1.113) | (0.844) |
| Constant | -68.685*** | -30.782* | -15.031*** | 3.115* | -82.340*** | -24.260 | -23.132*** | 0.259 |
| | (7.065) | (16.664) | (2.796) | (1.774) | (6.263) | (24.925) | (3.083) | (2.276) |
| R2a | 0.387 | 0.474 | 0.386 | 0.467 | 0.620 | 0.640 | 0.554 | 0.554 |
| *Joint significance* | | | | | | | | |
| W_ownership | 0.082* | 0.036** | 0.556 | 0.000*** | 0.001*** | 0.053* | 0.146 | 0.000*** |
| W_industry | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** |
| W_country | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** |
| W_time | 0.000*** | - | 0.000*** | - | 0.000*** | - | 0.000*** | - |
| Wald-Test: β=1 | 0.671 | 0.230 | 0.688 | 0.282 | 0.123 | 0.783 | 0.534 | 0.903 |
| *Tests on Exog.* | | | | | | | | |
| SGR_NEWPD | 0.000*** | 0.002*** | 0.000*** | 0.023** | 0.000*** | 0.003*** | 0.002*** | 0.029** |
| *Test on instr. val.* | | | | | | | | |
| J-Test | 0.957 | 0.319 | 0.893 | 0.664 | 0.189 | 0.857 | 0.330 | 0.202 |
| *First stage results* | | | | | | | | |
| F-test excl. instr. | 596.51*** | 212.32*** | 446.89*** | 349.74*** | 298.38*** | 54.09*** | 186.09*** | 112.81*** |
| *Tests: underident.* | | | | | | | | |
| KP LM | 245.5*** | 51.4*** | 1164.5*** | 618.4*** | 280.7*** | 40.0*** | 430.9*** | 327.5*** |
| *Test: weak instr.* | | | | | | | | |
| CD Wald F | 6245.3*** | 1647.8*** | 7435.2*** | 5645.5*** | 822.2*** | 180.1*** | 572.8*** | 273.5*** |
| KP Wald F | 776.1*** | 267.7*** | 1005.2*** | 434.1*** | 460.9*** | 59.2*** | 401.6*** | 175.3*** |
| *Weak instr. inf.* | | | | | | | | |
| AR Wald | 757.4*** | 380.1*** | 981.5*** | 318.6*** | 449.9*** | 154.8*** | 244.0*** | 146.0*** |
| SW LM | 54.1*** | 42.2*** | 60.0*** | 46.0*** | 87.0*** | 42.2*** | 71.6*** | 67.9*** |
| Obs | 55,441 | 12,092 | 56,859 | 44,349 | 10,093 | 3,438 | 8,584 | 6,225 |

*Notes: Additional control variables: dummies for industry, country and time. See also notes of Table 11.2.*

*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

**Table 11.13: Impact of innovation on employment growth over the business cycle in SME and large enterprises in services, 1998-2010**

| | Services,10-249 | | | | Services, 250+ | | | |
|---|---|---|---|---|---|---|---|---|
| | **Upturn** | **Boom** | **Downturn** | **Recession** | **Upturn** | **Boom** | **Downturn** | **Recession** |
| SGR_NEWPD | 0.981*** | 0.735*** | 1.024*** | 1.003*** | 1.040*** | 0.951*** | 0.898*** | 0.854*** |
| | (0.044) | (0.113) | (0.048) | (0.046) | (0.096) | (0.128) | (0.150) | (0.053) |
| PCONLY | 0.603 | -3.362 | 0.912 | -0.646 | -0.180 | 5.494 | -1.607 | -1.965 |
| | (1.390) | (2.967) | (1.148) | (0.873) | (1.701) | (5.157) | (1.642) | (1.405) |
| ORGA | -1.247 | 1.302 | -1.110 | 0.640 | -1.200 | 1.967 | 0.139 | 0.433 |
| | (0.821) | (1.411) | (0.819) | (0.571) | (1.815) | (2.620) | (1.119) | (1.176) |
| GDPGR | 1.938 | -1.391 | -0.613*** | 1.063*** | 1.965 | 1.521 | 2.766*** | -0.876** |
| | (2.062) | (1.358) | (0.201) | (0.320) | (1.798) | (7.132) | (0.983) | (0.396) |
| DGP | -0.335 | 0.419 | 0.044 | -0.212 | 0.395 | 2.657 | -0.021 | -0.377 |
| | (1.305) | (1.496) | (0.624) | (0.649) | (1.449) | (3.760) | (1.134) | (1.265) |
| FGP | -4.643*** | -1.879 | -0.171 | 0.060 | -0.121 | 4.726 | -1.103 | 3.093** |
| | (1.383) | (2.458) | (0.894) | (0.893) | (1.939) | (4.391) | (1.361) | (1.416) |
| Constant | -35.858 | 0.506 | -8.466** | 14.910*** | -32.675 | -38.563 | 9.215*** | -11.818 |
| | (25.572) | (11.987) | (3.309) | (1.319) | (22.240) | (64.650) | (2.834) | (8.013) |
| *Joint significance* | | | | | | | | |
| W_ownership | 0.002*** | 0.716 | 0.977 | 0.943 | 0.909 | 0.547 | 0.024** | 0.687 |
| W_industry | 0.059* | 0.019** | 0.000*** | 0.000*** | 0.087* | 0.001*** | 0.009*** | 0.000*** |
| W_country | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.27 | 0.000*** | 0.000*** |
| W_time | 0.032** | - | 0.985 | - | 0.682 | - | 0.016** | - |
| R2a | 0.246 | 0.350 | 0.283 | 0.357 | 0.376 | 0.446 | 0.537 | 0.478 |
| Wald-Test: β=1 | 0.661 | 0.019** | 0.615 | 0.939 | 0.677 | 0.701 | 0.494 | 0.006*** |
| *Tests on Exog.* | | | | | | | | |
| SGR_NEWPD | 0.000*** | 0.504 | 0.000*** | 0.051* | 0.065* | 0.544 | 0.719 | 0.702 |
| *Test on instr. val.* | | | | | | | | |
| J-Test | 0.517 | 0.600 | 0.109 | 0.419 | 0.862 | 0.298 | 0.395 | 0.695 |
| *1st stage results* | | | | | | | | |
| F-test excl. instr. | 149.11*** | 43.79*** | 153.52*** | 156.53*** | 84.05*** | 9.36*** | 65.78*** | 64.62*** |
| *Tests: underiden.* | | | | | | | | |
| KP LM | 260.4*** | 11.6*** | 631.6*** | 288.4*** | 174.414*** | 12.9*** | 184.7*** | 182.4*** |
| *Test: weak instr.* | | | | | | | | |
| CD Wald F | 2399.1*** | 365.7*** | 2162.5*** | 2692.4*** | 188.0*** | 32.5*** | 159.5*** | 198.0*** |
| KP Wald F | 260.8*** | 47.4*** | 237.2*** | 194.2*** | 109.7*** | 9.5* | 71.8*** | 104.6*** |
| *Weak instr. inf.* | | | | | | | | |
| AR Wald | 243.0*** | 23.0*** | 360.7*** | 245.7*** | 73.7*** | 13.5** | 22.6*** | 78.6*** |
| SW LM | 45.7*** | 15.3*** | 48.3*** | 47.7*** | 37.1*** | 8.4** | 23.6*** | 32.0*** |
| Obs | 37,887 | 6,635 | 45,030 | 40,573 | 5,658 | 1,180 | 5,148 | 5,176 |

*Notes: Additional control variables: dummies for industry, country and time. See also notes of Table 11.2.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

**Table 11.14: Impact of innovation on employment growth over the business cycle in domestically owned unaffiliated firms, 1998-2010**

| | Manufacturing - DUF | | | | Services - DUF | | | |
|---|---|---|---|---|---|---|---|---|
| | **Upturn** | **Boom** | **Downturn** | **Recession** | **Upturn** | **Boom** | **Downturn** | **Recession** |
| SGR_NEWPD | 1.023*** | 0.980*** | 1.013*** | 0.969*** | 1.010*** | 0.900*** | 0.947*** | 1.054*** |
| | (0.033) | (0.035) | (0.026) | (0.030) | (0.061) | (0.082) | (0.029) | (0.051) |
| PCONLY | 0.522 | 0.487 | -1.288 | -0.156 | 0.300 | -0.144 | 0.487 | -0.247 |
| | (1.056) | (1.508) | (1.022) | (1.322) | (1.842) | (5.408) | (1.014) | (1.110) |
| ORGA | -4.117*** | 0.227 | -1.887** | -0.728 | -2.999*** | 2.024 | -0.397 | 0.648 |
| | (0.714) | (0.840) | (0.830) | (0.565) | (1.126) | (2.764) | (0.785) | (0.765) |
| GDPGR | 2.843** | 4.007* | -0.530*** | -0.276 | 1.752 | -1.813 | -0.625** | 0.687** |
| | (1.147) | (2.170) | (0.189) | (0.337) | (2.522) | (2.385) | (0.286) | (0.275) |
| MEDIUM | -3.080*** | 1.124 | -1.136* | -1.891*** | -5.898*** | 0.157 | -3.670*** | -4.512*** |
| | (0.480) | (1.123) | (0.653) | (0.480) | (1.069) | (2.922) | (0.751) | (0.690) |
| LARGE | -6.235*** | -2.435 | -0.883 | -4.198*** | -6.236*** | -6.808* | -6.089*** | -6.217*** |
| | (0.923) | (1.522) | (1.109) | (0.918) | (1.849) | (3.610) | (1.102) | (1.476) |
| Constant | -36.219*** | -44.156** | -15.622*** | 2.526 | -19.206 | 3.261 | -5.227 | 15.905*** |
| | (11.738) | (18.572) | (2.686) | (2.021) | (25.930) | (20.181) | (3.710) | (1.120) |
| *Joint sig.* | | | | | | | | |
| W_industry | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.422 | 0.296 | 0.000*** | 0.000*** |
| W_country | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** |
| R2a | 0.307 | 0.499 | 0.365 | 0.455 | 0.195 | 0.331 | 0.269 | 0.337 |
| Wald-Test: β=1 | 0.485 | 0.569 | 0.616 | 0.301 | 0.871 | 0.222 | 0.064* | 0.284 |
| *Tests on exog.* | | | | | | | | |
| SGR_NEWPD | 0.000*** | 0.005*** | 0.000*** | 0.051* | 0.004*** | 0.975 | 0.000*** | 0.010** |
| *Test on instr. val.* | | | | | | | | |
| J-Test | 0.935 | 0.358 | 0.216 | 0.638 | 0.403 | 0.329 | 0.283 | 0.481 |
| *1st stage result* | | | | | | | | |
| F-test excl. instr. | 484.3*** | 236.8*** | 361.7*** | 265.0*** | 129.9*** | 61.5*** | 137.8*** | 151.7*** |
| *Tests: underiden.* | | | | | | | | |
| KP LM | 239.5*** | 38.8*** | 976.2*** | 461.3*** | 184.4*** | 10.3*** | 391.0*** | 203.7*** |
| *Test: weak instr.* | | | | | | | | |
| CD Wald F | 5756.4*** | 1299.8*** | 6689.1*** | 5083.3*** | 2033.1*** | 275.3*** | 5553.1*** | 1873.7*** |
| KP Wald F | 769.5*** | 265.5*** | 863.9*** | 340.9*** | 177.5*** | 65.4*** | 602.7*** | 132.9*** |
| *Weak instr. inf.* | | | | | | | | |
| AR Wald | 696.6*** | 353.7*** | 681.7*** | 296.4*** | 165.8*** | 53.3*** | 338.6*** | 300.4*** |
| SW LM | 51.4*** | 36.7*** | 82.7*** | 42.2*** | 39.7*** | 8.7** | 35.3*** | 37.0*** |
| Obs | 49,672 | 9,013 | 50,344 | 35,757 | 31,051 | 4,841 | 37,165 | 30,716 |

*Notes: Additional control variables: dummies for industry and country. See also notes of Table 11.2.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

**Table 11.15: Impact of innovation on employment growth over the business cycle in domestically owned group firms, 1998-2010**

| | Manufacturing - DGP | | | | Services - DGP | | | |
|---|---|---|---|---|---|---|---|---|
| | **Upturn** | **Boom** | **Downturn** | **Recession** | **Upturn** | **Boom** | **Downturn** | **Recession** |
| SGR_NEWPD | 0.968*** | 0.916*** | 1.009*** | 1.036*** | 1.009*** | 0.704*** | 0.987*** | 1.000*** |
| | (0.055) | (0.091) | (0.048) | (0.061) | (0.059) | (0.191) | (0.056) | (0.050) |
| PCONLY | -0.555 | -2.360 | -1.433 | -0.323 | 0.926 | -2.412 | -0.590 | 0.476 |
| | (1.608) | (3.392) | (1.591) | (1.326) | (2.530) | (3.598) | (1.972) | (1.527) |
| ORGA | -2.007 | 1.431 | -1.418 | -0.045 | -0.523 | -1.304 | -0.412 | 0.559 |
| | (1.319) | (2.016) | (0.909) | (0.925) | (1.712) | (3.086) | (1.515) | (0.847) |
| GDPGR | 0.185 | 0.835 | -0.596** | 0.777 | -0.548 | -3.943 | -0.591 | 1.345* |
| | (1.059) | (3.543) | (0.289) | (0.683) | (1.267) | (3.193) | (0.641) | (0.711) |
| MEDIUM | -0.757 | -2.307 | -1.407 | -2.582** | -4.021*** | -3.009* | -4.405*** | -3.366*** |
| | (1.009) | (1.665) | (1.223) | (1.266) | (1.333) | (1.597) | (1.090) | (0.906) |
| LARGE | -3.751*** | -6.010*** | -2.679*** | -4.394*** | -4.907** | -3.869* | -6.781*** | -3.671** |
| | (1.171) | (2.082) | (1.034) | (1.361) | (2.345) | (2.340) | (1.984) | (1.734) |
| Constant | -11.896 | -10.065 | -9.563* | 5.272 | -4.282 | 25.748 | 14.736* | 15.921*** |
| | (11.570) | (32.585) | (5.375) | (4.067) | (14.560) | (27.202) | (8.312) | (4.490) |
| *Joint sig.* | | | | | | | | |
| W_industry | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.029** | 0.000*** | 0.006*** |
| W_country | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** |
| R2a | 0.426 | 0.448 | 0.428 | 0.506 | 0.305 | 0.352 | 0.323 | 0.392 |
| Wald-Test: β=1 | 0.565 | 0.354 | 0.854 | 0.549 | 0.885 | 0.121 | 0.818 | 0.993 |
| *Tests on exog.* | | | | | | | | |
| SGR_NEWPD | 0.002*** | 0.206 | 0.002*** | 0.008*** | 0.008*** | 0.857 | 0.005*** | 0.095* |
| *Test on instr. val.* | | | | | | | | |
| J-Test | 0.646 | 0.152 | 0.709 | 0.899 | 0.695 | 0.527 | 0.698 | 0.405 |
| *1st stage result* | | | | | | | | |
| F-test excl. instr. | 113.3*** | 55.9*** | 216.4*** | 121.4*** | 150.0*** | 17.8*** | 146.7*** | 63.4*** |
| *Tests: underiden.* | | | | | | | | |
| KP LM | 102.6*** | 43.2*** | 304.5*** | 273.2*** | 203.4*** | 8.8** | 225.4*** | 118.9*** |
| *Test: weak instr.* | | | | | | | | |
| CD Wald F | 1051.2*** | 323.5*** | 1025.9*** | 740.2*** | 648.9*** | 68.0*** | 638.1*** | 822.1*** |
| KP Wald F | 113.7*** | 64.4*** | 263.9*** | 158.6*** | 178.6*** | 18.8** | 141.6*** | 75.8*** |
| *Weak instr. inf.* | | | | | | | | |
| AR Wald | 167.7*** | 35.8*** | 237.1*** | 139.8*** | 161.8*** | 23.7*** | 206.4*** | 123.1*** |
| SW LM | 38.5*** | 25.1*** | 46.8*** | 42.8*** | 32.1*** | 15.0*** | 32.8*** | 43.2*** |
| Obs | 11,329 | 4,212 | 9,978 | 9,784 | 10,319 | 2,290 | 10,477 | 10,933 |

*Notes: Additional control variables: dummies for industry and country. See also notes of Table 11.2.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

**Table 11.16: Impact of innovation on employment growth over the business cycle in domestically owned group firms, 1998-2010**

| | Manufacturing - DGP | | | | Services - DGP | | | |
|---|---|---|---|---|---|---|---|---|
| | **Upturn** | **Boom** | **Downturn** | **Recession** | **Upturn** | **Boom** | **Downturn** | **Recession** |
| SGR_NEWPD | 0.943*** | 0.900*** | 0.919*** | 0.931*** | 0.960*** | 0.895*** | 1.178*** | 0.930*** |
| | (0.078) | (0.053) | (0.065) | (0.051) | (0.154) | (0.347) | (0.099) | (0.071) |
| PCONLY | -2.255 | -4.092* | -4.488 | -1.906 | 0.153 | -11.375 | 1.954 | -2.583 |
| | (2.672) | (2.131) | (2.875) | (1.342) | (4.258) | (8.756) | (2.676) | (1.847) |
| ORGA | 1.159 | -1.114 | 0.643 | -0.611 | -2.387 | 2.041 | -2.139 | -2.794 |
| | (1.466) | (1.513) | (1.159) | (1.144) | (2.610) | (4.064) | (1.844) | (2.013) |
| GDPGR | 0.477 | 3.081*** | -0.178 | 0.534 | 2.739 | -10.825 | -0.582 | 1.656*** |
| | (3.409) | (0.994) | (0.307) | (0.512) | (1.897) | (7.864) | (0.605) | (0.514) |
| MEDIUM | -4.028** | -5.071*** | -0.627 | -2.839** | -0.259 | -2.316 | -1.000 | -4.813*** |
| | (1.890) | (1.791) | (1.600) | (1.275) | (1.766) | (3.342) | (1.300) | (1.552) |
| LARGE | -6.131*** | -4.844** | 0.124 | -4.790*** | -0.827 | 1.041 | -4.018** | -5.074*** |
| | (2.103) | (1.899) | (1.873) | (1.353) | (2.520) | (4.187) | (1.667) | (1.340) |
| Constant | -9.152 | -46.307*** | -26.753*** | 7.181*** | -46.812** | 83.673 | -14.211 | 16.582*** |
| | (31.245) | (10.584) | (4.368) | (2.759) | (19.590) | (67.391) | (8.837) | (2.663) |
| *Joint sig.* | | | | | | | | |
| W_industry | 0.021** | 0.756 | 0.000*** | 0.000*** | 0.796 | 0.016** | 0.000*** | 0.000*** |
| W_country | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** |
| R2a | 0.526 | 0.434 | 0.515 | 0.511 | 0.267 | 0.468 | 0.250 | 0.454 |
| Wald-Test: β=1 | 0.463 | 0.062* | 0.212 | 0.176 | 0.796 | 0.762 | 0.073* | 0.326 |
| *Tests on exog.* | | | | | | | | |
| SGR_NEWPD | 0.203 | 0.160 | 0.442 | 0.188 | 0.055* | 0.368 | 0.000*** | 0.846 |
| *Test on instr. val.* | | | | | | | | |
| J-Test | 0.184 | 0.375 | 0.983 | 0.103 | 0.491 | 0.458 | 0.598 | 0.630 |
| *1st stage result* | | | | | | | | |
| F-test excl. instr. | 148.1*** | 51.7*** | 178.3*** | 103.7*** | 36.6*** | 4.5** | 118.3*** | 102.0*** |
| *Tests: underiden.* | | | | | | | | |
| KP LM | 51.9*** | 220.9*** | 298.8*** | 110.2*** | 48.8*** | 6.8** | 124.6*** | 55.3*** |
| *Test: weak instr.* | | | | | | | | |
| CD Wald F | 183.8*** | 603.7*** | 614.9*** | 370.2*** | 352.9*** | 21.3*** | 300.9*** | 330.3*** |
| KP Wald F | 62.6*** | 188.5*** | 222.4*** | 58.4*** | 41.3*** | 4.4 | 102.6*** | 48.7*** |
| *Weak instr. inf.* | | | | | | | | |
| AR Wald | 83.1*** | 161.0*** | 95.6*** | 127.8*** | 22.0*** | 8.5** | 84.0*** | 108.5*** |
| SW LM | 33.5*** | 49.2*** | 48.0*** | 66.9*** | 13.8*** | 5.9* | 37.8*** | 28.5*** |
| Obs | 2,638 | 6,520 | 6,876 | 5,654 | 5,195 | 1,110 | 5,791 | 5,629 |

*Notes: Additional control variables: dummies for industry and country. See also notes of Table 11.2.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

**Table 11.17: Impact of innovation on employment growth in North-west Europe, manufacturing, 1998-2010**

| **Dep var:** | **Upturn** | **Boom** | **Downturn** | **Recession** |
|---|---|---|---|---|
| $EMP = l - (g_1 - \hat{\pi}_1)$ | **(1)** | **(2)** | **(3)** | **(4)** |
| SGR_NEWPD | 1.010*** | 0.944*** | 0.950*** | 0.916*** |
| | (0.038) | (0.040) | (0.032) | (0.048) |
| PCONLY | -2.478 | -1.841 | -2.116** | 0.488 |
| | (2.270) | (1.806) | (0.920) | (1.705) |
| ORGA | 0.045 | -0.618 | 0.166 | -0.850 |
| | (0.842) | (0.921) | (0.621) | (1.171) |
| GDPGR | -1.262*** | 1.069* | 0.241 | -1.192 |
| | (0.392) | (0.571) | (0.386) | (1.698) |
| MEDIUM | -3.383*** | -0.988 | -1.372** | -0.636 |
| | (0.820) | (1.123) | (0.611) | (0.585) |
| LARGE | -6.018*** | -4.391*** | -0.822 | -1.911** |
| | (1.110) | (1.481) | (1.051) | (0.759) |
| DGP | 1.709* | 4.469*** | 0.257 | 1.516** |
| | (0.883) | (1.222) | (0.781) | (0.766) |
| FGP | 0.951 | 1.644 | 1.066 | 0.411 |
| | (1.011) | (1.443) | (1.324) | (0.885) |
| Constant | 4.343 | -4.624 | -4.920** | 0.110 |
| | (4.511) | (3.582) | (2.468) | (2.582) |
| *Joint sign. (p-value)* | | | | |
| W_industry | 0.539 | 0.013** | 0.000*** | 0.000*** |
| R2a | 0.298 | 0.447 | 0.406 | 0.459 |
| RMSE | 25.263 | 22.799 | 24.840 | 18.477 |
| Wald-Test: β=1 | 0.787 | 0.161 | 0.123 | 0.085* |
| *Tests on Exogeneity* | | | | |
| SGR_NEWPD | 0.001*** | 0.032** | 0.166 | 0.495 |
| *Tests on instr. validity* | | | | |
| Sargan/Hansen J-Test | 0.846 | 0.168 | 0.515 | 0.836 |
| *First stage results* | | | | |
| RANGE | 16.485*** | 16.811*** | 17.797*** | 13.280*** |
| | (1.536) | (1.374) | (1.120) | (1.184) |
| COOP | 4.315*** | 3.904** | - | 4.326** |
| | (0.774) | (1.953) | | (1.804) |
| RD | 3.817*** | 9.779*** | 8.763*** | 6.381*** |
| | (1.247) | (1.491) | (1.091) | (2.106) |
| F test on excl. Instr. | 134.33*** | 177.68*** | 187.39*** | 211.71*** |
| *Tests on underident.* | | | | |
| Kleibergen-Paap LM test | 284.154*** | 22.535*** | 685.612*** | 214.264*** |
| *Test on weak instr.* | | | | |
| Cragg-Donald F test | 1248.448*** | 889.605*** | 1328.781*** | 886.361*** |
| Kleibergen-Paap F test | 180.370*** | 199.055*** | 468.733*** | 107.215*** |
| *Weak instr. rob. inf.* | | | | |
| Anderson-R. Wald test | 367.699*** | 397.062*** | 236.539*** | 495.283*** |
| Stock-Wright LM test | 26.684*** | 24.612*** | 17.649*** | 25.760*** |
| Obs | 13,953 | 9,530 | 11,493 | 12,977 |

*Notes: See Table 11.2.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

**Table 11.18: Impact of innovation on employment growth in South Europe, manufacturing, 1998-2010**

| **Dep var:** | **Upturn** | **Boom** | **Downturn** | **Recession** |
|---|---|---|---|---|
| $EMP = l - (g_1 - \hat{\pi}_1)$ | **(1)** | **(2)** | **(3)** | **(4)** |
| SGR_NEWPD | 1.021*** | 1.161*** | 1.051*** | 1.150*** |
| | (0.029) | (0.096) | (0.043) | (0.118) |
| PCONLY | -1.098 | 3.358 | -0.502 | 1.627 |
| | (0.897) | (2.599) | (1.322) | (2.213) |
| ORGA | -2.718*** | 0.746 | -2.559*** | -2.606** |
| | (0.619) | (1.446) | (0.833) | (1.249) |
| GDPGR | -2.045*** | 0.535 | -0.205 | -1.142*** |
| | (0.331) | (2.874) | (0.217) | (0.333) |
| MEDIUM | -2.090*** | 0.089 | -2.968*** | -1.414 |
| | (0.669) | (1.509) | (0.848) | (1.132) |
| LARGE | -2.299** | -2.945 | -4.162*** | -1.729 |
| | (0.969) | (2.377) | (1.051) | (1.345) |
| DGP | -2.656** | 0.576 | 1.102 | 0.458 |
| | (1.325) | (2.709) | (1.070) | (1.291) |
| FGP | -0.850 | -2.362 | -0.032 | -3.183** |
| | (1.545) | (2.454) | (0.970) | (1.262) |
| Constant | 12.657*** | -6.604 | 4.858*** | -1.527 |
| | (1.724) | (28.590) | (1.432) | (1.577) |
| *Joint sign. (p-value)* | | | | |
| W_industry | 0.000*** | 0.000*** | 0.000*** | 0.000*** |
| R2a | 0.372 | 0.434 | 0.388 | 0.495 |
| RMSE | 28.202 | 28.811 | 25.656 | 22.215 |
| Wald-Test: β=1 | 0.487 | 0.095* | 0.237 | 0.205 |
| *Tests on Exogeneity* | | | | |
| SGR_NEWPD | 0.001*** | 0.010*** | 0.003*** | 0.047** |
| *Tests on instr. validity* | | | | |
| Sargan/Hansen J-Test | 0.846 | 0.368 | 0.438 | 0.763 |
| *First stage results* | | | | |
| RANGE | 21.380*** | - | 20.869*** | - |
| | (1.969) | | (1.0887) | |
| COOP | - | 10.325* | - | 7.700*** |
| | | (5.477) | | (1.535) |
| RD | 14.577*** | 18.675*** | 7.489*** | 17.648*** |
| | (1.144) | (2.369) | (2.076) | (2.567) |
| F test on excl. Instr. | 414.20*** | 40.67*** | 352.99*** | 119.42*** |
| *Tests on underident.* | | | | |
| Kleibergen-Paap LM test | 76.328*** | 34.566*** | 442.800*** | 101.199*** |
| *Test on weak instr.* | | | | |
| Cragg-Donald F test | 2917.245*** | 155.677*** | 2927.747*** | 688.958*** |
| Kleibergen-Paap F test | 404.853*** | 48.290*** | 411.015*** | 60.488*** |
| *Weak instr. rob. inf.* | | | | |
| Anderson-R. Wald test | 603.132*** | 102.285*** | 576.314*** | 228.690*** |
| Stock-Wright LM test | 15.043*** | 20.481*** | 23.853*** | 15.020*** |
| Obs | 26,660 | 5,681 | 25,225 | 19,514 |

*Notes: See Table 11.2.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

**Table 11.19: Impact of innovation on employment growth in East Europe, manufacturing, 1998-2010**

| **Dep var:** | **Upturn** | **Boom** | **Downturn** | **Recession** |
|---|---|---|---|---|
| $EMP = l - (g_i - \hat{\pi}_i)$ | **(1)** | **(2)** | **(3)** | **(4)** |
| SGR_NEWPD | 0.968*** | 1.002*** | 0.943*** | 0.963*** |
| | (0.034) | (0.025) | (0.036) | (0.030) |
| PCONLY | 0.041 | 0.215 | -4.750* | -2.368** |
| | (1.668) | (2.583) | (2.466) | (0.995) |
| ORGA | -4.780*** | -1.174 | -1.450 | -1.296* |
| | (1.241) | (1.175) | (1.330) | (0.677) |
| GDPGR | 5.388*** | 0.807 | -0.087 | -0.407*** |
| | (0.667) | (0.645) | (0.173) | (0.105) |
| MEDIUM | -5.489*** | 2.684** | 1.553 | -5.032*** |
| | (0.939) | (1.280) | (1.388) | (0.744) |
| LARGE | -7.636*** | 1.428 | 1.628 | -8.290*** |
| | (1.197) | (1.639) | (1.470) | (0.962) |
| DGP | 1.491 | -1.473 | 1.605 | 1.574* |
| | (1.375) | (2.050) | (1.715) | (0.882) |
| FGP | 1.307 | 0.114 | (9.714) | -4.056*** |
| | (1.796) | (1.171) | | (0.898) |
| Constant | -49.756*** | -26.304*** | -7.104** | 9.036*** |
| | (6.132) | (9.714) | (3.233) | (0.987) |
| *Joint sign. (p-value)* | | | | |
| W_industry | 0.176 | 0.15 | 0.000*** | 0.000*** |
| R2a | 0.372 | 0.683 | 0.303 | 0.281 |
| RMSE | 38.763 | 19.767 | 38.231 | 23.522 |
| Wald-Test: β=1 | 0.346 | 0.946 | 0.113 | 0.212 |
| *Tests on Exogeneity* | | | | |
| SGR_NEWPD | 0.000*** | 0.002*** | 0.003*** | 0.001*** |
| *Tests on instr. validity* | | | | |
| Sargan/Hansen J-Test | 0.189 | 0.805 | 0.768 | 0.573 |
| *First stage results* | | | | |
| RANGE | 31.294*** | 36.685*** | 36.049*** | 19.990*** |
| | (1.491) | (3.303) | (1.433) | (0.942) |
| COOP | 8.711*** | 6.460* | 5.622*** | 2.728** |
| | (1.892) | (3.302) | (1.472) | (1.067) |
| F test on excl. Instr. | 254.24*** | 130.19*** | 350.4*** | 354.83*** |
| Tests on underident. | | | | |
| Kleibergen-Paap LM test | 237.811*** | 199.643*** | 714.301*** | 583.960*** |
| Test on weak instr. | | | | |
| Cragg-Donald F test | 4846.579*** | 574.041*** | 5359.603*** | 2935.105*** |
| Kleibergen-Paap F test | 507.825*** | 159.873*** | 601.381*** | 460.259*** |
| Weak instr. rob. inf. | | | | |
| Anderson-R. Wald test | 271.812*** | 366.949*** | 322.746*** | 482.718*** |
| Stock-Wright LM test | 54.788*** | 12.868*** | 53.532*** | 55.326*** |
| Obs | 26,862 | 2,986 | 30,461 | 18,690 |

*Notes: See Table 11.2.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

**Table 11.20: Impact of innovation on employment growth in North-west Europe, services, 1998-2010**

| **Dep var:** | **Upturn** | **Boom** | **Downturn** | **Recession** |
|---|---|---|---|---|
| $EMP = l - (g_1 - \hat{\pi}_1)$ | **(1)** | **(2)** | **(3)** | **(4)** |
| SGR_NEWPD | 1.034*** | 0.780*** | 0.973*** | 1.055*** |
| | (0.076) | (0.150) | (0.066) | (0.056) |
| PCONLY | 0.057 | -2.807 | 0.392 | -0.481 |
| | (2.724) | (5.696) | (1.333) | (1.535) |
| ORGA | -1.870 | 0.142 | -1.581 | 1.599* |
| | (1.288) | (2.411) | (1.049) | (0.920) |
| GDPGR | -0.915 | 1.413 | 2.476*** | -1.093 |
| | (0.707) | (0.873) | (0.262) | (1.242) |
| MEDIUM | -5.861*** | -1.651 | -2.494*** | -4.498*** |
| | (1.330) | (2.190) | (0.828) | (0.876) |
| LARGE | -9.590*** | -5.375** | -3.522* | -5.788*** |
| | (2.490) | (2.263) | (1.936) | (1.678) |
| DGP | 1.557 | 2.938 | -0.249 | 1.497 |
| | (1.706) | (2.096) | (0.873) | (0.975) |
| FGP | 0.702 | -0.788 | 0.800 | 3.732*** |
| | (1.820) | (3.108) | (1.265) | (1.357) |
| Constant | 8.821 | -9.699** | -12.223*** | 2.903 |
| | (6.180) | (4.856) | (1.093) | (2.302) |
| *Joint sign. (p-value)* | | | | |
| W_industry | 0.000*** | 0.002*** | 0.000*** | 0.004*** |
| R2a | 0.203 | 0.307 | 0.272 | 0.393 |
| RMSE | 32.809 | 33.525 | 30.759 | 21.243 |
| Wald-Test: β=1 | 0.657 | 0.142 | 0.682 | 0.319 |
| *Tests on Exogeneity* | | | | |
| SGR_NEWPD | 0.002*** | 0.688 | 0.009*** | 0.072* |
| *Tests on instr. validity* | | | | |
| Sargan/Hansen J-Test | 0.755 | 0.677 | 0.383 | 0.283 |
| *First stage results* | | | | |
| RD | 19.174*** | 20.744*** | 20.243*** | 17.233*** |
| | (2.502) | (3.425) | (1.335) | (1.994) |
| COOP | 13.606*** | 11.931*** | 13.421*** | 10.103*** |
| | (1.184) | (2.283) | (1.028) | (1.177) |
| F test on excl. Instr. | 79.77*** | 42.61*** | 307.74*** | 87.84*** |
| *Tests on underident.* | | | | |
| Kleibergen-Paap LM test | 178.090*** | 8.543** | 324.278*** | 155.427*** |
| *Test on weak instr.* | | | | |
| Cragg-Donald F test | 1332.852*** | 294.804*** | 919.117*** | 1152.496*** |
| Kleibergen-Paap F test | 154.221*** | 42.713*** | 222.603*** | 104.420*** |
| *Weak instr. rob. inf.* | | | | |
| Anderson-R. Wald test | 203.704*** | 25.989*** | 174.791*** | 178.929*** |
| Stock-Wright LM test | 17.124*** | 7.644** | 15.273*** | 25.281*** |
| Obs | 13,770 | 5,822 | 12,340 | 14,260 |

*Notes: See Table 11.2.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

**Table 11.21: Impact of innovation on employment growth in South Europe, services, 1998-2010**

| **Dep var:** | **Upturn** | **Boom** | **Downturn** | **Recession** |
|---|---|---|---|---|
| $EMP = l - (g_1 - \hat{\pi}_1)$ | **(1)** | **(2)** | **(3)** | **(4)** |
| SGR_NEWPD | 0.943*** | 0.822*** | 1.128*** | 1.031*** |
| | (0.064) | (0.105) | (0.082) | (0.033) |
| PCONLY | -2.244* | -6.271** | 3.947** | 0.130 |
| | (1.278) | (2.486) | (1.612) | (0.840) |
| ORGA | -2.490** | 4.855** | -2.477 | -0.853 |
| | (1.053) | (2.071) | (1.532) | (0.771) |
| GDPGR | -1.709*** | 8.202** | -0.790*** | -0.875*** |
| | (0.395) | (3.644) | (0.252) | (0.268) |
| MEDIUM | -3.031* | -1.715 | -3.032*** | -3.146*** |
| | (1.808) | (1.551) | (0.833) | (0.874) |
| LARGE | 0.083 | -5.068 | -6.286*** | -2.063 |
| | (1.923) | (3.174) | (1.745) | (1.355) |
| DGP | -3.134* | 0.715 | -0.643 | -0.794 |
| | (1.705) | (1.044) | (0.874) | (1.012) |
| FGP | -8.452*** | -2.212 | -0.851 | -2.467 |
| | (1.720) | (3.540) | (0.918) | (1.506) |
| Constant | 10.845*** | -83.815** | 9.920*** | 5.130*** |
| | (1.797) | (36.065) | (1.060) | (0.984) |
| *Joint sign. (p-value)* | | | | |
| W_industry | 0.795 | 0.006*** | 0.000*** | 0.000*** |
| R2a | 0.285 | 0.334 | 0.294 | 0.380 |
| RMSE | 34.024 | 35.602 | 30.265 | 24.049 |
| Wald-Test: β=1 | 0.373 | 0.090* | 0.119 | 0.354 |
| *Tests on Exogeneity* | | | | |
| SGR_NEWPD | 0.092* | 0.590 | 0.015** | 0.027** |
| *Tests on instr. validity* | | | | |
| Sargan/Hansen J-Test | 0.197 | 0.390 | 0.402 | 0.227 |
| *First stage results* | | | | |
| RD | 23.261*** | 24.034*** | 18.383*** | 17.576*** |
| | (3.689) | (3.438) | (2.731) | (1.405) |
| COOP | 16.970*** | 12.575** | 12.502*** | 13.637*** |
| | (1.440) | (5.462) | (1.400) | (1.856) |
| F test on excl. Instr. | 103.87*** | 29.47*** | 45.55*** | 273.60*** |
| *Tests on underident.* | | | | |
| Kleibergen-Paap LM test | 89.381*** | 19.997*** | 260.928*** | 184.955*** |
| *Test on weak instr.* | | | | |
| Cragg-Donald F test | 743.774*** | 76.572*** | 636.347*** | 699.778*** |
| Kleibergen-Paap F test | 97.240*** | 21.872*** | 64.489*** | 121.652*** |
| *Weak instr. rob. inf.* | | | | |
| Anderson-R. Wald test | 130.887*** | 27.700*** | 154.849*** | 365.475*** |
| Stock-Wright LM test | 13.722*** | 9.804*** | 16.080*** | 17.213*** |
| Obs | 14,852 | 2,452 | 17,771 | 17,792 |

*Notes: See Table 11.2.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

**Table 11.22: Impact of innovation on employment growth in East Europe, services, 1998-2010**

| **Dep var:** | **Upturn** | **Boom** | **Downturn** | **Recession** |
|---|---|---|---|---|
| $EMP = l - (g_1 - \hat{\pi}_1)$ | **(1)** | **(2)** | **(3)** | **(4)** |
| SGR_NEWPD | 0.935*** | 0.999*** | 0.980*** | 0.918*** |
| | (0.069) | (0.060) | (0.045) | (0.060) |
| PCONLY | -1.466 | 3.319 | -4.307** | -1.072 |
| | (2.882) | (2.092) | (2.030) | (2.252) |
| ORGA | 0.827 | -2.814 | -1.902 | -2.431** |
| | (3.300) | (2.067) | (1.435) | (1.152) |
| GDPGR | 2.871 | 1.288 | -0.399* | -0.575*** |
| | (2.055) | (1.283) | (0.210) | (0.106) |
| MEDIUM | -4.753*** | -2.245 | -3.765** | -4.877*** |
| | (1.630) | (1.946) | (1.602) | (0.822) |
| LARGE | -8.121*** | 3.468 | -7.868*** | -7.183*** |
| | (2.562) | (3.760) | (2.056) | (1.071) |
| DGP | -3.502 | 4.020 | 4.881** | -2.049 |
| | (2.841) | (2.446) | (2.264) | (1.620) |
| FGP | -9.196*** | -1.287 | 0.299 | -2.028* |
| | (2.803) | (1.489) | (2.308) | (1.176) |
| Constant | -21.060 | -23.936 | -0.539 | 15.016*** |
| | (17.738) | (19.348) | (4.211) | (0.908) |
| *Joint sign. (p-value)* | | | | |
| W_industry | 0.003*** | 0.000*** | 0.000*** | 0.000*** |
| R2a | 0.163 | 0.450 | 0.193 | 0.192 |
| RMSE | 50.682 | 27.734 | 46.128 | 28.650 |
| Wald-Test: β=1 | 0.352 | 0.984 | 0.663 | 0.171 |
| *Tests on Exogeneity* | | | | |
| SGR_NEWPD | 0.220 | 0.241 | 0.002*** | 0.111 |
| *Tests on instr. validity* | | | | |
| Sargan/Hansen J-Test | 0.223 | 0.865 | 0.016** | n.a |
| *First stage results* | | | | |
| RANGE | 22.138*** | 21.657*** | 36.762*** | 20.825*** |
| | (2.299) | (4.446) | (4.598) | (2.837) |
| COOP | 19.814*** | 29.474*** | 10.311*** | 13.524*** |
| | (2.329) | (4.104) | (2.926) | (1.711) |
| F test on excl. Instr. | 185.26*** | 35.28*** | 94.58*** | 57.87*** |
| *Tests on underident.* | | | | |
| Kleibergen-Paap LM test | 101.369*** | 58.074*** | 316.553*** | 59.362*** |
| *Test on weak instr.* | | | | |
| Cragg-Donald F test | 1279.010*** | 248.988*** | 3824.720*** | 1200.408*** |
| Kleibergen-Paap F test | 177.421*** | 43.630*** | 352.871*** | 57.874*** |
| *Weak instr. rob. inf.* | | | | |
| Anderson-R. Wald test | 126.114*** | 83.957*** | 195.792*** | 118.849*** |
| Stock-Wright LM test | 17.797*** | 6.961** | 30.811*** | 68.074*** |
| Obs | 17,944 | 2,124 | 23,389 | 15,226 |

*Notes: See Table 11.2.*
*Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.*

**Table 11.23: Impact of innovation on employment growth, accounting for individual heterogeneity and endogeneity, German manufacturing firms, 1994-2012**

| **Dep var:** | **OLS** | **FE** | **IV** | **IVFE** |
|---|---|---|---|---|
| $EMP = l - (g_i - \hat{\pi}_i)$ | **(1)** | **(2)** | **(3)** | **(4)** |
| MEDIUM | -0.576 | -5.333*** | -0.628 | -5.270*** |
| | (0.356) | (1.614) | (0.405) | (1.465) |
| LARGE | -1.617*** | -8.805*** | -2.491*** | -8.239*** |
| | (0.444) | (2.662) | (0.543) | (2.513) |
| DGP | -0.208 | -0.111 | -0.204 | -0.626 |
| | (0.402) | (0.835) | (0.468) | (0.920) |
| FGP | -0.956 | -0.698 | -0.643 | -1.267 |
| | (0.584) | (1.784) | (0.669) | (1.910) |
| Constant | 4.650*** | 9.256*** | 4.326*** | - |
| | (0.562) | (2.284) | (0.853) | |
| *Joint sign. (p-value)* | | | | |
| SGR_NEWPD, GDPGR_i and interactions | 0.000*** | 0.000*** | 0.000*** | 0.000*** |
| PCONLY, GDPGR_i and interactions | 0.000*** | 0.000*** | 0.000*** | 0.000*** |
| W_industry | 0.000*** | 0.200 | 0.000*** | 0.000*** |
| $R^2$ | 0.504 | 0.339 | 0.447 | 0.276 |
| RMSE | 24.709 | 19.438 | 25.105 | 24.164 |
| Wald-Test: β=1 | 160.92*** | 115.51*** | 0.94 | 0.62 |
| *Tests on Exogeneity* | | | | |
| SGR_NEWPD and interactions | n.a. | n.a. | 47.264*** | 11.211** |
| *Tests on instr. validity* | | | | |
| Sargan/Hansen J-Test | n.a. | n.a. | 0.758 | 0.961 |
| *F test of excluded instruments* | n.a. | n.a. | | |
| SGR_NEWPD | | | 724.61*** | 108.96*** |
| SGR_NEWPD x GDPGR_D | | | 380.08*** | 264.11*** |
| SGR_NEWPD x GDPGR_U | | | 272.07*** | 229.53*** |
| SGR_NEWPD x GDPGR_B | | | 217.22*** | 169.92*** |
| *Tests on underident.* | | | | |
| Kleibergen-Paap LM test | n.a. | n.a. | 991.940*** | 384.484*** |
| *Test on weak instr.* | | | | |
| Cragg-Donald F test | n.a. | n.a. | 641.450*** | 135.575*** |
| Kleibergen-Paap F test | n.a. | n.a. | 240.893*** | 83.195*** |
| *Weak instr. rob. inf.* | | | | |
| Anderson-R. Wald test | n.a. | n.a. | 1949.507*** | 225.621*** |
| Stock-Wright LM test | n.a. | n.a. | 1630.849*** | 210.066*** |
| Observations | 27,908 | 27,908 | 22,394 | 18,369 |

*Notes: Continued from Table 9.3. For details on the tests see notes of Table 11.2.*
*Source: Mannheim Innovation Panel; own calculation.*

**Table 11.24: Impact of innovation on employment growth, accounting for individual heterogeneity and endogeneity, German service firms, 1994-2012**

| **Dep var:** | **OLS** | **FE** | **IV** | **IVFE** |
|---|---|---|---|---|
| $EMP = l - (g_1 - \hat{\pi}_1)$ | **(5)** | **(6)** | **(7)** | **(8)** |
| MEDIUM | -1.630*** | -5.139** | -1.862*** | -5.847*** |
| | (0.414) | (2.298) | (0.437) | (1.913) |
| LARGE | -2.333*** | -9.799** | -2.337*** | -11.873*** |
| | (0.502) | (3.886) | (0.537) | (3.306) |
| DGP | -0.703 | -1.069 | -0.252 | 0.404 |
| | (0.441) | (1.033) | (0.471) | (0.954) |
| FGP | -0.085 | -2.309 | -0.323 | 0.160 |
| | (0.932) | (2.880) | (0.988) | (2.387) |
| Constant | 4.949*** | 6.774*** | 4.480*** | - |
| | (0.592) | (2.562) | (0.709) | |
| *Joint sign. (p-value)* | | | | |
| SGR_NEWPD, GDPGR_i and interactions | 0.000*** | 0.000*** | 0.000*** | 0.000*** |
| PCONLY, GDPGR_i and interactions | 0.000*** | 0.015** | 0.000*** | 0.000*** |
| W_industry | 0.000*** | 0.539 | 0.004*** | 0.459 |
| $R^2$ | 0.420 | 0.261 | 0.385 | 0.191 |
| RMSE | 24.818 | 18.386 | 24.471 | 23.308 |
| Wald-Test: β=1 | 37.53*** | 30.97*** | 9.20*** | 0.99 |
| *Tests on Exogeneity* | | | | |
| SGR_NEWPD and interactions | n.a. | n.a. | 18.482*** | 10.972** |
| *Tests on instr. validity* | | | | |
| Sargan/Hansen J-Test | n.a. | n.a. | 0.728 | 0.061* |
| *F test of excluded instruments* | n.a. | n.a. | | |
| SGR_NEWPD | | | 501.38*** | 65.28*** |
| SGR_NEWPD x GDPGR_D | | | 167.00*** | 112.83*** |
| SGR_NEWPD x GDPGR_U | | | 175.01*** | 145.73*** |
| SGR_NEWPD x GDPGR_B | | | 124.19*** | 78.00*** |
| *Tests on underident.* | | | | |
| Kleibergen-Paap LM test | n.a. | n.a. | 740.487*** | 242.655*** |
| *Test on weak instr.* | | | | |
| Cragg-Donald F test | n.a. | n.a. | 895.144*** | 148.996*** |
| Kleibergen-Paap F test | n.a. | n.a. | 209.923*** | 56.483*** |
| *Weak instr. rob. inf.* | | | | |
| Anderson-R. Wald test | n.a. | n.a. | 1483.794*** | 168.631*** |
| Stock-Wright LM test | n.a. | n.a. | 1115.427*** | 154.49*** |
| Observations | 21,163 | 21,163 | 18,290 | 14,252 |

*Notes: Continued from Table 9.3. For details on the tests see notes of Table 11.2.*
*Source: Mannheim Innovation Panel*

**Table 11.25: Impact of innovation on employment excluding firms with 5-9 employees, German manufacturing firms, 1994-2012**

| **Dep var:** | **OLS** | **FE** | **IV** | **IVFE** |
|---|---|---|---|---|
| $EMP = l - (g_i - \hat{\pi}_i)$ | **(1)** | **(2)** | **(3)** | **(4)** |
| MEDIUM | -1.087*** | -5.422*** | -1.035** | -5.305*** |
| | (0.371) | (1.618) | (0.423) | (1.473) |
| LARGE | -2.080*** | -8.882*** | -2.879*** | -8.297*** |
| | (0.457) | (2.661) | (0.556) | (2.520) |
| DGP | -0.357 | -0.063 | -0.310 | -0.536 |
| | (0.407) | (0.843) | (0.476) | (0.939) |
| FGP | -1.016* | -0.787 | -0.644 | -1.329 |
| | (0.586) | (1.762) | (0.671) | (1.913) |
| Constant | 5.426*** | 10.774*** | 4.756*** | - |
| | (0.597) | (2.359) | (0.944) | |
| *Joint sign. (p-value)* | | | | |
| SGR_NEWPD, GDPGR_i and interactions | 0.000*** | 0.000*** | 0.000*** | 0.000*** |
| PCONLY, GDPGR_i and interactions | 0.000*** | 0.000*** | 0.000*** | 0.000*** |
| W_industry | 0.000*** | 0.147 | 0.000*** | 0.001*** |
| $R^2$ | 0.516 | 0.352 | 0.455 | 0.285 |
| RMSE | 24.474 | 19.271 | 24.924 | 23.969 |
| Wald-Test: β=1 | 152.34*** | 112.42*** | 0.44 | 0.30 |
| *Tests on Exogeneity* | | | | |
| SGR_NEWPD and interactions | n.a. | n.a. | 45.564*** | 13.105** |
| *Tests on instr. validity* | | | | |
| Sargan/Hansen J-Test | n.a. | n.a. | 0.585 | 0.503 |
| *F test of excluded instruments* | n.a. | n.a. | | |
| SGR_NEWPD | | | 501.38*** | 65.28*** |
| SGR_NEWPD x GDPGR_D | | | 167.00*** | 112.83*** |
| SGR_NEWPD x GDPGR_U | | | 175.01*** | 145.73*** |
| SGR_NEWPD x GDPGR_B | | | 124.19*** | 78.00*** |
| *Tests on underident.* | | | | |
| Kleibergen-Paap LM test | n.a. | n.a. | 834.638*** | 336.267*** |
| *Test on weak instr.* | | | | |
| Cragg-Donald F test | n.a. | n.a. | 517.034*** | 115.448*** |
| Kleibergen-Paap F test | n.a. | n.a. | 199.162*** | 71.939*** |
| *Weak instr. rob. inf.* | | | | |
| Anderson-R. Wald test | n.a. | n.a. | 1734.296*** | 205.631*** |
| Stock-Wright LM test | n.a. | n.a. | 1463.097*** | 191.404*** |
| Observations | 25,407 | 25,407 | 20,215 | 16,657 |

*Notes: Continued from Table 9.4. For details on the tests see notes of Table 11.2.*
*Source: Mannheim Innovation Panel*

**Table 11.26: Impact of innovation on employment excluding of firms with 5-9 employees, German service firms, 1994-2012**

| **Dep var:** | **OLS** | **FE** | **IV** | **IVFE** |
|---|---|---|---|---|
| $EMP = l - (g_1 - \hat{\pi}_1)$ | **(5)** | **(6)** | **(7)** | **(8)** |
| MEDIUM | -1.946*** | -5.130** | -2.204*** | -5.806*** |
| | (0.432) | (2.307) | (0.456) | (1.923) |
| LARGE | -2.645*** | -9.900** | -2.666*** | -11.774*** |
| | (0.517) | (3.922) | (0.552) | (3.343) |
| DGP | -0.725 | -1.019 | -0.342 | 0.062 |
| | (0.448) | (1.053) | (0.479) | (0.970) |
| FGP | -0.541 | -2.174 | -0.704 | 0.105 |
| | (0.908) | (2.778) | (0.961) | (2.363) |
| Constant | 5.050*** | 7.792** | 4.729*** | - |
| | (0.646) | (3.074) | (0.778) | |
| *Joint sign. (p-value)* | | | | |
| SGR_NEWPD, GDPGR_i and interactions | 0.000*** | 0.000*** | 0.000*** | 0.000*** |
| PCONLY, GDPGR_i and interactions | 0.011** | 0.087 | 0.001*** | 0.003*** |
| W_industry | 0.000*** | 0.575 | 0.011** | 0.341 |
| $R^2$ | 0.450 | 0.291 | 0.414 | 0.222 |
| RMSE | 23.780 | 17.502 | 23.391 | 22.082 |
| Wald-Test: β=1 | 26.11*** | 20.72*** | 6.46** | 0.57 |
| *Tests on Exogeneity* | | | | |
| SGR_NEWPD and interactions | n.a. | n.a. | 12.413** | 5.073 |
| *Tests on instr. validity* | | | | |
| Sargan/Hansen J-Test | n.a. | n.a. | 0.381 | 0.289 |
| *F test of excluded instruments* | n.a. | n.a. | | |
| SGR_NEWPD | | | 413.83*** | 50.04*** |
| SGR_NEWPD x GDPGR_D | | | 139.43*** | 93.94*** |
| SGR_NEWPD x GDPGR_U | | | 148.11*** | 125.88*** |
| SGR_NEWPD x GDPGR_B | | | 106.55*** | 63.83*** |
| *Tests on underident.* | | | | |
| Kleibergen-Paap LM test | n.a. | n.a. | 553.520 | 192.989 |
| *Test on weak instr.* | | | | |
| Cragg-Donald F test | n.a. | n.a. | 702.757 | 114.953 |
| Kleibergen-Paap F test | n.a. | n.a. | 155.645 | 44.550 |
| *Weak instr. rob. inf.* | | | | |
| Anderson-R. Wald test | n.a. | n.a. | 1227.224 | 127.075 |
| Stock-Wright LM test | n.a. | n.a. | 930.287 | 116.960 |
| Observations | 17,428 | 17,428 | 15,003 | 11,741 |

*Notes: Continued from Table 9.4. For details on the tests see notes of Table 11.2.*
*Source: Mannheim Innovation Panel*

**Table 11.27: Non-linear and long-term impact of innovation on employment growth, German manufacturing firms 1994-2012**

| | Non-Linearities | Two-Period Lag | Three-Period Lag |
|---|---|---|---|
| | (1) | (2) | (3) |
| SGR_NEWPD | 0.894 | 1.040*** | 1.132*** |
| | (0.583) | (0.098) | (0.136) |
| PCONLY | -0.578 | -1.938 | -0.853 |
| | (1.006) | (1.589) | (1.896) |
| GDPGR_D | -5.809*** | -5.930*** | -7.613*** |
| | (1.360) | (0.850) | (1.020) |
| GDPGR_U | -11.804*** | -13.316*** | -13.751*** |
| | (1.605) | (0.878) | (1.032) |
| GDPGR_B | -11.773*** | -13.582*** | -13.526*** |
| | (0.735) | (1.119) | (1.217) |
| $SGR\_NEWPD^2$ | 0.000 | | |
| | (0.011) | | |
| $SGR\_NEWPD_{t-2}$ | | 0.094*** | |
| | | (0.023) | |
| $SGR\_NEWPD_{t-3}$ | | | 0.083*** |
| | | | (0.026) |
| $PCONLY_{t-2}$ | | 1.163 | |
| | | (1.277) | |
| $PCONLY_{t-3}$ | | | 0.910 |
| | | | (1.621) |
| MEDIUM | -5.231*** | -5.008** | -3.736 |
| | (1.632) | (2.400) | (2.802) |
| LARGE | -8.086* | -6.109 | 0.810 |
| | (4.419) | (3.964) | (4.028) |
| DGP | -0.660 | 0.016 | -2.759 |
| | (1.164) | (1.566) | (1.825) |
| FGP | -1.098 | -3.513 | -7.399** |
| | (4.437) | (3.099) | (3.195) |
| *Joint sign. (p-value)* | | | |
| W_industry | 0.048** | 0.151 | 0.022** |
| $R^2$ | 0.273 | 0.224 | 0.192 |
| RMSE | 24.208 | 23.822 | 23.418 |
| Wald-Test: β=1 | 0.03 | 0.17 | 0.95 |
| *Tests on Exogeneity* | | | |
| SGR_NEWPD (and $SGR\_NEWPD^2$) | 0.751 | 6.564*** | 8.227*** |
| *Tests on instr. validity* | | | |
| Sargan/Hansen J-Test | n.a. | 0.615 | 0.619 |
| F test of excluded instruments | 240.86*** | 87.75*** | 42.54*** |
| *Tests on underident.* | | | |
| Kleibergen-Paap LM test | 3.384* | 153.204*** | 78.127*** |
| *Test on weak instr.* | | | |
| Cragg-Donald F test | 2.378 | 151.834*** | 72.852*** |
| Kleibergen-Paap F test | 1.691 | 87.750*** | 42.545*** |
| *Weak instr. rob. inf.* | | | |
| Anderson-R. Wald test | 203.075*** | 80.919*** | 53.386*** |
| Stock-Wright LM test | 190.831*** | 75.045*** | 50.370*** |
| Observations | 18,369 | 7,303 | 5,524 |

*Notes: IV regressions with fixed effects. For details on the tests see notes of Table 11.2.*
*Source: Mannheim Innovation Panel*

**Table 11.28: Impact of innovation on labour productivity over the business cycle, Germany, 1992-2012, OLS estimations**

| | OLS | OLS | OLS |
|---|---|---|---|
| | **Baseline** | **BC** | **BC-Interactions** |
| LnMAT | 0.378*** | 0.378*** | 0.378*** |
| | (0.005) | (0.005) | (0.005) |
| LnCAP | 0.053*** | 0.053*** | 0.053*** |
| | (0.003) | (0.003) | (0.003) |
| PD | -0.006 | -0.006 | -0.011 |
| | (0.008) | (0.008) | (0.009) |
| PC | 0.016** | 0.016** | 0.015* |
| | (0.007) | (0.007) | (0.008) |
| GDPGR | | 0.004** | 0.002 |
| | | (0.002) | (0.002) |
| PD x GDPGR | | | 0.004 |
| | | | (0.002) |
| PC x GDPGR | | | 0.001 |
| | | | (0.003) |
| LnL | 0.001 | 0.001 | 0.001 |
| | (0.003) | (0.003) | (0.003) |
| EAST | -0.204*** | -0.204*** | -0.204*** |
| | (0.009) | (0.009) | (0.009) |
| DGP | 0.137*** | 0.137*** | 0.137*** |
| | (0.009) | (0.009) | (0.009) |
| FGP | 0.233*** | 0.233*** | 0.234*** |
| | (0.015) | (0.015) | (0.015) |
| LnAGE | 0.005 | 0.005 | 0.005 |
| | (0.005) | (0.005) | (0.005) |
| EXPORT | 0.066*** | 0.066*** | 0.066*** |
| | (0.010) | (0.010) | (0.010) |
| Constant | -1.277*** | -1.294*** | -1.292*** |
| | (0.081) | (0.079) | (0.079) |
| *Joint sign. (p-value)* | | | |
| W_time | 0.000*** | 0.000*** | 0.000*** |
| W_industry | 0.000*** | 0.000*** | 0.000*** |
| Adjusted R-squared | 0.673 | 0.673 | 0.673 |
| Observations | 35,686 | 35,686 | 35,686 |

*Notes: Method: Pooled OLS estimations. ***, ** and * indicate significance at the 1%, 5% and 10% level. Clustered standard errors are reported, clustered by the (individual) firm level. Industry and time dummies are included in each regression. For each set of dummies the p-value of a test on joint significance is reported. The table contains three different specifications and builds up stepwise. The baseline specification does not include neither a business cycle indicator nor interaction terms. The specification BC includes a business cycle indicator variable. The last specification includes a business cycle indicator as well as interaction terms between different kinds of innovations.*

*Source: Mannheim Innovation Panel (MIP), own calculation.*

**Table 11.29: Impact of the degree of innovation on labour productivity over the business cycle, Germany, 1992-2012, OLS estimations**

| | OLS | OLS | OLS |
|---|---|---|---|
| | Baseline | BC | BC-Interac-tions |
| LnMAT | 0.378*** | 0.378*** | 0.378*** |
| | (0.005) | (0.005) | (0.005) |
| LnCAP | 0.053*** | 0.053*** | 0.053*** |
| | (0.003) | (0.003) | (0.003) |
| MN | 0.014* | 0.014* | 0.011 |
| | (0.008) | (0.008) | (0.009) |
| FN | -0.009 | -0.009 | -0.014* |
| | (0.007) | (0.007) | (0.008) |
| PC | 0.014** | 0.014** | 0.013 |
| | (0.007) | (0.007) | (0.008) |
| GDPGR | | 0.004** | 0.002 |
| | | (0.002) | (0.002) |
| MN x GDPGR | | | 0.002 |
| | | | (0.003) |
| FN x GDPGR | | | 0.004 |
| | | | (0.003) |
| PC x GDPGR | | | 0.001 |
| | | | (0.003) |
| LnL | 0.001 | 0.001 | 0.001 |
| | (0.003) | (0.003) | (0.003) |
| EAST | -0.204*** | -0.204*** | -0.204*** |
| | (0.009) | (0.009) | (0.009) |
| DGP | 0.136*** | 0.136*** | 0.136*** |
| | (0.009) | (0.009) | (0.009) |
| FGP | 0.233*** | 0.233*** | 0.233*** |
| | (0.015) | (0.015) | (0.015) |
| LnAGE | 0.005 | 0.005 | 0.005 |
| | (0.005) | (0.005) | (0.005) |
| EXPORT | 0.065*** | 0.065*** | 0.065*** |
| | (0.010) | (0.010) | (0.010) |
| Constant | -1.277*** | -1.294*** | -1.292*** |
| | (0.081) | (0.079) | (0.079) |
| *Joint sign. (p-value)* | | | |
| W_time | 0.000*** | 0.000*** | 0.000*** |
| W_industry | 0.000*** | 0.000*** | 0.000*** |
| Adjusted R-squared | 0.673 | 0.673 | 0.673 |
| Observations | 35,686 | 35,686 | 35,686 |

*Notes: See Table 11.28.*
*Source: Mannheim Innovation Panel (MIP), own calculation.*

**Table 11.30: Complementarities among different types of innovation on labour productivity over the business cycle, Germany, 1992-2012, OLS estimations**

| | OLS | OLS | OLS |
|---|---|---|---|
| | **Baseline** | **BC** | **BC-Interac-tions** |
| LnMAT | 0.378*** | 0.378*** | 0.378*** |
| | (0.005) | (0.005) | (0.005) |
| LnCAP | 0.053*** | 0.053*** | 0.053*** |
| | (0.003) | (0.003) | (0.003) |
| PDONLY | -0.006 | -0.006 | -0.009 |
| | (0.009) | (0.009) | (0.010) |
| PCONLY | 0.015 | 0.015 | 0.017 |
| | (0.011) | (0.011) | (0.013) |
| PCAPD | 0.010 | 0.010 | 0.003 |
| | (0.008) | (0.008) | (0.009) |
| GDPGR | | 0.004** | 0.003 |
| | | (0.002) | (0.002) |
| PDONLY x GDPGR | | | 0.002 |
| | | | (0.003) |
| PCONLY x GDPGR | | | -0.001 |
| | | | (0.004) |
| PCAPD x GDPGR* | | | 0.005* |
| | | | (0.003) |
| LnL | 0.001 | 0.001 | 0.001 |
| | (0.003) | (0.003) | (0.003) |
| EAST | -0.204*** | -0.204*** | -0.204*** |
| | (0.009) | (0.009) | (0.009) |
| DGP | 0.137*** | 0.137*** | 0.137*** |
| | (0.009) | (0.009) | (0.009) |
| FGP | 0.233*** | 0.233*** | 0.233*** |
| | (0.015) | (0.015) | (0.015) |
| LnAGE | 0.005 | 0.005 | 0.005 |
| | (0.005) | (0.005) | (0.005) |
| EXPORT | 0.066*** | 0.066*** | 0.066*** |
| | (0.010) | (0.010) | (0.010) |
| Constant | -1.277*** | -1.294*** | -1.293*** |
| | (0.081) | (0.079) | (0.079) |
| *Joint sign. (p-value)* | | | |
| W_time | 0.000*** | 0.000*** | 0.000*** |
| W_industry | 0.000*** | 0.000*** | 0.000*** |
| Adjusted R-squared | 0.673 | 0.673 | 0.673 |
| Observations | 35,686 | 35,686 | 35,686 |

*Notes: See Table 11.28.*
*Source: Mannheim Innovation Panel (MIP), own calculation.*

**Table 11.31: Impact of innovation on labour productivity over the business cycle, Germany, 1992-2012, FE estimations**

| | FE | FE | FE |
|---|---|---|---|
| | **Baseline** | **BC** | **BC-Interactions** |
| LnMAT | 0.167*** | 0.167*** | 0.167*** |
| | (0.008) | (0.008) | (0.008) |
| LnCAP | 0.033*** | 0.033*** | 0.033*** |
| | (0.003) | (0.003) | (0.003) |
| PD | 0.010* | 0.010* | 0.007 |
| | (0.006) | (0.006) | (0.007) |
| PC | 0.007 | 0.007 | 0.006 |
| | (0.005) | (0.005) | (0.006) |
| GDPGR | | 0.009*** | 0.008*** |
| | | (0.001) | (0.001) |
| GDPGR*PD | | | 0.002* |
| | | | (0.001) |
| GDPGR*PC | | | 0.001 |
| | | | (0.002) |
| LnL | -0.169*** | -0.169*** | -0.169*** |
| | (0.016) | (0.016) | (0.016) |
| EAST | -0.028 | -0.028 | -0.029 |
| | (0.045) | (0.045) | (0.045) |
| DGP | 0.017** | 0.017** | 0.017** |
| | (0.009) | (0.009) | (0.009) |
| FGP | 0.048*** | 0.048*** | 0.048*** |
| | (0.017) | (0.017) | (0.017) |
| EXPORT | 0.026** | 0.026** | 0.026** |
| | (0.010) | (0.010) | (0.010) |
| Constant | -1.200*** | -1.119*** | -1.117*** |
| | (0.136) | (0.136) | (0.136) |
| LnL | -0.169*** | -0.169*** | -0.169*** |
| | (0.016) | (0.016) | (0.016) |
| *Joint sign. (p-value)* | | | |
| W_time | 0.000*** | 0.000*** | 0.000*** |
| W_industry | 0.010*** | 0.010*** | 0.010*** |
| *Different R2s* | | | |
| R2 - within | 0.259 | 0.259 | 0.260 |
| R2 - between | 0.150 | 0.150 | 0.150 |
| R2 - overall | 0.150 | 0.150 | 0.149 |
| Adjusted R2 | 0.673 | 0.673 | 0.673 |
| Rho | 0.918 | 0.918 | 0.918 |
| Observations | 35,686 | 35,686 | 35,686 |

*Notes: Method: Controlling for individual heterogeneity via Fixed-Effects (FE) estimations. ***, ** and * indicate significance at the 1%, 5% and 10% level. Clustered standard errors are reported, clustered by the (individual) firm level. Industry and time dummies are included in each regression. For each set of dummies the p-value of a test on joint significance is reported. The table contains three different specifications and builds up stepwise. The baseline specification does not include neither a business cycle indicator nor interaction terms. The specification BC includes a business cycle indicator variable. The last specification includes a business cycle indicator as well as interaction terms between different kinds of innovations. The different R2s indicate the percentage of within-, between- and overall-variance is explained by the model. The parameter indicates the size of the variance of the error term that is accounted for by the individual heterogeneity.*
*Source: Mannheim Innovation Panel (MIP), own calculation.*

**Table 11.32: Impact of the degree of innovation on labour productivity over the business cycle, Germany, 1992-2012, FE estimations**

| | FE | FE | FE |
|---|---|---|---|
| | **Baseline** | **BC** | **BC-Interac-tions** |
| LnMAT | 0.167*** | 0.167*** | 0.167*** |
| | (0.008) | (0.008) | (0.008) |
| LnCAP | 0.033*** | 0.033*** | 0.033*** |
| | (0.003) | (0.003) | (0.003) |
| MN | 0.016*** | 0.016*** | 0.014** |
| | (0.006) | (0.006) | (0.007) |
| FN | 0.002 | 0.002 | -0.001 |
| | (0.006) | (0.006) | (0.006) |
| PC | 0.007 | 0.007 | 0.007 |
| | (0.005) | (0.005) | (0.006) |
| GDPGR | | 0.009*** | 0.007*** |
| | | (0.001) | (0.001) |
| GDPGR*MN | | | 0.002 |
| | | | (0.002) |
| GDPGR*FN | | | 0.003* |
| | | | (0.002) |
| GDPGR*PC | | | 0.000 |
| | | | (0.002) |
| LnL | -0.168*** | -0.168*** | -0.168*** |
| | (0.016) | (0.016) | (0.016) |
| EAST | -0.027 | -0.027 | -0.028 |
| | (0.045) | (0.045) | (0.045) |
| DGP | 0.017** | 0.017** | 0.017** |
| | (0.009) | (0.009) | (0.009) |
| FGP | 0.047*** | 0.047*** | 0.047*** |
| | (0.017) | (0.017) | (0.017) |
| EXPORT | 0.026** | 0.026** | 0.026** |
| | (0.010) | (0.010) | (0.010) |
| Constant | -1.202*** | -1.120*** | -1.119*** |
| | (0.137) | (0.136) | (0.136) |
| *Joint sign. (p-value)* | | | |
| W_time | 0.000*** | 0.000*** | 0.000*** |
| W_industry | 0.010*** | 0.010*** | 0.010*** |
| *Different R2s* | | | |
| R2 - within | 0.260 | 0.260 | 0.260 |
| R2 - between | 0.151 | 0.151 | 0.150 |
| R2 - overall | 0.151 | 0.151 | 0.150 |
| Adjusted R2 | 0.259 | 0.259 | 0.259 |
| Rho | 0.918 | 0.918 | 0.918 |
| Observations | 35,686 | 35,686 | 35,686 |

*Notes: See Table 11.31.*
*Source: Mannheim Innovation Panel (MIP), own calculation.*

**Table 11.33: Complementarity among different types of innovation on labour productivity over the business cycle, Germany, 1992-2012, FE estimations**

| | FE | FE | FE |
|---|---|---|---|
| | **Baseline** | **BC** | **BC-Interac-tions** |
| LnMAT | 0.167*** | 0.167*** | 0.167*** |
| | (0.008) | (0.008) | (0.008) |
| LnCAP | 0.033*** | 0.033*** | 0.033*** |
| | (0.003) | (0.003) | (0.003) |
| PDONLY | 0.008 | 0.008 | 0.006 |
| | (0.007) | (0.007) | (0.008) |
| PCONLY | 0.004 | 0.004 | 0.004 |
| | (0.007) | (0.007) | (0.008) |
| PCAPD | 0.018** | 0.018** | 0.013* |
| | (0.007) | (0.007) | (0.008) |
| GDPGR | | 0.009*** | 0.008*** |
| | | (0.001) | (0.001) |
| GDPGR*PDONLY | | | 0.002 |
| | | | (0.002) |
| GDPGR*PCONLY | | | 0.000 |
| | | | (0.002) |
| GDPGR* PCAPD | | | 0.003** |
| | | | (0.002) |
| LnL | -0.169*** | -0.169*** | -0.169*** |
| | (0.016) | (0.016) | (0.016) |
| EAST | -0.028 | -0.028 | -0.029 |
| | (0.045) | (0.045) | (0.045) |
| DGP | 0.017** | 0.017** | 0.017** |
| | (0.009) | (0.009) | (0.009) |
| FGP | 0.048*** | 0.048*** | 0.048*** |
| | (0.017) | (0.017) | (0.017) |
| EXPORT | 0.026** | 0.026** | 0.026** |
| | (0.010) | (0.010) | (0.010) |
| Constant | -1.200*** | -1.119*** | -1.117*** |
| | (0.136) | (0.136) | (0.136) |
| *Joint sign. (p-value)* | | | |
| W_time | 0.000*** | 0.000*** | 0.000*** |
| W_industry | 0.010*** | 0.010*** | 0.010*** |
| *Different R2s* | | | |
| R2 - within | 0.260 | 0.260 | 0.260 |
| R2 - between | 0.150 | 0.150 | 0.150 |
| R2 - overall | 0.150 | 0.150 | 0.149 |
| Adjusted R2 | 0.259 | 0.259 | 0.259 |
| Rho | 0.918 | 0.918 | 0.918 |
| Observations | 35,686 | 35,686 | 35,686 |

*Notes: See Table 11.31.*
*Source: Mannheim Innovation Panel (MIP), own calculation.*