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Employment Effects of Innovations over the Business Cycle: Firm-Level Evidence from European Countries

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Abstract

A growing literature investigates how firms' innovation input reacts to changes in the business cycle. However, so far there is no evidence whether there is cyclicality in the effects of innovation on firm performance as well. In this paper, we investigate the employment effects of innovations over the business cycle. Our analysis employs a large data set of manufacturing firms from 26 European countries over the period from 1998 to 2010. Using the structural model of Harrison et al. (2014), our empirical analysis reveals four important findings: First, the net effect of product innovation on employment growth is pro-cyclical. It turns out to be positive in all business cycle phases except for the recession. Second, product innovators are more resilient to recessions than non-product innovators. Even during recessions they are able to substitute demand losses from old products by demand gains of new products to a substantial degree. As a result their net employment losses are significantly lower in recessions than those of non-product innovators. Third, we only find resilience for SMEs but not for large firms. Fourth, process and organizational innovations displace labor primarily during upturn and downturn periods.

JEL: O33, J23, C26, D2

Keywords: Innovation, employment, business cycle, resilience, Europe

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1. Introduction

The global economic crisis set off in 2008 has been a serious threat to the stability of most economies in the world. More than 5.37 million jobs (-2.4%) were destroyed between 2008 and 2010 just in Europe. The challenge European policymakers face has been to overcome the crisis and to improve long-term competitiveness and to stimulate growth. Research and development (R&D) and innovation activities are typically regarded as efficient instruments to spur firms' competitiveness and, consequently, economic growth and job creation. For this reason, improving the conditions for research and innovation is one of the main objectives of Europe 2020 – EU's large-scale growth strategy implemented in 2010 (EC, 2012). The key issue whether such a strategy can be successful depends on the extent to which EU countries are able to translate new products and technologies into employment growth during a recession.

In this paper, we analyze the cyclicality of the link between innovation and job creation for a large set of European firms. Our central research question is: How do different types of innovation affect employment growth during different phases of the business cycle? In this sense, is innovation equally employment-creating in all phases of the business cycle or do we observe a pro- or counter-cyclical effect of innovation on employment growth? Investigating employment creation and destruction of innovation over the business cycle, allows us to answer in particular the intriguing research question whether or not economic activities of innovators are more resilient to negative economic shocks[1]. The answers largely rely on two different effects. The first effect refers to the dependency of firms' innovation activities on business cycle fluctuations. A growing literature has studied firms' innovation input behavior over the business cycle and has found that firms expand these activities during economic upturns (see e.g. Barlevy, 2007; Fabrizio and Tsolmon, 2014). The second effect describes the impact of innovation output on firms' employment growth. The literature has shown that this effect depends on several mechanisms in a complex manner. A main conclusion that can be drawn is that the effect is considerably driven not only by the specific type of innovation but also by the demand for firms' products (see Pianta, 2005 for an overview). Product innovations have mainly been found to stimulate firms' labor demand, whereas the effect of process and organizational innovations is ambiguous. Even though the literature stresses that demand-driven effects are crucial for employment consequences of innovation, there is no firm-level study yet investigating the firms' ability to transform innovation into employment growth over the business cycle. We contribute to the literature by providing first evidence regarding firm-level employment growth effects of innovation over different phases of a business cycle.

[1] Regional-industry level evidence points towards this direction. Delgado et al. (2015) found that strong regional clusters in terms of patenting have facilitated employment resilience in the US during the 2007-2009 recession.

Our analysis disentangles this complex relationship by using the structural model of Harrison et al. (2014). This model is conceived to examine the labor-creating and labor-destructing effects of innovations. In this respect, the model establishes a theoretical link between firm-level employment growth and innovation output in terms of (i) the sales growth generated by product innovations, i.e. new or improved products, and (ii) the efficiency gains attributable to process innovations, i.e. new or improved processes. We extend the model's standard specification by allowing efficiency improvements to depend on organizational innovations as well. Schumpeter (1934) already emphasized that firms implement new organizational structures from time to time and do not only rely on product and process innovations. Controlling for organizational innovations also allows us to identify the employment growth effects of process innovations more accurately.

To estimate the model, we use data from the Europe-wide Community Innovation Survey (CIS). Our sample covers information on manufacturing firms from 26 European countries and includes more than 200,000 firm-year observations. We observe them for the period from 1998 to 2010, which is reasonably long and allows us to capture potential business cycle effects. The estimations are weighted, i.e. our findings are representative for the manufacturing sectors of the countries covered. To analyze the cyclicality of the employment growth effects of innovation, we use *country-specific* GDP growth rates to create dummy variables dividing the business cycle into four different phases, i.e. upturn, boom, downturn and recession. Furthermore, we study whether or not employment creation and destruction of innovation over the business cycle differs by firm size. Prior empirical evidence has shown that jobs are typically created in small and medium-sized enterprises (SMEs) (see e.g. Neumark et al., 2011).

Our empirical analysis reveals four important findings. First, the net employment growth effect of product innovators is pro-cyclical. It turns out to be positive in all business cycle phases except for the recession. This means, the potential labor-creating effect exceeds the potential labor-destructing effect of product innovations except during recessions. Second, product innovators are more resilient to recessions than firms that have not introduced product innovations (non-product innovators). When facing negative economic growth, product innovators on average cut jobs. However, the level of job destruction is much more modest as compared to the job destruction of non-product innovators. Third, this resilience of product innovators is, however, only found in SMEs but not in large firms. Fourth, on average, process and organizational innovations particularly reduce labor demand of firms during upturn and downturn periods. Overall, our results suggest that product innovators are an important driving force for firm-level employment growth. They are particularly important for securing jobs during recessions. In contrast, process and organizational innovations tend to displace employment.

The paper is structured as follows. The next section reviews the relevant literature and develops the hypotheses, while Section 3 describes the underlying theoretical and econometric model. Section 4 explains the empirical implementation by discussing the data, descriptive statistics and estimation approach. Section 5 presents the empirical results. Section 6 briefly summarizes and concludes.

2. Related literature and hypotheses

This section reviews the literature relevant to our analysis and develops hypotheses. First, we present the basic findings on firms' innovation activities and their business cycle dependency. Second, we shortly describe the theory on the employment growth effects of different types of innovation and present the main empirical findings. Third, based on the literature review we develop our hypotheses on the employment effects of innovations over the business cycle.

2.1. Innovation activities and the business cycle

The literature on the relationship between the business cycle and innovation has mostly focused on innovation input. During recessions, firms shift more resources to productivity-enhancing activities, such as innovative investment. This counter-cyclical pattern arises because the opportunity costs of long-term innovative investment are lower than short-time capital investment during recessions (see e.g. Bean, 1990; Gali and Hammour, 1991; Aghion and Saint-Paul, 1998). In contrast to these predictions, recent empirical studies find a pro-cyclical pattern of innovative investment. Some authors attribute this result to the cash-flow dependency of financing innovation activities (see e.g. Himmelberg and Petersen, 1994; Mulkay et al., 2001; Ouyang, 2011). Other authors argue that the investment decision is strategically postponed to high demand periods to maximize the innovations' expected profitability (see e.g. Barlevy, 2007). Aghion et al. (2010, 2012) find evidence for pro- and counter-cyclicality. Accordingly, pro-cyclicality arises for financially constrained firms, whereas non-constrained firms act counter-cyclically.

In addition, there is some research on the timing of the market introduction and commercialization of innovations. Shleifer (1986), Francois and Lloyd-Ellis (2003) and Barlevy (2007) develop similar models and argue that the innovators expect imitators to enter after the implementation of innovations.[2] Anticipating this, the innovators postpone the product commercialization to periods of high demand. Only this allows them to capture most of the profits. By using US firm-level data, Fabrizio and Tsolmon's (2014) empirical results support this pro-cyclicality. Furthermore, Axalorglou (2003) uses industry-level data and also finds a positive relationship between growth and the introduction of new products.

2.2. Employment effects of innovations

Technological progress may be labor-saving or labor-creating, and may or may not cause a change in the skill composition (see Vivarelli, 2014 for an overview). In what follows, we neglect the skill

[2] In their model, Francois and Lloyd-Ellis (2003) do not build on imitation. Instead, they assume that after the implementation knowledge disseminates to the rivals. This eventually limits the innovators' time as successful incumbents.

aspect because our data does not include information on skills but only allows us to study total employment growth effects of innovations at the firm level.[3]

Theoretical contributions do not provide clear-cut predictions on whether or not innovations create or destroy jobs (see Petit, 1995; Blechinger et al., 1998 for overviews). Identifying the employment growth impact rather requires separating the effects of product from the effects of process innovations. At the firm level, product innovations may affect employment via three channels. First, introducing new products on the market generates new demand and therefore increases labor demand (*direct demand effect of product innovation*). The second channel is related to the relative productivity between new and old products. If new products are produced more (less) efficiently than old products, they will require less (more) input for a given output. This dampens (strengthens) the positive demand effect, thus also employment growth (*productivity effect of product innovation*). The third channel refers to an *indirect demand effect of product innovation*. According to this, new product demand may replace the demand for the innovators' old products to some degree. This "product cannibalization" reduces labor demand related to the old products. In contrast, the innovators' labor demand will increase if new and old products complement each other. In this case, new product demand stimulates old product demand. Therefore, at the firm level product innovations only unambiguously increase firms' employment levels in case the relationship is complementary. Further employment effects arise at the macro and the sector level.[4] For instance, the increase in new product demand may come at the expense of lower demand for rivals' products (business stealing effect). This reduces the rivals' labor demand. However, product and labor demand of those competitors that offer products complementary to the innovators' new products eventually increase.

Despite ambiguous theoretical predictions, the majority of empirical studies find product innovations to create jobs (see e.g. Entorf and Pohlmeier, 1990; Brouwer et al., 1993; König et al., 1995; Van Reenen, 1997; Smolny, 2002; Garcia et al., 2004; Hall et al., 2008; Peters, 2008; Lachenmaier and Rottmann, 2011; Dachs and Peters, 2014; Harrison et al., 2014). This implies that the employment-inducing effects outweigh the potential employment-reducing effects of product innovations. However, only Garcia et al. (2004), Hall et al. (2008), Peters (2008), Dachs and Peters (2014) and Harrison et al. (2014) explicitly disentangle the labor-creating from the labor-reducing effects of product innovations.

In contrast to product innovations, the direct effect of process innovations is an increase in the innovators' production efficiency (*productivity effect of process innovation*). This type of efficiency gain implies that the same level of output can be produced with less input, e.g. labor. Hence, the

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[3] Two strands of the literature center on the impact of innovation on skills: The literature on skill-biased technological change (see e.g. Caroli and Van Reenen, 2001; Acemoglu, 2002; Bresnahan et al., 2002; Piva et al., 2005) and on routine-biased technological change (see e.g. Autor et al., 2003 and Goos et al., 2014).

[4] For empirical research, see e.g. Freeman et al. (1982), Vivarelli and Pianta (2000), Leitner et al. (2011), Pianta and Lucchese (2012) and Damijan et al. (2014).

productivity effect of process innovation is likely to reduce the innovators' demand for labor. However, as efficiency improvements cause marginal production costs to decline, they open up possibilities for price reductions. Lower prices stimulate the innovators' product demand. In this way, price cuts can alleviate the employment losses related to the productivity effect or even reverse them (*price effect of process innovations*). The magnitude of the price effect is determined by the size of the price reduction, the price elasticity of demand and the competitive environment, in particular competitors' reaction to price reductions.

Empirical results for the effect of process innovations are inconclusive. Mainly based on reduced form regressions, Entorf and Pohlmeier (1990), Van Reenen (1997) and Hall et al. (2008) report no significant effect of process innovations on employment, whereas König et al. (1995) and Lachenmaier and Rottmann (2011) even find that process innovations increase the firms' employment level. Using the same structural approach as this paper, Peters (2008), Dachs and Peters (2014) and Harrison et al. (2014) find evidence for a small negative gross effect of process innovation, i.e. process innovations cut labor due to improved productivity. But the growth of demand for old products – partly provoked by price reductions following the increase in efficiency – is strong enough to compensate for it.

The majority of the employment studies focus on product and process innovations (technological innovations). This is a significant drawback because analyzing employment effects of innovations also requires the adoption of a non-technological perspective in the form of organizational innovations (Edquist et al., 2001). Schumpeter (1934) already stated that firms not only implement new products and processes, but also adjust their business practices and reorganize their organizational structures. However, organizational innovations have largely been neglected for some time due to measurement and definition problems (Lam, 2005; Armbruster et al., 2008). OECD and Eurostat (2005) provide the first harmonized definition of organizational innovations and how to measure them in innovation surveys. Evangelista and Vezzani (2011) analyze CIS data of several European countries and descriptively show that there are more organizational innovators than product and process innovators. By using a different data set covering information on a large set of European firms, Tether and Tajar's results (2008) disclose a very similar pattern.

There is no theoretical model explicitly considering employment effects of organizational innovations. However, Ichniowski et al. (1996) review the literature on workplace innovations and performance. They argue that these kinds of innovations should increase productivity, which should lead to lower costs and higher product demand. Indeed, empirical research supports the productivity-enhancing effect of organizational innovations (see e.g. Ichniowski et al., 1997; Black and Lynch, 2004; Gera and Gu, 2004). Like in the case of process innovations, the evidence as to the employment growth effect of organizational innovations is ambiguous as well. Greenan (2003) shows that a shift towards a flexible enterprise increases the firms' job destruction rate. Likewise, Bauer and Bender (2004) find delayering and the transfer of responsibilities to significantly decrease net employment growth rates, whereas team work causes the employment level to increase. Positive employment effects have also been found, for instance, by Falk (2001), Addison et al. (2008) and Evangelista and Vezzani (2011).

2.3. Hypotheses: Employment effects of innovations over the business cycle

Based on the related literature presented in Section 2.2, it is evident that product demand plays an important role for employment growth effects of technological and non-technological innovations. These demand effects are likely to vary with different phases of a business cycle as do the productivity effects of process and organizational innovations. In this section, we develop a set of hypotheses about the employment growth effects of different types of innovations at different phases of the business cycle.

The gross employment effect of product innovations depends on two effects: (i) the size of the direct demand effect and (ii) the size and direction of the productivity effect. The latter refers to the productivity of new products, i.e. the level of output per unit of input, relative to the productivity of old products. As this is mainly technology-driven, we do not expect the relative productivity to be significantly affected by macroeconomic demand conditions.

Hypothesis H1a: The productivity effect of product innovations is independent of the business cycle.

Instead, we expect the direct demand effect to vary with the business cycle. In line with the literature presented in Section 2.1, we assume that innovators are more successful in selling new products during positive growth periods. In this situation, incomes are increasing and budget restrictions are less tight. In contrast, we expect product innovations to have a lower direct demand effect during downturn and recession periods. Furthermore, the utilization of production capacities is pro-cyclical (see e.g. Corrado and Mattey, 1997; Fagnart et al., 1999). Smolny (2002) finds that higher rates of capacity utilization stimulate employment growth. Given these two stylized facts, we expect product innovators to be more likely to expand their employment when facing demand increases due to new products in upturn and boom periods as they already produce at high or full capacity. During recessions, product innovations are accordingly expected to have less of an effect on employment because direct demand effects tend to be weaker and firms are already struggling with excess capacity. For these reasons, we expect a pro-cyclical demand effect of product innovation to always be positive.

Hypothesis H1b: The direct demand effect of product innovations is pro-cyclical and always positive.

Hypotheses H1a and H1b capture the gross employment effect of product innovations. To obtain the net employment effect of product innovations, it is further necessary to consider the indirect demand effect. In case of a complementary relationship between the innovators' new and old products, a higher (lower) direct demand effect is also associated with a higher (lower) indirect demand effect.

Instead, if new and old products were substitutes, we would expect the demand for old products to disproportionately decline during downturns and recessions compared to upturns and booms. This decline may be reinforced by firms that face pressure to reduce their product range during downturn and recession periods. Bernard et al. (2010), Broda and Weinstein (2010) and Bilbiie et al. (2012) find product creation to be pro-cyclical, whereas product destruction and drop-out rates are counter-cyclical. This should rather affect old than new products. This means that at least some fraction of the sluggish demand levels inherent to downturns and recessions can not only be attributed to tighter budget constraints but also to the reduction of product variety. In total, combining the three transmission mechanisms of product innovations (direct demand effect, productivity effect and indirect demand effect) on employment growth, the net employment effect is ambiguous. Prior empirical evidence, however, has demonstrated that the labor-creating effect tends to outweigh the labor-destructing effect of product innovation leading to a positive net employment growth effect. Therefore, we expect the net effect of product innovation in general to be positive and to vary with the business cycle. If the net effect becomes negative, it is most likely to happen during a recession. Overall, we expect the net effect of product innovations to be pro-cyclical and smallest in recession periods.

Hypothesis H1c: The net employment effect of product innovations follows a pro-cyclical pattern, and is assumed to be smallest in recessions.

There are two basic mechanisms underlying the employment growth effect of process innovations: (i) a labor-destructing productivity effect and (ii) a labor-creating price effect. During downturns and recessions, the lack of demand may discourage the introduction of new products but increases the competition based on costs and prices (Spiegel and Stahl, 2014). In this situation, process innovations play an important role in improving productivity, which goes at the cost of job losses (Pianta and Lucchese, 2012). For a demand-inducing price-effect to occur, the cost reductions need to be passed on to the product price. However, firms may be less inclined to reduce prices, as profits usually decline during downturns and recessions. Therefore, we expect the labor-destructing productivity effect to prevail during downturns and recessions. In contrast, process innovators may be less eager to increase productivity during upturn and boom periods. Tether and Tajar (2008) find that the main strength of process innovations is the flexibility and adaptability of production to market needs. This orientation of process innovators may allow them to better exploit generic periods of high demand on a large scale. Therefore, we expect that process innovators may be more focused on meeting the market needs during booms than during recessions. This is less likely to be job-destructing. Even if process innovators increase productivity during boom periods, we expect the labor-creating price effect to occur, at least in part. Overall, we expect either stronger net job destruction or less net job creation during downturns and recessions as compared to upturns and booms. This leads to the following hypotheses:

Hypothesis H2a: The labor-destructing productivity effect of process innovations is strongest during downturns and recessions, followed by upturns and booms.

Hypothesis H2b: Process innovations induce either stronger net job destruction or less net job creation in downturns and recessions than in upturns and booms.

The literature presented in Section 2.2 suggests that the employment effect of organizational innovations is driven by the same two mechanisms observed for process innovations. That is, a direct productivity effect may reduce the innovators' labor demand and a potentially counteracting price effect may stimulate firms' employment growth. Lundvall and Kristensen (1997) show that firms' propensity to use organizational innovations as an efficiency-enhancing instrument is increasing in competitive pressure. As discussed for process innovations, the competitive pressure is probably highest during downturn and recession periods. This rather reduces labor demand. For these reasons, we expect that the business cycle effects of organizational innovations on employment growth largely correspond to the effects of process innovations.

Hypothesis H3a: The labor-destructing productivity effect of organizational innovations is strongest during downturns and recessions, followed by upturns and booms.

Hypothesis H3b: Organizational innovations induce either stronger job destruction or less net job creation in downturns and recessions than in upturns and booms.

3. Empirical model

In order to test our hypotheses, we adopt the approach developed by Harrison et al. (2008, 2014) that establishes a theoretical link between firm-level employment growth and different types of innovations. The main virtue of the model is that it relies on innovation output indicators. This means that it incorporates the demand situation of the respective firms, which is an important element of firms' labor demand. Its empirical implementation is targeted at using information provided by CIS data. In its original form, the model has been used to analyze employment effects of product and process innovation for European, Latin American and Chinese firms (see e.g. Benavente and Lauterbach, 2007; Hall et al., 2008; Mairesse et al., 2011; Crespi and Tacsir, 2013; Harrison et al., 2014). We follow Peters et al. (2013) and Damijan et al. (2014) and extend the model by including organizational innovations as well. Furthermore, we estimate the model for a large set of European firms observed during a reasonably long period that covers different business cycle periods. In the following, we briefly describe the model; for more details see Harrison et al. (2008, 2014).

The model is based on a two-product framework, i.e. a firm can produce two different (sets of) products, at two points in time $t = (1, 2)$. At the beginning, at $t = 1$, a firm produces a certain product or product portfolio, which by definition is labelled as old (or existing) products. Between $t = 1$ and

$t = 2$, a firm may introduce one or more new or significantly improved products (product innovations). The new products can (partially or totally) replace the old ones in case they are substitutes. They enhance the demand of the old product in case of a complementary relationship. Hence, at the end of that intermediate period, $t = 2$, the firm produces either only old products, only new products or both types of products.

To produce the respective output, we assume an underlying production function that is linear homogeneous in the conventional inputs labor, capital and material. In addition, the final output depends on Hicks neutral productivity of the respective product j at time t, captured by θ_{jt}. With respect to old products, a firm can increase the production efficiency between $t = 1$ and $t = 2$ by implementing process and organizational innovations. In addition to a firm's own innovation-related productivity improvements, productivity gains may be caused by learning effects, spillovers, inputs of higher quality, training, selling or shutting down of unprofitable business units or mergers and acquisitions. As by definition new products are not produced at $t = 1$, firms cannot improve the productivity of new products. However, it is important whether or not the productivity of new products will be higher or lower compared to the one of old products. Based on these considerations, Harrison et al. (2008, 2014) derive the following labor demand equation (for ease of presentation, firm indices i and time indices t are suppressed:

(1) $$l = \alpha + y_1 + \beta y_2 + u$$

Employment growth l originates from four main sources in the model: (i) efficiency gains in the production of old products, α, (ii) the growth rate of the real output of old products, y_1, (iii) the real output growth rate due to new products, y_2 and (iv) the relative productivity of new products, β.[5] The error term u captures unanticipated productivity shocks in the production of old products at $t = 2$.[6]

The output growth of old products, y_1, is likely to depend on the demand for new products, at least to some degree. That is, it captures indirect demand effects: Negative output growth will arise if new products are substitutes to old products (cannibalization effect), whereas the growth rate will be stimulated in case of a complementary relationship. Furthermore, the effect of y_1 also captures (i) demand changes provoked by innovations introduced by competitors (business stealing effects), (ii) demand increases due to innovation-related price reductions (price effect), (iii) changes in consumer preferences, (iv) policy-induced demand changes and (v) business cycle effects. Data limitations

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[5] Please note that as new products have not been produced at $t = 1$, y_2 cannot measure the real output growth of new products. Instead, y_2 measures the output of the new products (excluding unanticipated shocks) at $t = 2$ relative to the output of the old products at $t = 1$. Therefore, it captures the real output growth rate *due to* new products.

[6] The production functions of old and new products at $t = 2$ include unanticipated productivity shocks u and υ, respectively. In deriving equation (1), Harrison et al. (2014) show that υ cancels out. The production functions of both products also allow for unobserved firm fixed effects, η_i in every period. These firm fixed effects also vanish in the growth rate formulation.

restrict us in disentangling the underlying effects from each other. However, the data we use allow us at least to separate the business cycle effects from the other demand-side effects.

The term βy_2 captures the *gross employment growth induced by new products*, which consists of two channels. The first one refers to the *demand growth due to new products* (relative to the old products), y_2. The second one, β, involves the *productivity effect of new products*. This relative productivity is defined as $\beta = \theta_{11}/\theta_{22}$, i.e. as efficiency of old products in $t = 1$, θ_{11}, relative to the efficiency of new products in $t = 2$, θ_{22}. Ceteris paribus, new products will generate higher employment growth if their production is less efficient than the production technology of the old products, i.e. if $\theta_{22} < \theta_{11}$. In contrast, new products will induce relatively less labor demand if new products are produced more efficiently, that is for $\beta < 1$. According to our hypothesis H1a, we expect β to be independent of the business cycle.

In principle, an increase in the efficiency in the production of old products reduces firms' labor demand. Hence, we expect α to be negative. Harrison et al. (2014) suggest separating the non-innovation-related and innovation-related efficiency improvements. With respect to the latter, they only account for process innovation-induced improvements. We extend the model by separately investigating the employment impact of efficiency improvements of organizational innovations as well. Rewriting equation (1) yields:

$$l = \alpha_0 + \alpha_1 pc + \alpha_2 orga + y_1 + \beta y_2 + u \qquad (2)$$

In addition to equation (1), equation (2) disentangles the productivity effect of old products into three components: α_0, α_1 and α_2. The first effect, α_0, represents the average efficiency gains of old products not related to innovations. The components α_1 and α_2 measure the *productivity effect, i.e. gross effect, of process (pc) and organizational ($orga$) innovations*, respectively.

Unfortunately, we cannot estimate equation (2) as we cannot observe real output growth rates in our data. Instead, we replace the unobserved real growth rates by the observable nominal growth rates measured as sales growth. This yields the following equation:

$$l - (g_1 - \tilde{\pi}_1) = \alpha_0 + \alpha_1 pc + \alpha_2 orga + \beta g_2 + \varepsilon \qquad (3)$$

The nominal sales growth of the old products, g_1, and of the new products, g_2, are defined as $g_1 = y_1 + \pi_1$ and $g_2 = (1 + \pi_2) y_2$. The coefficient of the real output growth of old products, y_1, is equal to one and can be subtracted from l. The variables g_1 and g_2 can be calculated by using CIS data presented in Section 4.1. The sales growth rate of the old products, g_1, is defined as the total sales growth rate minus the sales growth rate due to new products. The term π_1 measures the unobserved price growth rate of old products at the firm level. Potential data sources usually do not provide price data on a firm level. Therefore, we proxy π_1 by the price growth rate of old products at a 2-digit industry level, $\tilde{\pi}_1$. The firm-level indicator π_2 is defined as the price difference between new products at $t = 2$ and old products at $t = 1$ in relation to the price of the old products at $t = 1$. The problem is that we cannot observe this price information, not even on an industry level. However, substituting a real by a nominal growth rate requires price growth information to adequately estimate the effect. As a result, our estimation of β suffers from an endogeneity bias caused by measurement errors and we use an instrumental variable (IV) approach to deal with this endogeneity problem.[7] A similar problem would arise for the estimated coefficients of α_1 and α_2 if $\tilde{\pi}_1$ was a weak proxy variable for π_1.[8] In this case the price growth on an industry level would substantially diverge from the firm-level price growth. Therefore, the new error term incorporates these potential sources of endogeneity, so that $\varepsilon = -E(\pi_1 - \tilde{\pi}_1) - \beta\pi_2 y_2 + u$.

Even in the case $\tilde{\pi}_1$ is a good proxy variable for π_1, what we assume, the estimates of our innovation indicators can still suffer from an endogeneity bias. For instance, innovations are typically the result of investment decisions. If those decisions were correlated with any unobserved productivity shocks u appearing at $t = 2$ the estimated coefficients would indeed be biased. However, those decisions usually take place before the realization of the shocks, i.e. before $t = 2$. This means that we do not expect serious endogeneity problems due to simultaneity. This has been confirmed by Harrison et al. (2014) who tested the exogeneity assumption of process innovations for manufacturing firms of four different European countries and did not find evidence for process innovations to be an endogenous explanatory variable in the econometric model.

Overall, subtracting the proxy for the real output growth of old products, $(g_1 - \tilde{\pi}_1)$, from employment growth, l, allows us to estimate the gross effect of process, organizational and product innovations.[9] Indeed, we cannot directly estimate the indirect demand effect, thus the net employment growth effect (H1c) of product innovations. In order to do so, we would need more detailed demand data to disentangle the different components of changes in y_1. However, as we will explain in more detail in Section 4.2 and Section 4.4, we will use a decomposition analysis to show the indirect and net employment growth effect for product innovators. Unfortunately, this is not possible for the net effect of process and organizational innovations. Therefore, the analysis of hypotheses H2b and H3b remain open for future research.

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[7] We explain our identification and estimation strategy below in Section 4.3.

[8] The estimates are only unbiased if $\widetilde{\pi_1}$ corresponds to π_1. We would underestimate the productivity effects of process and organizational innovation, otherwise.

[9] Instead of using $l - (g_1 - \tilde{\pi}_1)$ as dependent variable, we could have used l as dependent variable and $(g_1 - \tilde{\pi}_1)$ as additional explanatory variable. However, in line with the model, we would have restricted the coefficient to be one, which would have generated the same results. Therefore, we still can interpret the results in terms of employment growth.

4. Data and estimation method

4.1. Data

We use micro data from the European-wide Community Innovation Survey (CIS).[10] This survey rests on a European-wide harmonized questionnaire. It is biannually conducted by the national statistical offices or legalized national institutions of the European Union's member states, Iceland and Norway.[11] The CIS applies the definitions and methodology of the Oslo Manual on innovation surveys (see OECD and Eurostat, 2005). The target population covers all legally independent enterprises with 10 or more employees in manufacturing, mining, energy and water supply and selected services. The survey collects data on firms' innovation expenditures, different innovation output indicators and other business-related information, e.g. employment and sales. Each CIS wave covers a three-year period. Hence, we have calculated all our growth rates between t and t-2.

We employ five waves of CIS data that cover the years 1998-2000 (CIS3), 2002-2004 (CIS4), 2004-2006 (CIS2006), 2006-2008 (CIS2008) and 2008-2010 (CIS2010). For the empirical analysis, we focus on employment effects of innovation in manufacturing firms only. Furthermore, we define two samples. Sample 1 includes 201,691 firm-year observations and depicts our main sample. It is used for estimating the econometric model with organizational innovation (equation (3)). One limitation of the data is that only a limited number of countries provided information on organizational innovation in CIS2006 as this question was not compulsory in this wave (see Table A-1 in the Appendix). As the period 2004-2006 marked a boom period in many European countries, the drop in the number of observations is particularly strong for the boom sample. To check whether this substantially affects the estimated employment effects of product and process innovation, we additionally estimate the model excluding organizational innovation. This allows us to use sample 2 that contains 225,544 firm-year observations. Table 1 gives an overview of the distribution of the CIS waves. The distribution among the CIS waves shows that the first three CIS waves exhibit the smallest sample sizes, whereas more than half of the observations stem from CIS2008 and CIS2010 in sample 1.

Within the manufacturing sector, the manufacturing of basic and fabricated metals, food and beverages as well as the textile industry hold the highest shares of observations (see Table A-2 in the Appendix). The vehicle industry along with the industries of chemicals, rubber and plastics as well as non-metallic mineral products, have the lowest shares in our sample.

[10] We accessed CIS micro data at Eurostat's Safe Center in Luxembourg.

[11] Prior to CIS2006 (2004-2006), the survey was conducted every fourth year.

Table 1: Distribution of CIS sample by waves

CIS-waves	Observation period	Sample 1		Sample 2	
		N	%	N	%
CIS 3	1998-2000	40,044	19.85	40,044	17.75
CIS 4	2002-2004	43,397	21.52	43,431	19.26
CIS2006	2004-2006	13,116	6.50	35,970	15.95
CIS2008	2006-2008	52,008	25.79	52,870	23.44
CIS2010	2008-2010	53,126	26.34	53,229	23.60
Total	1998-2010	201,691	100	225,544	100

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

Note: Sample 1 refers to the model that includes organizational innovation; sample 2 refers to the model that excludes organizational innovation.

Although all EU countries are required by law[12] to conduct the CIS, they are not obliged to transfer micro data to Eurostat. In total, micro data are available for all five waves for 11 out of 26 countries. Five countries provide micro data only for one or two waves. The sample sizes between the countries differ substantially (see Table A-1 in the Appendix), partly due to the country size and partly because the CIS is compulsory for the firms in some countries like France and Italy, whereas it is voluntarily in other countries. To get representative results, we apply weighting factors to all descriptive statistics and estimations.[13]

Another limitation of the data is that firm-level observations cannot be linked between subsequent CIS waves due to missing firm identifiers. Hence, we can only apply pooled OLS and IV estimators. In order to account for the fact that some firms are repeatedly observed and the i.i.d. assumption may be violated, we will use clustered standard errors at the industry-country level to allow for correlation among the error terms within the cluster.

4.2. Variables

In accordance with the underlying model, the dependent variable, EMP, is defined as $l - (g_1 - \tilde{\pi}_1)$. The employment growth, l, is measured as the relative change in the number of employees (head counts) between and t and t-2. The real output growth due to old products, $g_1 - \tilde{\pi}_1$, denotes the difference between (i) the nominal sales growth rate of old products (g_1 / SGR_OLDPD) and (ii) the growth rate of prices for old products at the industry level ($\tilde{\pi}_1$ / PRICEGR).[14] The nominal sales growth rate due to old products (g_1 / SGR_OLDPD) is calculated as the total sales growth rate minus the sales growth rate due to new products (g_2 / SGR_NEWPD; see below). To calculate $\tilde{\pi}_1$ we use producer price indices at the 2-digit country-industry level as published by Eurostat.

[12] Up to 2010, CIS has been collected under Commission Regulation (EC) No 1450/2004. From 2012 onwards, Commission Regulation No 995/2012 applies.

[13] Weighting is implemented by using sample weights that extrapolate to the population number of firms in each stratum.

[14] Lower-case letters denote the model variables whereas upper-case letters describe their empirical counterparts in the data. Remember that our growth rates are defined as the growth between t and t-2.

Process innovation (pc) is represented by the dummy variable PC that takes on the value one if firms have introduced only process innovations but no product innovations between t and t-2. According to the Oslo Manual, a process innovation is the implementation of a new or significantly improved production process, distribution method, or supporting activity. This definition includes process innovations that are introduced to support the launch of product innovations (see OECD and Eurostat, 2005, paragraph 164). According to our theoretical model, however, α_1 captures efficiency gains of process innovation related to the production of old products. Our focus on pure process innovators in the empirical analysis allows us to identify the employment effect of process innovations related to old products more accurately.

Organizational innovations involve new methods in the firms' business practices, workplace organizations or external relations. According to the Oslo Manual, they are intended to e.g. lower administrative costs and to increase labor productivity. However, they are not considered as an enabler for product innovations. One example of an organizational innovation is firms' reduction of hierarchy levels (delayering). A flatter management structure lowers costs and should increase firms' productivity as there are fewer management hurdles to overcome within a decision process. We measure organizational innovations ($orga$) by the indicator ORGA that takes on the value one if firms introduced at least one organizational innovation between t and t-2.

Our key variable for measuring product innovation output is the sales growth rate due to new products (g_2). Its empirical counterpart, SGR_NEWPD, is calculated as year t's sales share with new products, which have been introduced between t and t-2, multiplied by the ratio of year t's sales divided by the sales of t-2.

Beyond the information required by the model's structural equation, employment growth is likely to be influenced by a set of other characteristics. An important determinant for employment growth is firm size. According to Gibrat's law, firms grow proportionally and independently of firm size. In contrast, Mansfield (1962) finds that smaller firms' growth rates are higher and also more volatile. Jovanovic (1982) provides a theoretical background for Mansfield's related analyses. His model suggests that surviving young and small firms grow faster than older and larger ones because of managerial efficiency and learning by doing. To control for size effects we include the dummy variables, MEDIUM – taking on the value one for firms with 50-249 employees – and LARGE, for firms with at least 250 employees.[15] Firms with less than 50 employees, SMALL, build our reference category. All size dummies are related to the period t-2. Furthermore, we control for ownership effects as employment grows slower and is also more volatile in foreign-owned firms (Dachs and Peters 2014). We include two dummy variables indicating that a firm belongs to a firm group that has a domestic (DGP) and foreign headquarter (FGP), respectively. Domestic unaffiliated firms serve as

[15] To further scrutinize size heterogeneity, we split our sample into SMEs and large firms (see Section 5.2).

reference group (DUF).[16] A set of time, industry and country dummies based on the information presented in Table A-1 and Table A-2 is also included.

To properly examine business cycle effects, we split our estimation sample into the four phases of the business cycle. In general, the business cycle describes fluctuations in economic activity that an economy experiences over a period of time. A business cycle consists of four phases: upturn, boom, downturn and recession. Our analysis uses real GDP growth rates on a country level, provided by Eurostat. Based on that, we define our business cycle indicator as follows:

Table 2: Definition of the four business cycle phases

Business cycle phase	GDP growth is…
Upturn	increasing and positive
Boom	increasing and positive and subsequently decreasing
Downturn	decreasing but (still) positive
Recession	negative

One potential issue is the time period used to calculate this indicator. Statistical offices often use quarterly data on GDP growth to define a business cycle. In empirical work, it is also common to employ one-year growth rates. The CIS data covers a three-year period, in CIS2010 for instance the period 2008-2010. Hence, we use two-year GDP growth rates, i.e. in the example above the growth rate between 2008 and 2010.

Splitting the sample according to the business cycle phases ignores the information about the strength of GDP growth, which varies considerably across European countries. For this reason, we include in our estimations the information about country-level real GDP growth rates (GDPGR) between t and t-2. This captures general demand effects. Firm-specific demand effects are already covered by g_1 and g_2. Therefore, our equation to be estimated is the following:

$$EMP_{t|t-2} = \alpha_0 + \alpha_1 PC_{t|t-2} + \alpha_2 ORGA_{t|t-2} + \beta SGR\_NEWPD_{t|t-2} + X_t\gamma + v_t \qquad (4)$$

The matrix X_t includes our control variables MEDIUM, LARGE, DGP, FGP and GDPGR as well as the time, industry and country dummies for each firm i at time t. The remaining variables, the error term ε_t and γ in equation (4) denote vectors.

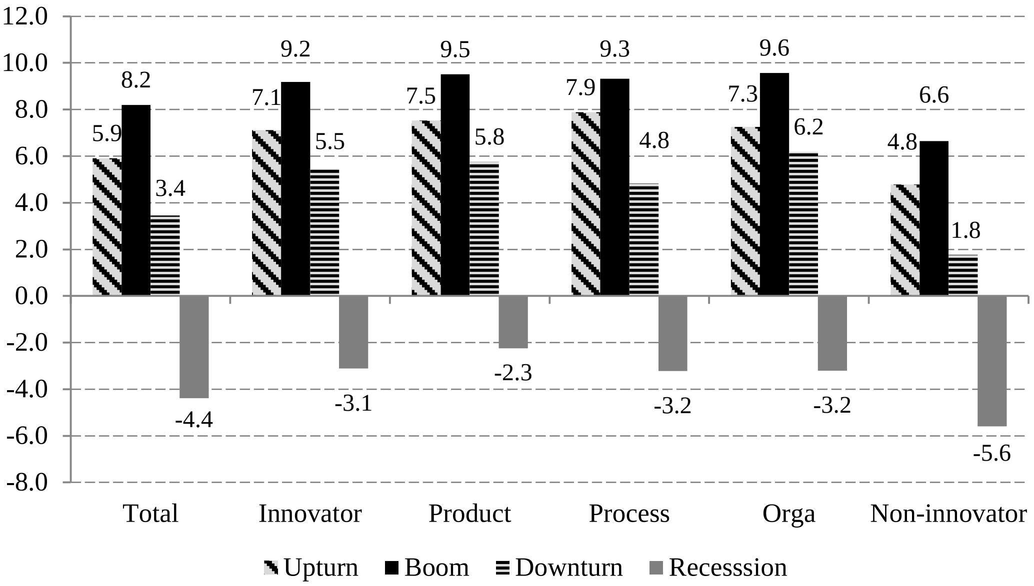
4.3. Descriptive statistics

About half of the firms (49.5%) can be classified as innovators having introduced at least one product (27%), process (11%) or organizational innovation (32%) (see Table A-3 in the Appendix). This

[16] See Table A-3 for a distribution of the respective firm groups included in our sample.

section presents basic descriptive results on the relationship between innovation and employment growth in different phases of the business cycle. For the total sample, Figure 1 shows that the average employment growth rates across all firms follow a pro-cyclical pattern. During upturn periods, firm-level employment has grown by 5.9%. It has increased by 8.2% during booms, whereas the growth rate diminished to 3.4% during downturn periods. The level of employment has been reduced by -4.4% during recessions.[17]

Figure 1: Employment growth by innovation status in different business cycle periods, in %



Source: CIS3, CIS4, CIS2006, CIS2008, CIS2010, Eurostat; authors' own calculation.
Note: Depicted are weighted average two-year employment growth rates; the group "Innovator" refers to firms that have implemented at least one process, product or organizational innovation between t and t-2.

This pro-cyclical relationship holds for each type of innovator and non-innovator, respectively. It means that each group has suffered from employment reductions during recessions and has achieved employment growth during the other periods. More importantly, we observe substantial differences in average employment growth between the group of innovators and the group of non-innovators in each phase of the business cycle. For instance, during booms, innovators have raised their employment level by 9.2%, whereas non-innovators' employment has increased by 6.6%. Such a strong difference is observed for all types of innovators. The most notable difference concerns the recession period. Innovators have decreased their employment level by -3.1% during recessions, whereas non-innovators have cut employment by almost twice as much (-5.6%). This implies that innovators, particularly product innovators, have been more resilient to periods of negative economic growth. The

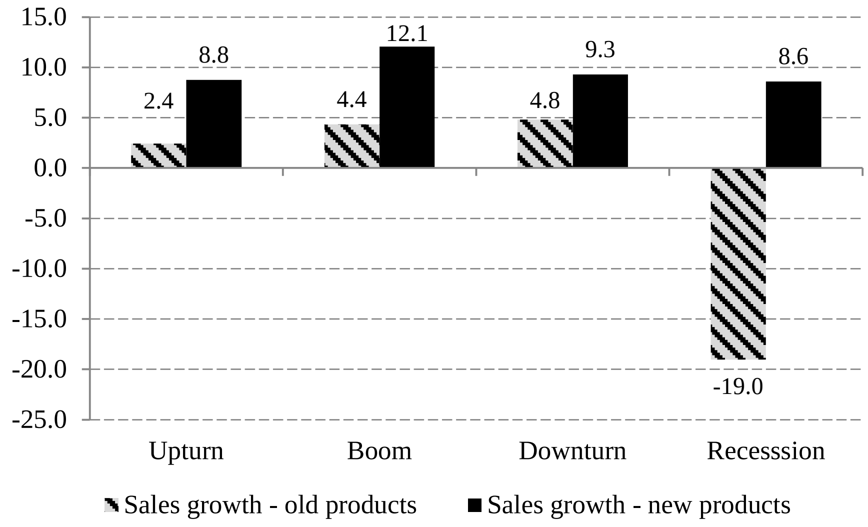
[17] The employment growth rates are not directly comparable to official employment statistics. First, CIS applies the lower threshold of 10 employees. Second, employment changes due to firms exiting and entering are not captured by CIS data because survey response is conditional on surviving and employment growth rates are not defined for newly established firms. Third, official statistics are based on a different calculation method which is the ratio of the sum of changes in employment for all firms to the sum of employed personnel.

difference in the employment growth rates between innovators and non-innovators may be due to the innovators' superior adaptability to shocks (Meghir et al., 1996). Accordingly, innovating firms are more flexible and have lower adjustment costs of employment when faced with negative shocks. Of course, it might also be that innovators and non-innovators differ in other firm characteristics that contribute to the better employment performance of innovators in general and to the stronger resilience of innovators in recessions in particular. The econometric analysis is aimed at disentangling the role of innovation while controlling for these other firm characteristics.

Figure 2 brings two key variables of the empirical model into focus: the average nominal sales growth rates due to new and to old products. New product sales as well as old product sales follow a pro-cyclical pattern. New product sales have increased by 8.8% during upturn periods and by 12.1% during booms. The strong demand has slowed down to 9.3% during downturn periods. The weakest demand has occurred in recessions, with a growth rate of 8.6%. Pairwise mean difference tests show that the average sales growth rates due to new products are significantly different at the 1% level between upturn and boom, boom and downturn and downturn and recession, respectively. Hence, we find support for our hypothesis H1b. New product sales are pro-cyclical and always positive. Despite significant differences across business cycle periods – except for the comparison between upturn and recession – it is remarkable how much sales growth is generated with new products even in recessions. If we focus only on product innovators, the sales growth due to new products is about 30% in the recession, only little less than in the boom period (33%), see Table A-5. This finding will become important in explaining employment growth differences of innovators and non-innovators in the recession.

Sales growth due to old products is substantially lower than due to new products in all phases of the business cycle. While the gap remains rather stable for upturn, boom and downturn – ranging from 4.5 to 7.7 percentage points – it stands out in the recession. Sales with old products have severely suffered from a drop in demand and declined by -19%. Table A-5 in the Appendix shows that this substantial decline is partly due to a reduction in demand for old products of product innovators (-37%). It may have been caused by significant product cannibalization or a reduction in the innovators' product range. Another explanation relates to tighter budget constraints during recessions. The potential for budget restrictions is indicated by the sales loss of non-innovators, i.e. firms that only offered old products and did not introduce any innovation between t and t-2. Their sales growth rate decreased by -12.5% during recessions. This decline is substantially larger than the *net* loss in sales of product innovators (-7.1%).

Figure 2: Sales growth due to new and old products, in %



Source: CIS3, CIS4, CIS2006, CIS2008, CIS2010, Eurostat; own calculation.
Note: Weighted figures.

4.4. Estimation approach and identification

As discussed in Section 3, the estimation of the relative productivity effect of product innovation, β, is subject to a measurement error of the sales growth rate due to new products. Therefore, we employ a weighted instrumental variable (IV) approach to estimate equation (4) consistently. In our case, variables qualifying as instruments should be correlated with the sales growth due to new products (i.e. innovation success) and should be uncorrelated with the error term. In particular, the instruments have to be uncorrelated with the relative price difference of new and old products. We cannot use any lagged values of the endogenous right-hand variable as instrument because Eurostat does not provide firm identifiers. Instead, our identification strategy is based on three external instruments. We expect these variables to be important in explaining innovation success and to be uncorrelated with the relative price difference of new to old products.

Following Harrison et al. (2014), we use RANGE as instrument. RANGE is a binary indicator measuring whether the implemented product innovations have been aimed at increasing the product range or not. We assume RANGE to be correlated with the expectations of new product sales. Enlarging the range of products is a strategic decision that may require more resources than other product innovations. We expect that those firms put more effort into the development and the market introduction. This means, they may spend more on e.g. R&D, the product design and marketing activities. If firms invest more for product innovations it should also have a positive effect on the new products' success. Enlarging the range of products, however, does not imply any particular direction of the changes in prices. New products added to the firm's product portfolio might be of higher (lower) quality sold at higher (lower) prices than existing products of similar quality and price. Our second instrument is a binary indicator as well. It takes on the value one if the firm actively cooperated in innovation projects with other agents, COOP. Other agents include, for instance, suppliers, research institutions and competitors. Firms benefit from knowledge spillovers in cooperation projects. We expect these spillovers to increase the likelihood of successfully developing new products which should be in turn correlated with higher expected new product sales. Furthermore, cooperating firms may establish new ways (or channels) of distributing the products. This should also be correlated with higher expected sales with new products. However, we do not expect this to significantly affect the relative price between old and new products. Our third instrument, RD, indicates whether a firm performs R&D activities on a continuous base or not. A continuous research effort should be related to a higher likelihood of inventing new technologies and as a result of higher expected sales with new products. However, we do not expect a more continuous research effort to be substantially linked to the relative price difference.

5. Empirical evidence on employment effects of innovation over the business cycle

5.1. Full sample results

5.1.1. Regression results

Table 3 presents the regression results of the basic OLS estimations. We split the sample into the four phases of a business cycle, i.e. upturn, boom, downturn and recession. The coefficient of the sales growth rate due to new products (SGR_NEWPD) is central to our analysis on the relationship between employment growth and product innovation.

The coefficient measures the average employment effect of the relative efficiency of the production between old and new products. The results show that the relative production efficiency, $\hat{\beta}$, is smaller than one. This means, producing new products is more efficient than producing old products resulting in less labor demand. Efficiency gains range between 9.7% and 13.4%. To test whether these estimates are significantly different from one, we performed Wald tests. Each displayed p-value of the Wald test suggests that the relative production efficiency is significantly smaller than one. However, we suspect SGR_NEWPD to be endogenous due to measurement error and hence $\hat{\beta}$ to be downward biased. To address endogeneity, we conduct IV estimations as explained in Section 4.4.

Table 3: Employment effects of innovation over the business cycle, OLS estimations

	Business cycle phase			
Dep. var.: EMP	**Upturn**	**Boom**	**Downturn**	**Recession**
SGR_NEWPD	**0.866*** **	**0.892*** **	**0.879*** **	**0.903*** **
	(0.014)	(0.015)	(0.011)	(0.013)
PC	**-3.090*** **	-1.374	**-3.486*** **	-1.188
	(0.817)	(1.310)	(0.846)	(0.887)
ORGA	**-0.967** **	**1.360* **	0.376	0.187
	(0.398)	(0.693)	(0.548)	(0.457)
GDPGR	**3.727*** **	**-0.509** **	**-0.611*** **	**-0.362* **
	(0.554)	(0.202)	(0.177)	(0.217)
MEDIUM	**-2.906*** **	0.084	-0.845	**-1.910*** **
	(0.470)	(0.859)	(0.556)	(0.499)
LARGE	**-4.263*** **	**-3.135** **	-0.777	**-3.792*** **
	(0.613)	(1.216)	(0.725)	(0.648)
DGP	-0.957	**3.330*** **	0.629	**1.327* **
	(0.708)	(1.164)	(0.655)	(0.676)
FGP	-0.787	0.969	0.237	**-1.730*** **
	(0.791)	(1.159)	(0.657)	(0.650)
Constant	**-67.655*** **	1.383	**-14.920*** **	**2.972* **
	(7.270)	(1.729)	(2.614)	(1.600)
Observations	67,468	15,863	67,179	51,181
R2_adjusted	0.383	0.495	0.393	0.467
Further test				
Wald-test for β=1 (p-value)	**0.000*** **	**0.000*** **	**0.000*** **	**0.000*** **

Note: * p<0.1; ** p<0.05; *** p<0.01; sample 1; weighted OLS estimations; clustered standard errors in parentheses (clustered by 2-digit industry and country); time, industry and country dummies are included and each set of dummies is jointly significant.

Our main results, the IV estimates, are presented in Table 4. The test on exogeneity corroborates our suspicion that the sales growth due to new products is endogenous. The tests reject the null hypothesis of exogeneity for all business cycle phases at least at the 5% level. The IV results disclose positive and significant estimates for $\hat{\beta}$ across all phases of the business cycle. These estimates are larger than the OLS estimates. Except for the downturn period, the coefficients are only slightly smaller than one. The Wald tests confirm that each of the four coefficients is not significantly different from one. Hence, new and old products are produced equally efficient, on average. According to the structural model, the coefficient indicates that a 1% increase in the sales due to new products leads to a 1% increase in gross employment, independent of the cyclical situation. The finding that $\hat{\beta}$ is not significantly different from one in all four estimates confirms our hypothesis H1a stating that the productivity effect of product innovation is independent of the business cycle.

Table 4: Employment effects of innovation over the business cycle, IV estimations

	Business cycle phase			
Dep. var.: EMP	**Upturn**	**Boom**	**Downturn**	**Recession**
SGR_NEWPD	**0.991*** **	**0.971*** **	**1.003*** **	**0.988*** **
	(0.022)	(0.031)	(0.026)	(0.029)
PC	**-1.665** **	-0.173	**-1.816***	-0.214
	(0.821)	(1.401)	(0.941)	(1.038)
ORGA	**-2.284*** **	0.536	**-1.393** **	-0.716
	(0.463)	(0.743)	(0.614)	(0.501)
GDPGR	**3.637*** **	2.823	**-0.600*** **	-0.017
	(0.555)	(1.812)	(0.175)	(0.278)
MEDIUM	**-3.090*** **	-0.014	**-1.260** **	**-2.026*** **
	(0.463)	(0.863)	(0.597)	(0.503)
LARGE	**-4.728*** **	**-3.577*** **	**-1.358***	**-3.976*** **
	(0.612)	(1.284)	(0.791)	(0.667)
DGP	**-1.487***	**3.203*** **	0.566	**1.244***
	(0.792)	(1.165)	(0.648)	(0.663)
FGP	-1.113	1.039	0.123	**-1.825*** **
	(0.804)	(1.147)	(0.659)	(0.628)
Constant	**-67.158*** **	**-33.436** **	**-15.094*** **	**3.013***
	(7.291)	(15.817)	(2.647)	(1.647)
Observations	67,468	15,863	67,179	51,181
R2_adjusted	0.377	0.492	0.387	0.464
Further tests				
Wald-test for β=1 (p-value)	0.691	0.349	0.908	0.681
Test on exogeneity (p-value)				
SGR_NEWPD	**0.000*** **	**0.004*** **	**0.000*** **	**0.024** **
Test on instrument validity				
Hansen J test (p-value)	0.375	0.311	0.160	0.220
Difference-in-Hansen test (p-value)				
RANGE	0.237	0.132	0.264	0.163
COOP	0.469	0.340	**0.056***	0.929
RD	0.162	0.413	0.809	0.112
First stage results of SGR_NEWPD				
RANGE	**21.885*** **	**20.747*** **	**23.241*** **	**19.504*** **
	(0.771)	(1.226)	(0.956)	(1.027)
COOP	**4.984*** **	**4.852*** **	**5.602*** **	**2.717** **
	(0.801)	(1.808)	(0.770)	(1.104)
RD	**10.112*** **	**7.172*** **	**5.731*** **	**5.937*** **
	(1.279)	(1.298)	(1.392)	(1.439)
F test on excluded instruments (F)	**436.24*** **	**228.91*** **	**321.22*** **	**265.71*** **
Test on underidentification				
Kleibergen-Paap LM test (chi2)	**297.655*** **	**61.597*** **	**1326.516*** **	**706.997*** **
Test on weak instruments				
Kleibergen-Paap F test (F)	**560.833*** **	**300.275*** **	**801.494*** **	**346.558*** **
Inference robust to weak identification				
Anderson-Rubin Wald test (chi2)	**926.194*** **	**462.643*** **	**986.760*** **	**335.099*** **
Stock-Wright LM test (chi2)	**65.384*** **	**45.523*** **	**87.832*** **	**48.947*** **

Note: * p<0.1; ** p<0.05; *** p<0.01; sample 1; weighted IV regressions; clustered standard errors in parentheses; time, industry and country dummies are included and each set of dummies is jointly significant.

The coefficient of PC measures the productivity effect (gross employment effect) of process innovations. The significantly negative coefficients in the upturn and downturn period indicate that the implemented process innovations have been labor-destructing, on average. The coefficients are negative, though insignificant for booms and recessions. The finding for the boom period is in line with our hypothesis H2a. We expect either no or at least the smallest labor-destructing productivity effect during booms because process innovations are more likely to be aimed at increasing capacity and flexibility than efficiency in this situation. The insignificant estimate for the recession, however, is counterintuitive as we expected stronger negative effects for downturns and recessions. For this reason, we can only partially confirm hypothesis H2a. The employment effects of organizational innovations are very similar to the ones of process innovations. That is, as expected organizational innovations significantly reduce the innovators' labor demand during upturn and downturn periods. The positive though insignificant effect in the boom period is again in line with hypothesis H3a. Like for process innovation, we do not find significant labor-displacing effects of organizational innovations in the recession. This similarity may be attributable to the assumption that organizational and process innovations rely on the same channels to influence employment growth. As a result, we only partially confirm hypothesis H3a as well.

With respect to the control variables, an interesting finding is that affiliates of foreign multinational firms (FGP) grow with a significantly lower rate reduced during recessions than domestically owned firms. An explanation could be that foreign-owned firms are more exposed to fluctuations of the world market via exporting activities. In addition, the negative coefficient may also imply that multinational firms rather prefer to lay off employees abroad than at home during recessions. The results furthermore corroborate that firm size matters for employment growth. In all business cycle phases, large firms (LARGE) and medium-sized firms (MEDIUM) have lower employment growth rates than the reference category of small firms, even though the effect of MEDIUM for booms is not significant. This is in line with findings of Mansfield (1962) and the predictions of Jovanovic (1982). Furthermore, higher GDP growth is associated with significantly higher employment growth rates during upturn periods. The negative effect of GDP growth for downturn periods is, however, a bit puzzling. One explanation could be that a relatively high GDP growth rate within a downturn period may mean that the downturn "has just" started.[18] In this situation, firms may anticipate a downturn period. As a result, they may become more reluctant in hiring new employees at the onset of an economic downturn, which would reduce the firms' employment growth. This partly prevents the situation of dismissing employees due to excessively high labor costs if product demand further decreases. The national labor markets of EU countries are relatively well protected against dismissals. For instance, many of the EU countries, which are also members of the OECD, have strict employment protection laws (see OECD, 2013, Chapter 2). Hence, it is not easily feasible for firms to lay off employees. The insignificant effect for recession periods implies that once GDP growth becomes negative the exact level of the economic slump does not significantly affect the firms' labor demand.

[18] Remember that according to our definition of a downturn, GDP growth is decreasing but not negative (see Table 2).

We carefully test our identification strategy using various tests. The consistency of the IV estimator depends on the validity of instruments. Therefore, we perform a Hansen J test on overidentifying restrictions for overall instrument validity. As we use three instruments, we also perform the Difference-in-Hansen C test to test for exogeneity of a single instrument. Using a conventional level of significance of 5%, all tests confirm that our instrument set is valid (see Table 4, Table 5 and in section 5.2.1 Table 6 as well).[19] In addition, 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. All first stage regressions show our instruments to be strongly correlated with SGR_NEWPD, as is also supported by the significant test statistics of the Anderson-Rubin Wald test and the Stock-Wright LM test. Furthermore, the F test of excluded instruments always yields a statistic clearly being larger than ten. The regression output tables also display the Kleibergen-Paap LM test on underidentification as well as the F test proposed by Kleibergen and Paap (2006). All these tests indicate our instruments to be neither invalid nor weak.

As explained in Section 4.1, the information on organizational innovation is only available for very few countries in CIS2006. Including this indicator in our estimations reduces our sample by about 24,000 observations. This affects primarily the boom period. For this reason, we exclude organizational innovation and re-estimate our model using the larger sample 2 to check for substantial differences in the estimates. Table 5 presents the results of these regressions. Overall, the estimates are very robust. The main difference compared to Table 4 is that the estimated employment growth effect of SGR_NEWPD slightly weakens. However, based on the corresponding Wald test we still find all of them not to be significantly different from one on the conventional 5% level. Hence, the overall conclusion of hypothesis H1a remains, i.e. the productivity effect of product innovations is independent of the business cycle.

[19] At the 10% level, overall instrument validity cannot be rejected either. However, COOP and RANGE are only valid on a 5% level for downturns in Table 4, Table 5 and Table 6 and in booms in Table 5, respectively.

Table 5: Employment effects of innovation over the business cycle (excluding organizational innovation), IV estimations

	Business cycle phase			
Dep. var.: EMP	**Upturn**	**Boom**	**Downturn**	**Recession**
SGR_NEWPD	**0.966*** **	**0.960*** **	**0.980*** **	**0.980*** **
	(0.020)	(0.023)	(0.022)	(0.027)
PC	**-2.283*** **	-0.698	**-2.080** **	-0.359
	(0.799)	(0.935)	(0.841)	(0.988)
GDPGR	**3.703*** **	**-1.179*** **	-0.072	-0.006
	(0.551)	(0.456)	(0.219)	(0.277)
MEDIUM	**-3.113*** **	-0.004	**-1.386** **	**-2.095*** **
	(0.450)	(0.714)	(0.544)	(0.515)
LARGE	**-4.906*** **	**-2.818** **	**-1.755** **	**-4.162*** **
	(0.587)	(1.106)	(0.762)	(0.685)
DGP	**-1.908** **	**2.714*** **	0.427	**1.185* **
	(0.786)	(0.986)	(0.616)	(0.668)
FGP	**-1.430* **	1.208	-0.385	**-1.881*** **
	(0.779)	(0.980)	(0.621)	(0.615)
Constant	**-64.522*** **	3.931	**-21.702*** **	**2.973* **
	(7.871)	(4.476)	(3.215)	(1.639)
Observations	70,396	31,345	72,519	51,284
R2_adjusted	0.381	0.463	0.377	0.463
Further tests				
Wald-test for β=1 (p-value)	**0.079* **	**0.077* **	0.357	0.455
Test on exogeneity (p-value)				
SGR_NEWPD	**0.000*** **	**0.001*** **	**0.000*** **	**0.024** **
Test on instrument validity				
Hansen J test (p-value)	0.319	0.245	0.153	0.223
Difference-in-Hansen test (p-value)				
RANGE	0.258	**0.095* **	0.303	0.196
COOP	0.323	0.366	**0.054* **	0.959
RD	0.139	0.327	0.703	0.102
First stage results of SGR_NEWPD				
RANGE	**22.796*** **	**21.910*** **	**24.991*** **	**20.380*** **
	(0.779)	(1.043)	(0.943)	(1.024)
COOP	**5.818*** **	**5.724*** **	**6.180*** **	**3.470*** **
	(0.812)	(1.460)	(0.697)	(1.107)
RD	**11.241*** **	**8.168*** **	**6.320*** **	**6.495*** **
	(1.243)	(1.156)	(1.341)	(1.463)
F test on excluded instruments (F)	**452.6*** **	**320.64*** **	**342.75*** **	**245.55*** **
Test on underidentification				
Kleibergen-Paap LM test (chi2)	**347.758*** **	**145.609*** **	**1707.381*** **	**843.865*** **
Test on weak instruments				
Kleibergen-Paap F test (F)	**648.335*** **	**527.052*** **	**976.183*** **	**423.313*** **
Inference robust to weak identification				
Anderson-Rubin Wald test (chi2)	**1054.433*** **	**667.648*** **	**1111.730*** **	**352.731*** **
Stock-Wright LM test (chi2)	**76.322*** **	**49.252*** **	**103.455*** **	**48.449*** **

Note: * p<0.1; ** p<0.05; *** p<0.01; sample 2; weighted IV regressions; clustered standard errors in parentheses; time, industry and country dummies are included and each set of dummies is jointly significant.

5.1.2. Employment decomposition

The main specification we estimate by the IV approach allows us to identify the gross employment effect of product, process and organizational innovation. We complement our estimation results with a decomposition analysis. This allows us to quantify the absolute *contribution* of different sources to average employment growth for different types of firms. In particular, we are able to disentangle the employment effects of product, process and organizational innovations from effects originating from general demand and productivity trends. We follow the decomposition procedure proposed by Harrison et al. (2014) and Peters et al. (2013):

$$(5) \qquad \bar{l} = \hat{\alpha}_0 + \hat{\alpha}_1\overline{pc} + \hat{\alpha}_2\overline{orga} + \overline{[1 - I(g_2 > 0)]}\ \overline{(g_1 - \tilde{\pi}_1)} + \overline{I(g_2 > 0)}\ \ \overline{(g_1 - \tilde{\pi}_1)} + \overline{I(g_2 > 0)}\hat{\beta}\bar{g}_2$$

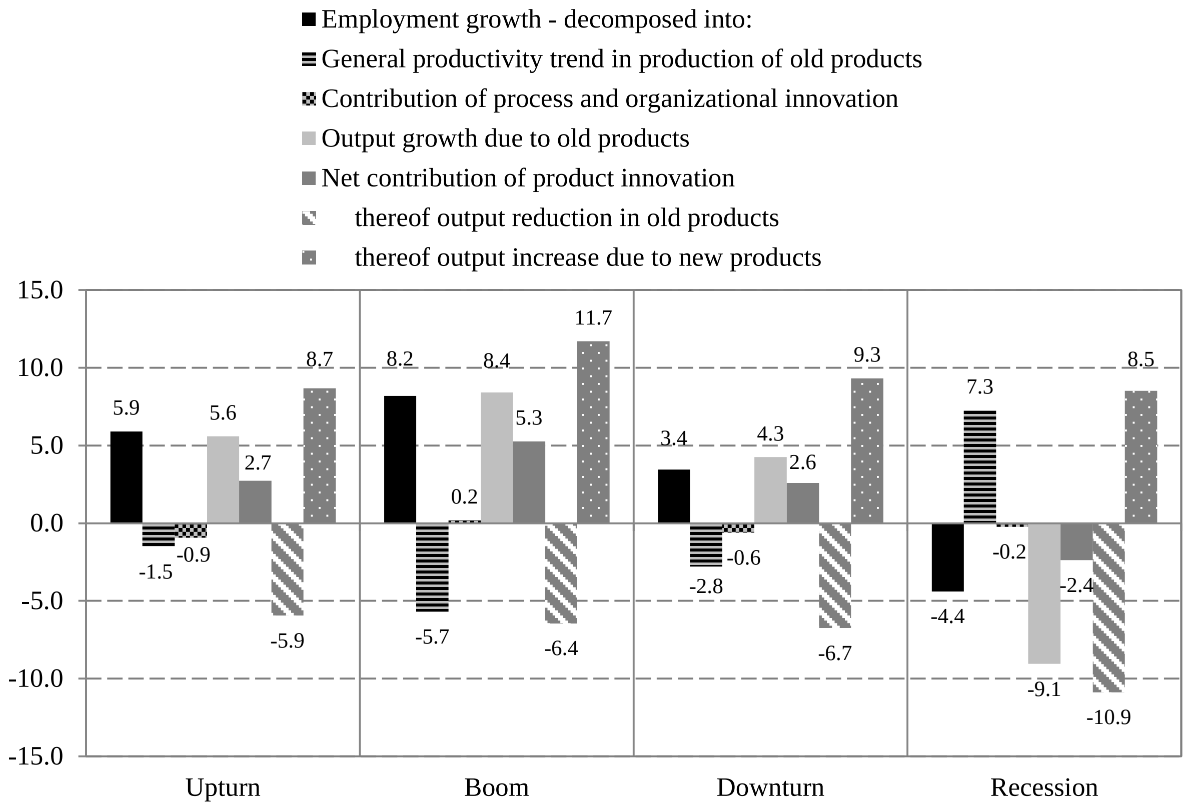
In equation (5), bars denote mean values. Hence, the first term, $\hat{\alpha}_0$, measures the contribution of the general productivity trend in the production of old products to average employment growth, $\bar{l}$. It accounts for all changes in efficiency and employment that are not attributable to firms' own innovations. For instance, $\hat{\alpha}_0$ captures average employment effects of training, improvements in the human capital endowment and productivity effects from spillovers. The general productivity trend captures the general industry-, country-, time-, size-, GDP- and ownership-specific productivity trend. It is measured as the average effect across innovators and non-innovators. The second ($\hat{\alpha}_1$) and the third ($\hat{\alpha}_2$) terms capture the productivity effects of the share of process and organizational innovators, respectively.

The term $\overline{I(g_2)}$ measures the proportion of product innovators, whereas $\overline{1 - I(g_2)}$ measures the share of non-product innovators. This implies that the fourth component, $\overline{[1 - I(g_2)](g_1 - \tilde{\pi}_1)}$ captures the average employment growth caused by the average real growth of old product demand of the share of non-product innovators. A demand increase of old products can be due to a change in consumers' preferences, price reductions but also due to rivals' product innovations (business stealing effect). In contrast, the fifth term $\overline{I(g_2 > 0)}\ \ \overline{(g_1 - \tilde{\pi}_1)}$ accounts for indirect effects related to the demand for old products of the proportion of product innovators. These indirect demand effects may reflect cannibalization effects, $\overline{(g_1 - \tilde{\pi}_1)} < 0$, and complementary effects, $\overline{(g_1 - \tilde{\pi}_1)} > 0$, respectively. $\overline{I(g_2 > 0)}\hat{\beta}\bar{g}_2$ measures the average employment growth due to average increases in the demand for new products of the share of product innovators. The sum of the fifth and sixth term denotes the net contribution of product innovators to employment growth.

To sum up, we calculate this decomposition by inserting the estimated coefficients $\hat{\alpha}_0$, $\hat{\alpha}_1$, $\hat{\alpha}_2$ and $\hat{\beta}$, the weighted shares of process, organizational, non-product and product innovators and weighted averages for employment, price and sales growth rates (either for all firms or for the corresponding group of firms). The decomposition analysis shows that the net contribution of product innovations to average employment growth depends on (i) the demand increase for new products, $\bar{g}_2$ ("innovation success”), (ii) the estimate of the relative production efficiency between old and new products, $\hat{\beta}$, (iii) possible shifts in the demand for old products, $\overline{(g_1 - \tilde{\pi}_1)}$, and (iv) the proportion of product innovators $\overline{I(g_2 > 0)}$.

Figure 3 provides a graphical illustration of the decomposition of average employment growth during the four phases of a business cycle. The sources (i) general productivity trend in the production of old products, (ii) productivity effect of process innovations and organizational innovations, (iii) output growth of non-product innovators due to old products and (v) the net employment contribution of product innovations sum up to the total average employment growth, which is also presented in Figure 1.[20] The figure further splits the net contribution of product innovation into the increase in output due to new products and shifts in demand for old products.

Figure 3: Contribution of innovation types to employment growth over the business cycle, in %



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

Note: Decomposition of the weighted-average two-year employment growth rate; the decomposition is based on the regression results presented in Table 4.

This figure reiterates the strictly pro-cyclical pattern of the average employment growth, as was shown in Figure 1. Most importantly, it discloses that the *net contribution of product innovation (dark grey bar) on employment growth is strictly pro-cyclical* as well. This implies that the net employment effect

[20] We combine the effects of process and organizational innovations because their separate contributions are very small in size.

of product innovation is tightly connected to the specific macroeconomic growth period. According to this figure, product innovation has increased average employment by 2.7% during upturns. This shows that product innovation creates much more employment due to the demand effect than it destroys due to the productivity effect and substitution effect between old and new products. This effect is even stronger in an economic boom (+5.3%). In downturns, the gross employment creation effects of product innovation (white-dotted grey bar) shrink, but the net effect remains positive and of similar size than in upturns (2.6%). Only in the recession, the net contribution of product innovation is negative because output from new products does not grow fast enough to compensate losses in old products (-2.4%). These findings are in line with our hypothesis H1c. This pro-cyclicality can be explained by the proc-cyclical direct demand effect of product innovation. But severe product cannibalization and product range reduction also play an important role for this finding. In every business cycle phase, the introduction of new products is associated with a decline in the demand for old products (white-striped grey bar). This fall is rather low in periods of positive economic growth (-5.9% and -6.4%) but becomes much larger in recessions (-10.9%). Overall, our findings reveal that new products are an important driver for job creation in upturns, booms and downturns.

However, Figure 3 also reveals that – except for the recession – the main source for job creation is output growth due to old products of non-product innovators (light grey bar). Its contribution to average employment growth amounts to 5.6 percentage points during upturns, 8.4 during booms and 4.3 during downturns. At first glance, this finding might be counter-intuitive as the total sales growth rates of product innovators are larger across all periods than those of non-product innovators (Table A-5) and given that we have found the same efficiency between old and new products. The larger employment contributions of old products are due to a much larger share of non-product innovators (73%) than product innovators (27%; see Table A-3).

The second novel and intriguing finding of our analysis is that *product innovators are more resilient to recessions than non-product innovators*. Product innovators are able to compensate employment losses caused by demand reductions of old products by demand gains of new products. This ability is particularly valuable during recession periods. While product innovators have experienced a similar decline in employment due to the lower demand for old products (-10.9%) than non-product innovators (-9.1%), their employment gains from additional demand for their new products (+8.5%). This demand growth due to new products has remained remarkably high during the recession (see also Figure 2). As a result net employment losses of product innovators are significantly lower (-2.4%) in recessions than those of non-product innovators (-9.1%). Therefore, product innovations seem to have an employment-preserving effect and make the innovators more resilient when facing negative economic shocks. Labor-destructing productivity effects of process and organizational innovations do not affect employment growth on a large scale. Taken together, both types of innovations are weakly labor-creating during booms and they modestly displace labor demand during the three other business cycle phases, primarily during upturns and downturns.

Another factor dampening employment fluctuations over the business cycle is the general productivity trend in the production of old products. The general productivity trend curbed employment growth during upturns, booms and downturns, but it is strikingly positive during recessions (7.3%). Hence, results indicate firms' tendency towards labor hoarding during recession periods. This means, they reduce their staff by less than the demand for their products has fallen (Bhaumik, 2011). In general, labor hoarding results in a decrease of productivity. Our finding is in line with other studies. Leitner and Stehrer (2012) observe frequent labor hoarding during the recent crisis in Central and Eastern European countries. Labor hoarding may have occurred or intensified by effective short-time work programs during the 2008/2009 recession many EU governments have offered. Balleer et al. (2016) for Germany and Boeri and Brücker (2011) for a set of European countries find that short-time work had a positive effect in terms of job savings during the recent recession, even though it did not save as many jobs as the utilization of short-time work could have saved (Boeri and Brücker, 2011).

5.2. Results for SMEs and large firms

5.2.1. Regression results

Small and medium-sized enterprises have been found to be the most important driver for employment growth (see Neumark et al., 2011; Haltiwanger et al., 2013). In particular, small enterprises are more flexible to react to new opportunities and are able to survive in niche markets. They primarily benefit from the personal engagement of the entrepreneur who transfers her knowledge on technologies and markets (see e.g. Thurik, 2009 for an overview). At the same time, there are many arguments put forward in the literature why large firms exhibit advantages in the innovation process (see e.g. Kleinknecht, 1989; Cohen, 1995, 2010). They have more internal financial means and better access to external funding to finance innovation projects more easily. Large and diversified firms also have more potential application possibilities for new knowledge (Rosenberg, 1990). Data from the recent economic crisis provides evidence that innovation activities in larger firms have been less affected by the recession. This supports the view that large firms have advantages in the innovation process (see e.g. Paunov, 2012; Rammer, 2012; Archibugi et al., 2013). This speaks in favor of a larger contribution of innovation to employment growth in large firms, in particular in the recession. To directly account for size differences in the employment effects of innovations, we split our sample into two size classes, i.e. SMEs (10-249 employees) and large firms (250+ employees). Table 6 presents the split sample estimation results of employment growth on innovation.

Table 6: Employment effects of innovation over the business cycle, SMEs and large firms

	Number of employees: 10-249				Number of employees: 250+			
Dep. var.: EMP	**Upturn**	**Boom**	**Downturn**	**Recession**	**Upturn**	**Boom**	**Downturn**	**Recession**
SGR_NEWPD	**0.994*** **	**0.972*** **	**1.005*** **	**0.982*** **	**0.953*** **	**1.013*** **	**1.030*** **	**0.979*** **
	(0.024)	(0.032)	(0.025)	(0.029)	(0.031)	(0.049)	(0.042)	(0.045)
PC	-1.222	-0.350	**-1.795***	-0.413	**-2.999*** **	-0.175	0.521	0.443
	(0.792)	(1.493)	(0.977)	(1.076)	(1.107)	(2.064)	(1.193)	(1.214)
ORGA	**-2.065*** **	0.566	**-1.553****	-0.813	**-2.871*** **	-1.695	-0.798	-0.839
	(0.449)	(0.703)	(0.648)	(0.515)	(0.695)	(1.053)	(0.749)	(0.565)
GDPGR	**3.772*** **	2.473	**-0.655*** **	0.169	**6.020*** **	1.129	**-0.949*** **	0.335
	(0.532)	(1.916)	(0.188)	(0.289)	(0.556)	(2.721)	(0.206)	(0.419)
DGP	**-1.564***	**3.159****	0.654	0.763	**-3.393*** **	**2.090***	**-1.731***	-0.986
	(0.834)	(1.253)	(0.675)	(0.678)	(0.963)	(1.164)	(0.934)	(0.788)
FGP	-1.533	1.064	-0.108	**-2.384*** **	**-3.209*** **	-0.290	-0.419	**-3.426*** **
	(0.969)	(1.191)	(0.779)	(0.648)	(0.995)	(1.424)	(1.117)	(0.857)
Constant	**-68.663*** **	**-30.858***	**-15.021*** **	**3.088***	**-82.340*** **	-24.198	**-23.176*** **	0.359
	(7.064)	(16.670)	(2.794)	(1.767)	(6.263)	(24.882)	(3.080)	(2.271)
Observations	55,397	12,092	56,859	44,340	10,093	3,438	8,582	6,220
R2_adjusted	0.386	0.474	0.387	0.466	0.620	0.640	0.553	0.557
Further tests								
Wald-test for β=1 (p-value)	0.806	0.387	0.834	0.532	0.123	0.798	0.479	0.634
Test on exogeneity SGR_NEWPD (p-value)	**0.000*** **	**0.002*** **	**0.000*** **	**0.036****	**0.000*** **	**0.003*** **	**0.002*** **	**0.046****
Test on instrument validity								
Hansen J- test (p-value)	0.654	0.465	0.180	0.391	0.189	0.983	0.490	0.373
Diff-in-Hansen test (p-value)								
RANGE	0.419	0.216	0.215	0.284	0.189	0.859	0.831	0.494
COOP	0.613	0.509	**0.065***	0.992	-	0.903	0.491	0.160
RD	0.357	0.460	0.999	0.195	0.189	0.961	0.258	0.587
F test on excluded instruments (F)	**447.52*** **	**207.5*** **	**312.97*** **	**283.25*** **	**298.38*** **	**48.29*** **	**125.47*** **	**79.06*** **
Test on underidentification: Kleib.-Paap LM (chi2)	**265.775*** **	**61.121*** **	**1223.529*** **	**673.479*** **	**280.652*** **	**43.189*** **	**438.128*** **	**342.047*** **
Test on weak instruments: Kleib.-Paap F (F)	**530.720*** **	**252.667*** **	**724.798*** **	**326.223*** **	**460.893*** **	**53.828*** **	**282.665*** **	**122.303*** **
Inference robust to weak identification: And.-Rub. Wald (chi2)	**858.517*** **	**428.026*** **	**991.793*** **	**324.717*** **	**449.902*** **	**215.935*** **	**258.671*** **	**142.058*** **

Note: * p<0.1; ** p<0.05; *** p<0.01; weighted IV regressions; clustered standard errors in parentheses. For large firms, estimates for the upturn period are based on the instrument set RANGE and RD because COOP turned out to be invalid in this regression. For convenience we excluded the estimates of the first stage from this table. Each instrument, however, is positive and highly significant in the first stage as also indicated by the high F statistics.

For both SMEs and large enterprises, higher sales growth rates due to new products are associated with significantly higher employment growth rates in all phases of a business cycle. The effect slightly differs between the phases but none of the coefficients is significantly different from one. This supports our hypothesis H1a for SMEs as well as for large firms. In the previous section we found that process innovations displace labor in upturns and downturns. Results in Table 6 show that the finding for downturns is primarily driven by SMEs, whereas process innovation-induced labor displacement effects in upturns are driven by large enterprises. This implies that there are different dynamics between SMEs and large firms regarding the labor destruction of process innovations. There are no significant labor-destructing effects in all other phases. Overall, we do not find support for H2a.

For SMEs, the findings for organizational innovations are in line with the results for the main sample (sample 1). This supports our hypothesis H3a. The exception is again the recession period for which we find a negative though insignificant effect. For large firms, we only confirm significant labor-destructing effects of organizational innovation during upturn phases.

5.2.2. Employment decomposition

Table 7 presents the decomposition results for the different size classes. Average employment growth exhibits a pro-cyclical pattern for both SMEs and large enterprises. In this respect, it is particularly intriguing that large firms on average have only created employment during boom phases. In contrast, average employment growth is positive for SMEs in all phases of the business cycle except for the recession. The decomposition for SMEs is very similar to the one for the total sample presented in Figure 3, which is not surprising given their weight in firm population. That is, product innovation is an important driver of employment growth in SMEs. The net employment effect of product innovation is pro-cyclical and positive in upturn, boom and downturn periods. However, in all three business cycle phases, the largest contribution to average employment growth in SMEs stems from output growth for existing products of non-product innovators. This pattern reverses in the recession. Whereas SMEs without product innovations experience a strong decline in their demand for existing products, SMEs introducing new products yield new product sales that have almost been sufficiently high to compensate for the loss in demand of old products. This creates stronger resilience of product-innovating SMEs in recession periods. Labor-destructing effects of process and organizational innovations are small in SMEs, in particular compared to those generated by the general productivity trend. The recession period is again an exception in which the general productivity trend indicates substantial labor hoarding in SMEs.

Table 7: Contribution of innovation to employment growth for SMEs and large firms, in %

Size	Components	Upturn	Boom	Downturn	Recession
10-249 employees	**Employment growth** - decomposed into:	**4.8**	**7.4**	**2.8**	**-4.8**
	General productivity trend in production of old products	**-2.5**	**-5.6**	**-2.9**	**7.3**
	Contribution of process and organizational innovation	**-0.8**	**0.2**	**-0.2**	**-0.3**
	Output growth due to old products for non-product innovators	**5.4**	**8.0**	**3.9**	**-9.5**
	thereof for non-innovators	2.6	4.6	2.1	-7.3
	thereof for process innovators not being organizational innovators	0.5	0.7	0.4	-0.6
	thereof for organizational innovators not being process innovators	1.6	1.8	0.8	-1.1
	thereof for organisational and process innovators	0.7	0.9	0.6	-0.5
	Net contribution of product innovation for product innovators	**2.6**	**4.8**	**2.5**	**-2.3**
	thereof output reduction in old products	-5.8	-6.1	-6.5	-10.6
	thereof output increase due to new products	8.5	10.9	9.0	8.2
250+ employees	**Employment growth** - decomposed into:	**-3.0**	**3.7**	**-2.7**	**-8.5**
	General productivity trend in production of old products	**-6.9**	**-7.1**	**-8.1**	**3.7**
	Contribution of process and organizational innovation	**-2.0**	**-1.1**	**-0.4**	**-0.5**
	Output growth due to old products for non-product innovators	**2.2**	**3.0**	**1.3**	**-5.6**
	thereof for non-innovators	0.1	1.2	0.3	-3.2
	thereof for process innovators not being organizational innovators	0.2	0.2	0.2	-0.6
	thereof for organizational innovators not being process innovators	1.6	0.9	0.4	-1.1
	thereof for organisational and process innovators	0.4	0.7	0.4	-0.8
	Net contribution of product innovation for product innovators	**3.6**	**8.9**	**4.5**	**-6.1**
	thereof output reduction in old products	-12.0	-11.6	-13.9	-20.1
	thereof output increase due to new products	15.6	20.6	18.3	13.9

Note: Decomposition of the weighted-average two-year employment growth rate; the decomposition is based on the regression results presented in Table 6.

However, the decomposition analysis reveals a very different pattern for large firms. First, large firms experienced much higher employment losses than SMEs due to improvements in productivity during upturn, boom and downturn periods. Large firms realized efficiency gains of about 7 to 8% primarily as a result of the general productivity trend, i.e. selling unprofitable business units, mergers and acquisitions, learning effects or alike. Displacement effects of organizational and process innovation-induced productivity gains are much smaller, but still larger than in SMEs. Second, larger employment gains due to product innovation counteract the larger efficiency gains in large firms. Like for SMEs we find the net employment effect of product innovation to be pro-cyclical and positive in upturn, boom and downturn periods. In contrast to SMEs, the contribution of product innovation to average employment growth exceeds by far the one stemming from output growth for existing products of non-product innovators. Furthermore, employment creation due to demand growth for new and old products is not sufficiently high to outweigh employment losses due to efficiency gains in upturn and downturn periods. Third, the most striking result concerns the recession period. In contrast to SMEs, among the group of large firms non-product innovators perform better in terms of employment growth than product innovators (-5.6% vs. -6.1%). That is, we do not find large firms to be more resilient to economic crises. One explanation could be that large firms possess comparative advantages generating process innovations whereas small firms benefit relatively more from product innovation (Cohen and Klepper, 1996). Hence, large firms have a stronger incentive to invest in process innovation. The focus on process innovation relative to product innovation might be even stronger in recession periods due to lower product demand and increased competition based on costs and prices (Spiegel and Stahl, 2014).

6. Conclusion

This paper is the first to examine the effects of different types of innovations on employment growth over the business cycle. A special focus is devoted to the question whether innovations can be regarded as a means to become more resilient to economic crises. Despite the literature argues that employment impacts of innovation crucially depend on product demand-driven effects, there is no firm-level evidence on this question yet. We analyze the labor-creating and labor-destructing effects of product, process and organizational innovations over the business cycle using the structural model developed by Harrison et al. (2014). We estimate the model with CIS firm-level data from 26 European countries covering the period from 1998 to 2010. In total, our sample includes more than 200,000 firm-year observations of the manufacturing sector. To account for business cycle heterogeneity in the effects of innovation on employment, we split our estimations into the four phases (upturn, boom, downturn, recession) of a business cycle based on country-specific GDP growth rates.

Descriptive statistics already reveal an interesting pattern: Average employment growth is pro-cyclical for each type of innovators and for non-innovators. However, employment grows much faster for innovators than for non-innovators in each phase of a business cycle. This gap in employment growth between innovators and non-innovators widens during downturn and recession periods.

To estimate the employment growth effects of innovation, we rely on IV estimations using a sensible identification strategy to correct for potential measurement error. In addition, we quantify the actual contributions of different types of innovators and non-innovators to average employment growth by performing a decomposition analysis. Our empirical analysis reveals four major findings. First, the net employment growth effect of product innovators is strictly pro-cyclical. This effect is positive during upturn, boom and downturn periods and indicates the labor-creating effect to exceed the labor-destructing effect of product innovations. The reverse pattern emerges in recessions in which the net employment growth effect turns negative, indicating average labor-destruction. Second, product innovators are more resilient to recessions than non-product innovators. Indeed, when facing negative economic growth, product innovators on average cut jobs. However, the level of job destruction is only modest compared to the job destruction in firms that have not implemented any product innovations between t and t-2. Third, we find resilience only in SMEs but not in large firms. Fourth, on average, process and organizational innovations particularly reduce the innovators' labor demand during upturn and downturn periods. That is, the innovators implemented new processes and business practices, respectively, that enhanced the production efficiency at the cost of reduced labor demand.

Our results have important policy implications. First, we show the strong and positive linkage between innovation and employment which supports a stronger alignment between these two policy fields. Second, the employment-preserving effect of product innovations during recessions is a strong argument for a counter-cyclical public support of product innovation activities. Increasing the public funding for innovation activities during a recession may help firms to stabilize expectations and overcome potential financing constraints. However, the precise timing of such measures can be cumbersome. Automatic stabilizers in public support schemes such as an automatic increase in the tax credit for R&D in a recession may be an answer to the timing problem. In times of a recession, firms may have already downsized their R&D personnel or other innovation-related expenditures before a government adopts and actually pays the counter-cyclical innovation support.

Our study is subject to some limitations. First, the lack of firm identifiers does not allow us to analyze employment growth effects for the same firm over time. However, we can split the observed firms into the respective business cycle phases. This allows us to analyze the employment growth dynamics for different types of innovators and non-innovators for specific growth periods. Second, the correct identification of the gross effect of process and organizational innovation actually depends on the availability of data on firm-level price changes of old products. This type of data is generally not available in firm-level data sets. Therefore, we use industry-level price growth rates as proxy variable. Larger deviations between firm- and industry-level prices may bias our results. Third, due to lack of firm-level price data we are also not able to estimate the net employment effect of process and organizational innovations. That is, we only get an estimate for the labor destruction due to productivity enhancements but not for the potentially induced labor creation due to price reductions. Fourth, authors have argued that organizational innovation is a fuzzy concept and difficult to define (Lam, 2005; Armbruster et al., 2008). Hence, organizational innovation is more likely to be subject to potential mismeasurement. We use data from the harmonized CIS that includes clearly defined questions about organizational innovations. Still, survey respondents may be less sure about the meaning of “organizational innovations” compared to product or process innovation.

Despite the limitations, our analysis draws a positive picture of the ability of innovation to create new employment. This puts our results in some contrast to other recent research, which points to potential negative effects of new process and automatization technologies on employment (see e.g. Frey and Osborne, 2013; Brynjolfsson and McAfee, 2014). It may be that potential losses from innovation are more visible than the potential benefits of new technologies from today’s perspective. There may also be a tendency to underestimate benefits and overestimate losses from technological change. The most important lesson policymakers can learn from our results is that innovations create new jobs particularly during recessions.

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A. Appendix

Table A-1: Country coverage and distribution of the CIS survey waves

Country	Country	Wave					Manufacturing	
		1	2	3	4	5	N	%
Belgium	BE	+	-	-	-	-	652	0.3
Bulgaria	BG	+	+	+	+	+	26,716	13.2
Cyprus	CY	-	-	+	+	+	1,217	0.6
Czech Republic	CZ	+	+	+	+	+	11,722	5.8
Germany	DE	+	-	-	+	+	5,501	2.7
Denmark	DK	+	+	(+)	-	-	748	0.4
Estonia	EE	+	+	(+)	+	+	3,631	1.8
Spain	ES	+	+	(+)	+	+	38,816	19.2
Finland	FI	+	-	-	-	-	900	0.4
France	FR	+	+	-	+	+	26,559	13.2
Greece	GR	+	+	(+)	-	-	1,318	0.7
Croatia	HR	-	-	-	-	+	1,212	0.6
Hungary	HU	+	+	(+)	+	+	7,145	3.5
Iceland	IS	+	+	-	-	-	315	0.2
Italy	IT	+	+	-	+	+	25,929	12.9
Lithuania	LT	+	+	(+)	+	+	2,564	1.3
Luxembourg	LU	+	+	(+)	+	+	581	0.3
Latvia	LV	+	+	(+)	+	+	2,201	1.1
Malta	MT	-	-	(+)	+	-	224	0.1
Netherlands	NL	-	-	-	+	+	3,445	1.7
Norway	NO	+	+	-	-	+	3,883	1.9
Portugal	PT	+	+	(+)	+	+	9,576	4.7
Romania	RO	+	+	+	+	+	18,477	9.2
Sweden	SE	+	-	-	-	+	3,035	1.5
Slovenia	SI	-	+	-	+	+	2,022	1.0
Slovakia	SK	+	+	(+)	+	+	3,302	1.6
Total		21	18	4 (15)	18	20	201,691	100

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

Note: Values in parentheses reflect that the data for the respective country is available but not the organizational innovation indicator.

Table A-2: Distribution of CIS sample by industry

Industry	Variable	Nace Rev. 1.1.	Nace 2	Total	
				N	%
Food / beverages / tobacco	FOOD	15-16	10-12	28,860	14.31
Textile / wearing apparel / leather	TEXT	17-19	13-15	28,937	14.35
Wood / paper / printing	WOOD	20-21, 22.2-22.3	16-18	22,820	11.31
Chemicals	CHEM	24	20-21	10,698	5.30
Rubber / plastics	PLAS	25	22	11,021	5.46
Non-metallic mineral products	NONM	26	23	11,493	5.70
Basic and fabricated metals	BASM	27-28	24-25	28,000	13.88
Machinery	MACH	29, 33.3	28, 33	20,518	10.17
Electrical engineering	ELEC	30-32, 33.2, 33.4-33.5	26-27	14,973	7.42
Vehicles	VEHI	34-35	29-30	9,548	4.73
N.e.c.	NEC	36, 33.1	31-32	14,823	7.35
Total				201,691	100

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

Note: Until CIS2006 the industry classification was based on NACE Revision 1.1, since CIS2008 NACE Revision 2 has been used as industry classification system.

Table A-3: Descriptive statistics on firm characteristics

Firm groups	Total
	%
Non-innovators	50.5
Product innovators	27.0
Process innovators	11.1
Organisational innovators	32.1
Small firms	77.0
Medium-sized firms	18.8
Large firms	4.2
Firms pertaining to a domestic enterprise group	81.6
Firms pertaining to a foreign enterprise group	13.0
Firms not pertaining to an enterprise group	5.4

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

Note: Weighted statistics; process innovators refer to firms that implemented only process innovations (PC) during t and t-2.

Table A-4: Distribution of the CIS sample by business cycle phase

Observation period	Business cycle phases			
	Upturn	Boom	Downturn	Recession
1998-2000	23,756	12,420	3,868	0
2002-2004	41,767	785	845	0
2004-2006	0	2,434	10,682	0
2006-2008	0	224	51,784	0
2008-2010	1,945	0	0	51,181
Total	67,468	15,863	67,179	51,181
in %	33.45	7.87	33.31	25.38

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

Table A-5: Sales growth due to new and old products by innovator and business cycle, in %

Firm type	Business cycle phase	Total	Old products	New products
All firms	Upturn	11.2	2.4	8.8
	Boom	16.4	4.4	12.1
	Downturn	14.1	4.8	9.3
	Recession	-10.4	-19.0	8.6
Innovators	Upturn	13.6	-4.4	18.0
	Boom	17.3	-2.4	19.7
	Downturn	16.4	-4.0	20.4
	Recession	-8.2	-25.9	17.7
Non-innovators	Upturn	8.9	8.9	0.0
	Boom	15.0	15.0	0.0
	Downturn	12.2	12.2	0.0
	Recession	-12.5	-12.5	0.0
Process innovators	Upturn	14.0	14.0	0.0
	Boom	17.4	17.4	0.0
	Downturn	16.3	16.3	0.0
	Recession	-9.1	-9.1	0.0
Product innovators	Upturn	14.8	-22.7	37.5
	Boom	17.8	-15.3	33.1
	Downturn	16.4	-19.7	36.1
	Recession	-7.1	-37.0	29.9
Organizational innovators	Upturn	14.1	-2.1	16.2
	Boom	17.8	-1.2	19.0
	Downturn	17.7	-1.6	19.4
	Recession	-8.0	-24.4	16.4

Source: CIS3, CIS4, CIS2006, CIS2008 and CIS2010, Eurostat; own calculation.
Note: Weighted statistics; non-innovators did not introduce product, process or organizational innovations during t and t-2; "Process innovators" refers to pure process innovators (PC).

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