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Zentrum für Europäische
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Abstract

The global economic crisis of 2008/2009 hit many firms hard. Faced with rapidly declining sales and highly uncertain economic prospects, firms had to cut costs and reconsider their business strategies. With respect to innovation, cost cutting often means to stop or under-resource innovation projects which may harm a firm's long-term competitiveness. Firms may therefore refrain from reducing innovation budgets during crises but rather deliberately allocate more resources to innovation activities in order to update their product portfolio for the following recovery. Our analysis examines the effects of changes in innovation budgets during the most recent economic crisis on firms' post-crisis innovation performance. Based on firm-level panel data from the German Innovation Survey covering the period 2006 to 2012, we find a positive effect of crisis adjustment. Raising the ratio of innovation expenditure to sales does increase subsequent sales of market novelties, but not of product imitations. Our findings are dependent upon the way business cycle effects are measured, however. While the results hold for macroeconomic business cycle indicators (change in real GDP), they do not for demand changes in a firm's primary sales market. This may imply that lower opportunity costs of innovation during an economic crisis are transferred into higher post-crisis new product sales by firms in markets less strongly affected by the crisis.

JEL-Classification: O31, O32, E32, L25, D22

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1. Introduction

The global economic crisis of 2008/2009 had substantial impacts on the economy. Most attention has been paid to financial markets, monetary policy and government deficits. But also other areas of the economy were heavily affected that have a potential impact on future growth prospects. One of these is innovation, i.e. productivity-enhancing technological change (see Filippetti and Archibugi, 2011). Research on previous economic crises has shown that innovation expenditures tend to react pro-cyclical since resource allocation on innovation projects is often simultaneously determined with firm performance (Hall and Mairesse, 1995; Guellec and Ioannidis, 1999; Smolny, 2003; Barlevy, 2007). If a firm's cash flow diminishes due to an unexpected drop in sales, funding of innovation becomes difficult and some projects need to be stopped while others are scaled down. An unplanned reduction in innovation effort due to an exogenous shock can have negative impacts both on firms and the economy as a whole. From a firm perspective, stopping or downscaling of innovation projects can harm a firm's competitiveness when the pipeline of new products dries out and efficiency gains from new technologies remain unutilised. From a macroeconomic perspective, lower investment in innovation may reduce the total knowledge stock of an economy, which is likely to reduce future productivity growth. For these reasons, overcoming the recent crisis and ensuring long-term competitiveness is a major concern for both firms and policymakers.

In this paper, we examine the impact of firms' innovation budget adjustments with regard to the shock of 2009 on post-crisis innovation performance measured by the sales share of product innovations. The empirical part of the paper rests on a panel data set of German firms operating in a variety of manufacturing and service sectors. The data contains information on innovation expenditures, product innovation success and other business-related characteristics. We observe the seven-year period 2006 to 2012 that basically covers not only the crisis period of 2008/2009 but also pre-crisis (i.e. 2006-2007) and post-crisis (i.e. 2010-2012) years that were characterized by high growth rates. The crisis became critical for the majority of firms in Germany in late 2008 while the business climate recovered in early 2010. 2009 was the year with the largest drop of Germany's GDP since World War II. With data from these different periods at hand, we are able to compare the effects of the firms' crisis adjustments with adjustment effects accruing during economically stable growth periods.

We find that an increase of a firm's innovation intensity (i.e. innovation budget over sales) does not significantly increase the post-crisis innovation performance of product innovations when measuring a firm's exposure to the economic crisis by the change in sales volumes in the firms main market. However, a positive crisis adjustment effect appears when we use GDP growth as business cycle indicator instead of industry-level indicators. This result is in line with previous research that has stressed the importance of counter-cyclical innovation behaviour. Higher expected future returns to innovation in a recession serve as incentives for higher innovation spending during recessions (see for instance Hall, 1991; Aghion et al., 2010). The rest of the paper is organized as follows. Section 2 gives an overview on the literature on business cycle impacts on innovation. Section 3 presents and discusses our three hypotheses. Section 4 explains the conceptual framework and describes the panel data set we use. Section 5 presents estimation results and robustness checks, while Section 6 concludes.

2. Literature Review

This paper examines the effect of a crisis-related adjustment of innovation activities on subsequent innovation success. The corresponding literature on the relationship between the business cycle and innovation has mostly focused on impacts on innovation input. The overall consensus in theoretical and empirical literature is that firms act in a pro-cyclical fashion (see Geroski and Walters, 1995). Innovation activities tend to increase during economic growth periods and tend to decrease in recessions. This pro-cyclicality is mainly caused by the innovator's dependency on internal cash flow for funding innovation (see e.g. Hall, 1992; Himmelberg and Petersen, 1994; Harhoff, 1998; Mulkay et al., 2001; Rafferty, 2003; Rafferty and Funk, 2008; Fabrizio and Tsolomon, 2014). Due to asymmetric information between the innovator and the lender, potential creditors do not have strong incentives to finance a company's innovation projects (Hall, 2002). Firms hence depend on past and current profits to sufficiently finance innovation projects on their own. In general, firms' profits are higher in growth periods and lower or negative during recessions. Barlevy (2007) develops and estimates a model that proves R&D investment to be pro-cyclical. Accordingly, pro-cyclicality causes R&D investment to be inefficiently low during recessions, though innovators that would expand their R&D activities in economic downturns could gain from this increased investment in upswing periods. However, this long-term focus increases the risk of spillover effects to rival innovators leading to a profit risk for the original innovators. As a result, original innovators are more focused on making short-term profits they could generate by stronger investment during economic upswing periods.

One of the most prominent analyses of business cycle fluctuations and innovation was conducted by Schumpeter (1942). In his theory of creative destruction, recessions reorganize markets and encourage firms to innovate, while firms unable to innovate or to restructure exit the market (Caballero and Hammour, 1994). This so called "cleansing" effect, which indicates a potential counter-cyclical firm behaviour, is similar to the so called "opportunity cost" effect which has been found by, for instance, Hall (1991), Gali and Hammour (1991), Aghion and St. Paul (1998). Accordingly, the opportunity costs – in terms of forgone output – of (long-term) innovative investment compared to (short-term) capital investment is lower in recessions than in growth periods. Recent contributions in the literature of innovation and economic growth deals with that opportunity cost effect. In particular, they examine the role of financial constraints for the cyclicality of R&D investment. Since a firm largely finances its innovation projects from cash flow and is supposed to be credit-constrained during recession periods, the continuation as well as the start of innovation projects may have to be postponed during recessions. Aghion et al. (2012) use a sample of 13,000 French firms that have been observed over the period 1993-2004. They find evidence that credit-constrained firms reveal a higher share of R&D investment during periods of flourishing sales, underpinning the hypothesis of pro-cyclicality. The relationship, however, turns out to be counter-cyclical, i.e. firms invest more in R&D during recessions in case they are not credit-constrained. Bovha-Padilla et al. (2009) and López-Garcia et al. (2012) as well as Aghion et al. (2010) estimate a similar model by using Slovenian and Spanish firm-level data as well as OECD country-level data. They also find empirical evidence for pro-cyclicality (counter-cyclicality) if firms are credit-constrained (not credit-constrained). Bovha-Padilla et al. (2009) disentangle and estimate different forms of financial constraints. Firms that are owned by a foreign company and receive governmental subsidies or that have a high asset endowment do not reveal any significant pro- or countercyclical R&D behaviour. Ouyang (2011) empirically examines the opportunity cost hypothesis and finds an asymmetric response of R&D to demand shocks. A positive demand shock causes R&D expenditures to decrease due to rising opportunity costs while a negative demand shock decreases R&D investment due to liquidity constraints. The liquidity constraint effect, however, outweighs the opportunity cost effect, resulting in a pro-cyclical R&D investment.

While the majority of the analyses focus on innovation input, there is only scarce research on the relationship between the business cycle and innovation output. Schumpeter (1934) refers to extra-normal, monopolistic profits as the main incentive for innovators. These so called “Schumpeterian” profits may be highest during economic upswing periods when competitive pressure is limited due to a robust demand environment leading to a positive relationship between innovation output and the business cycle. Schmookler (1966) and Shleifer (1986) similarly argue that the introduction of innovations strongly depends on the demand situation. Accordingly, the commercial exploitation of new products requires consumers to have a higher willingness to pay compared to old products. This higher willingness to pay is rather present during periods of market expansion when the consumers’ budget restrictions are not as tight as during recession periods. This implies that firms will have little incentives to introduce new products on the market when demand is low. Further, Judd (1985) argues that markets seem to have a limited capacity for absorbing new products. Firms are therefore more likely to introduce new products during periods of market expansions. Geroski and Walters (1995) draw on a data set including patent activities of British firms. They examine the period 1948-1983 and find that economic growth granger causes the introduction of innovations.

Impacts of the most recent economic crisis on innovation have been investigated by Archibugi et al. (2013a,b). They find negative consequences on innovation expenditures. This result is confirmed by a study of Laperche et al. (2011) on adjustment strategies of large French enterprises which predominantly aimed at focussing R&D activities on fewer projects and streamlining R&D costs. To the best of our knowledge, there is no empirical study yet that examines the impact of the recent recession on innovation output.

3. Hypotheses

The research question of this paper is whether firms that expanded their level of innovation activities during the recent economic crisis were able to achieve higher innovative benefits in the following period. We develop three hypotheses to test our research question. We start from the basic assumption that investment in innovation has positive returns, meaning that a higher level of innovation activities (i.e. the share of innovative effort in a firm's total activities) should result in higher innovation performance (e.g. the share of new product sales). There is ample evidence in the literature that this basic assumption holds (see Crépon et al., 1998). A more interesting case is whether a short-term increase in innovative effort will also translate into a short-term (though lagged) increase in innovation success (and, vice versa, whether a decrease causes falling innovation success). Under a stable economic environment, firms will attempt to maintain an optimal level of innovation activities which allows them to steadily fill their pipeline of new products, continuously advance their production methods and keep pace with technological change. This optimal level will largely depend on the type of technical change and the competitive environment under which a firm operates. Since both factors rarely change from year to year, a firm's optimal investment level for innovation will be largely constant in the short run. Adjustments of a firm's level of innovative efforts will primarily reflect changes in strategic priorities of a firm, e.g. entering new product markets or new technologies. Thus, we would expect the innovation success to increase as a consequence of a positive adjustment in innovative efforts.

For a crisis period, the situation may be different. An economic crisis induced by an adverse shock is typically characterized by unexpectedly falling sales and deteriorating profits, which calls for cost cuts and challenges firms' attempt to maintain their target level of innovation. Most firms will react in such a situation by reducing their expenditures along with diminished returns, including expenditures for innovation and other investment. Reductions in operating costs and standard capital expenditures (i.e. replacing outdated fixed assets) will have limited impacts on a firm's short-run competitive situation since both can be easily and immediately increased in case the business climate improves. However, cuts in innovation expenditures may have different impacts. If such cuts result in stopping (some) innovation projects, firms cannot easily re-start them in the following period and achieve immediate results (in terms of new products) since innovation projects typically stretch over a multi-annual period until they are successfully completed (see Aschhoff et al., 2013: 65, on the average length of innovation projects). What is more, stopping some projects reduces a firm's portfolio of new products, which limits the firm's ability to react on changing consumer preferences and competitor strategies. This particularly applies to an uncertain market environment and to rapidly changing demand, which is typically the case in a crisis and post-crisis period (Devinney, 1990; Klingebiel and Rammer, 2014). If cost cuts in innovation expenditures reduce the budget per project, the quality of the outcome of each project may suffer, i.e. new products may be less competitive due to less advanced and tested technological features. We hence expect that firms able to maintain or increase their level of innovation activities during negative growth periods will benefit from higher innovation success in the following period.

This positive impact of resilience in innovation will differ by the type of innovation a firm aims for. In general, the more ambitious a firm's innovation activities, the more difficult, costly and time-consuming it will be to solve technological challenges and successfully market a new product. Reducing the budgets for more ambitious projects is likely to deteriorate project prospects more heavily compared to the case of less ambitious projects. We hence expect that increasing the level of innovation activities also during negative growth will be more beneficial to ambitious innovations. In the literature, different concepts of innovative ambition have been proposed, such as radical innovation (based on radically new technology) and disruptive innovation (innovations that change the way markets operate). We use a rather simple measure, the degree of novelty for the firm's customers. If a new product has not been available to a firm's customer before, this represents a product new to the market ("market novelty"). Since innovation competition is usually high in most markets, introducing a market novelty requires substantial innovative effort and risk.

To summarise, our three hypotheses read as follows:

H1: *Under stable economic conditions, an increase in the level of innovation activities translates into a short-term increase in innovation success.*

H2: *During an economic crisis, an increase in the level of innovation activities translates into an increase in post-crisis innovation success.*

H3: *Independent of the economic condition, the positive impact of an increase in the level of innovation activities on innovation success is higher for more ambitious innovations.*

4. Methodology and Data

4.1. Empirical Model

Our analysis rests on a firm-level innovation performance model (see Crépon et al., 1998). The success of a firm's product innovations (*IS*) basically depends on the level of expenditures devoted to the development and introduction of product innovations divided by the level of a firm's sales (i.e. innovation intensity - *II*) while considering the business cycle in terms of growth periods (*GR*) as well as a vector of other firm characteristics (*X*), including size, age and sector affiliation. In order to isolate the effect of a change in the level of innovation activities, we decompose *II* into two components: (i) the level of the innovation intensity in the previous year (II_{t-1}) and (ii) the change of the innovation intensity between the current and the previous year ($\Delta II_{t|t-1}$). In order to identify the effects of innovation budgeting for different business cycle periods we split the variable $\Delta II_{t|t-1}$ by annual growth dummies. We assume a one-year lag between investment in innovation and returns from innovation, i.e. *IS* is measured for the year t+1. In order to examine our third hypothesis, we distinguish two types *j* of new products: market novelties and new products only new to the firm ("product imitations"). The empirical model can be written as follows:

$$IS_{ij,t+1} = \beta_0 + \beta_1\, II_{i,t-1} + \beta_2\, \Delta II_{i,t|t-1} * GR_{t|t-1} + \beta_3\, X_{\mathrm{i,t}} + \mu_{i,t} \qquad [1]$$

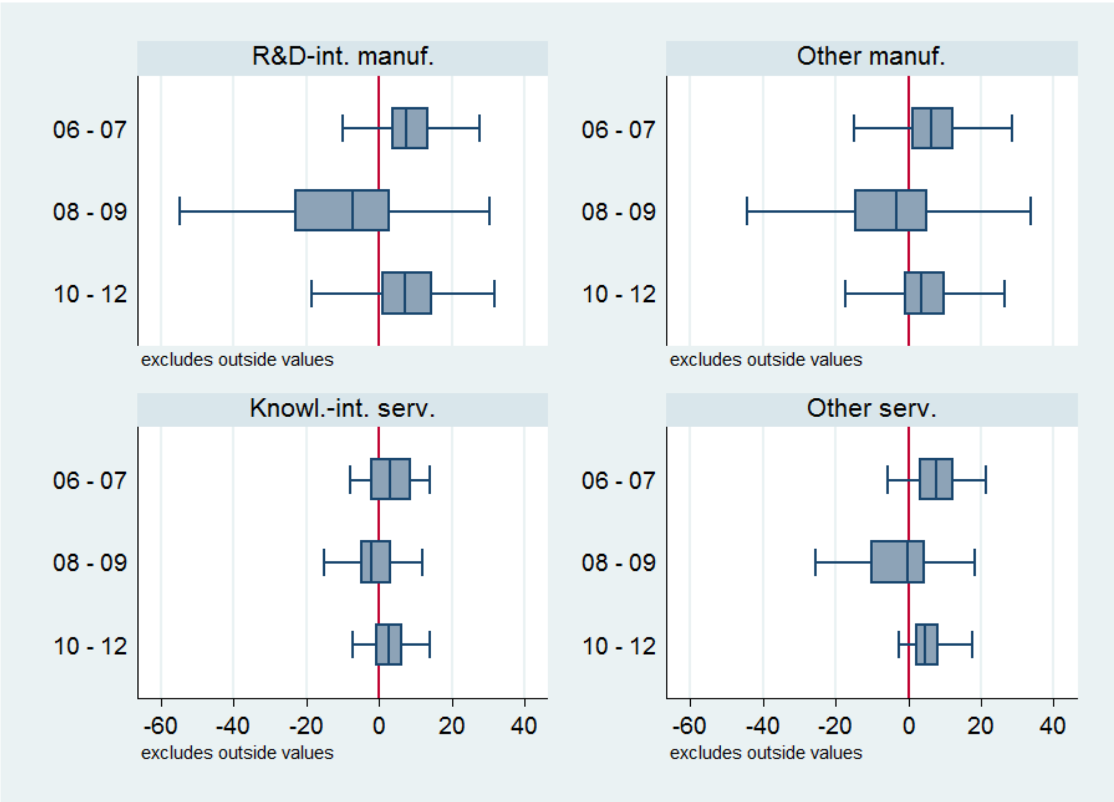
[1] is estimated by a fixed-effects (FE) panel model and – as a robustness check – by a random-effects (RE) Tobit model. Applying this approach, we basically evaluate the impact of changes in the level of innovation expenditures on changes in innovation success in the following year.

A critical issue of estimating [1] relates to the way $\Delta II_{t|t-1}$ is measured. We defined the innovation intensity as the ratio of innovation expenditures (*IE)* over a firm's sales level (*S*). Taking the annual difference of it would mean to subtract the value of *II* at time t-1 from the value of *II* at time t. If we had constructed $\Delta II_{t|t-1}$ that way we would have mismeasured it since, for instance, a large (positive) difference could not have only been caused by greater innovative effort but also by a decreased sales level while holding the level of innovative effort constant. Therefore, we defined $\Delta II_{t|t-1}$ as $(IE_t - IE_{t-1})/S_{t-1}$. Hence, we basically study the impact of short-term economic fluctuations on adjustments in firms' innovation budgets. We believe that our measure for innovative effort to be superior over the absolute volume of innovation expenditures since relating innovation budgeting to the previous sales level directly captures the firm's capacity to conduct innovation activities and it properly captures the extent of a firm's adjustment strategy to a shock.

4.2. Business Cycles 2006-2012 in Germany

From a business cycle perspective, one can divide our observed period, 2006-2012, into three sub periods. The first period, the years 2006 and 2007, was characterised by a prosperous macroeconomic environment in Germany with annual real GDP growth rates ranging between 3 and 4 percent. The second period, the period of the most recent economic crisis, covers the years of 2008 and 2009. Although the year 2009 represents the severest economic crisis in German post-war economic history, with a decline in real GDP by 5.5 percent, the recent crisis already became apparent for the firms in the second half of the year 2008. The last period, the years 2010 to 2012, was a time of economic upswing with real GDP growth rates exceeding again 3 percent in 2010 and 2011. However, GDP growth is only a rough business cycle indicator from a firm perspective since it only represents an average annual value across all markets. It does not account for heterogeneous industry-specific impacts of shocks. For instance, while many industries have been severely affected by the shock in 2009, some industries have already been suffering in 2008 and some have not been affected. A more accurate economic indicator thus refers to a firm's primary sales market, i.e. the industry a firm generates most of its sales in.

Figure 4-1: Sales growth on an industry level (in percent) by the observed periods



Source: Destatis and MIP; authors' own calculations.

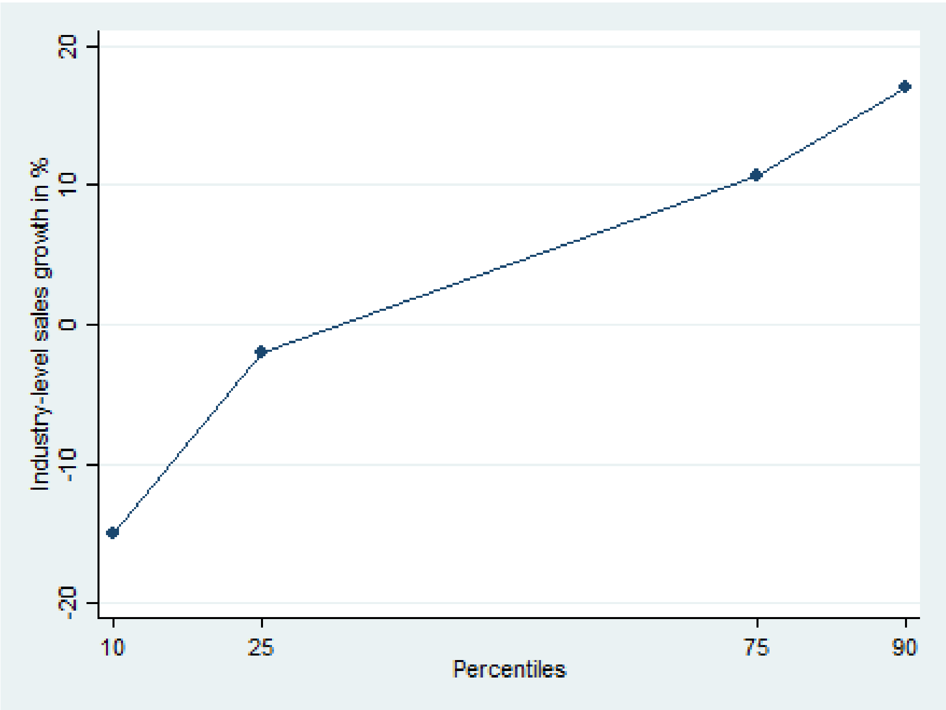
Figure 4-1 presents box plots for the sales growth rates in each observed period, separated by highly aggregated industry classifications, i.e. R&D-intensive manufacturing (R&D-int. manuf.), other manufacturing (other manuf.), knowledge-intensive services (knowl.-int. serv.) and other services (other serv.).[1] The median values of all industries for the pre- and post-crisis periods are positive, which indicates to an average growth of these industry aggregates. In contrast to the positive growth periods, the median values for the crisis period are below zero indicating an economic drop, on average. However, the variance of the sales growth rates is very high

[1] We used a highly aggregated classification for the sake of simplicity. Using more disaggregated information discloses stronger heterogeneities.

compared to the pre- and post-crisis periods. This is a clear evidence for the heterogeneous impact of the crisis on the industry level.

Using time dummies or GDP growth to identify crisis effects may hence not be a reliable strategy. Instead, we constructed three dummy variables indicating whether the firm's industry was high-growing ($HG_{t|t-1}$), medium-growing ($MG_{t|t-1}$) or low-growing ($LG_{t|t-1}$) between t and t-1. In doing so, we constructed two different sets of binary dummy variables. On the one hand, considering a more strict definition of high- and low-growing industries, we used the lowest and highest decile of the industry-level sales growth rate as the lower and the upper bound (thresholds). On the other hand, for a more tolerant definition of high- and low-growing industries, we used the lowest and highest quartile of the industry-level sales growth rate as thresholds. Figure 4-2 shows the plotted percentiles of the industry-level sales growth rate. That is, 10 percent of the growth rates are smaller than -12.7 percent, 25 percent of the growth rates are smaller than -1.4 percent, 75 percent of the values are smaller than about 10 percent, while 90 percent of the values are smaller than 16.5 percent.

Figure 4-2: Plotted percentiles of annual industry-level sales growth (in percent) during 2006-2012



Source: Destatis and MIP; authors' own calculation.

Table 4-1 presents an overview on the two dummy variables sets. For instance, regarding the strict definition, an industry is considered as high-growing if its sales level increased by more than 16.5 percent in t compared to t-1. An industry is considered as low-growing if its sales level decreased by more than (-)12.7 percent in t compared to t-1. The annual sales level in a medium-growing industry did not decrease by more than (-)12.7 percent and did not increase by more than 16.5 percent. For reasons of comparison, we also included three dummy variables measuring high, medium and low growth by using Germany's GDP growth rates taking 0 and 3 percent real growth as thresholds.

Table 4-1: Business cycle indicators (in percent)

	Industry-level sales growth		**real GDP growth (percent)**
Thresholds:	*Strict (10 / 90 percent)*	*Tolerant (25 / 75 percent)*	
High growth	>= 16.5	>= 10	>= 3
Medium growth	>= -12.7 to < 16.5	>= -1.4 to < 10	>= 0 to < 3
Low growth	< -12.7	< -1.4	< 0

Note: low (medium) growth of the GDP indicator only appeared in 2009 (2008), high growth appeared in the other periods.
Source: Destatis and MIP; authors' own calculation.

Following the definitions in Table 4-1, we incorporate these different indicators into our analysis by splitting the business cycle measure (*GR*) in [1] into the three sets of dummy variables. Each set is separately estimated for each dependent variable and captures high growth ($HG_{t|t-1}$), (ii) medium growth ($MG_{t|t-1}$) and (iii) low growth ($LG_{t|t-1}$) periods. This allows us to estimate a separate coefficient for each budget adjustment in each growth period. Our equation to be estimated hence reads as follows:

$$IS_{ij,t+1} = \beta_0 + \beta_1\, II_{i,t-1} + \beta_2\, \Delta II_{i,t|t-1} * HG_{t|t-1} + \beta_3\, \Delta II_{i,t|t-1} * MG_{t|t-1} + \beta_4\, \Delta II_{i,t|t-1} * LG_{t|t-1} + \beta_5\, X_{i,t} + \mu_{i,t} \qquad [2]$$

4.3. Data

The empirical analysis is based on data from the Mannheim Innovation Panel (MIP). The MIP is conducted by the ZEW since 1993 on behalf of the German Federal Ministry for Education and Research (BMBF). The MIP is the German contribution to European Commission's Community Innovation Surveys (CIS) and is based on the methodology proposed in the Oslo Manual for collecting innovation data (OECD and Eurostat, 2005).[2] Further, industry-level data on a 4-digit level obtained from the Federal Statistical Office of Germany (Destatis) allows us to construct our business cycle indicators. In order to observe firms' innovation expenditures and innovation performance over a longer period, we use seven consecutive survey waves. The resulting panel data set covers the period of 2006-2012.

Almost all model variables are directly taken from the innovation survey data and rely on the standard measurements used in the CIS.[3] The share of new product sales refers to sales in year

[2] For further details see Aschhoff et al. (2013) and Peters and Rammer (2013).

[3] For a summary of the variables, see Table A-1.

t+1 from product innovations introduced in the previous three-year period. Innovation expenditures cover the expenditures for research and development (R&D) as well as additional expenditures required to develop and introduce new products such as the design, marketing, training, acquisition of external knowledge and technologies and acquisition of machinery and software needed to produce and distribute innovations. The direct impact of the business cycle on a firm's resources is measured by the sales growth in t compared to the previous year t-1. Control variables include five size dummies, firm age and the squared firm age to capture potential non-linear age effects as well as a firm's export market orientation and whether the firm belongs to an enterprise group. Furthermore, we consider whether a firm conducts internal R&D on a continuous base or an occasional base to better qualify a firm's innovation expenditures. In order to control for likely complementary effects of process innovations on product innovation success we also include a process innovation indicator. Since the share of new product sales may also be affected by productivity effects, we additionally include a firm's capital intensity (capital per employee). Furthermore, we have to control for potential financial constraints. For that reason, we use a firm's credit rating indicator ranging from 1 (very good financial standing) to 6 (almost bankrupt).[4] Industry and time dummies control for industry-specific and time-specific variations in a firm's capacity to generate new product sales.

Since the focus of the empirical analysis is on the share of new product sales, we restrict our sample to firms with product innovation activities. This includes (i) firms that introduced product innovations during t-2 and t, (ii) firms that have conducted product innovation activities during t-2 and t but haven't completed any by the end of year t (i.e. these activities were still ongoing at the end of year t), and (iii) firms that conducted product innovation activities during t-2 and t but stopped them by the end of year t.

The total size of our sample includes 2,143 firms. As the panel data set is unbalanced, we do not have observations for each firm in each year.[5] The average number of observations per firm within the seven-year observational period is 3.7. This gives a total number of 8,095 firm-year observations.

In order to avoid a potential endogeneity bias due to unobserved individual heterogeneity, we estimate FE models instead of pooled OLS models. While the dependent variables are continuously distributed, a significant share of firms reports a value of 0. One reason for this is that firms only had ongoing or stopped product innovation activities and did not introduce any new products between t-2 and t. In addition, firms may have introduced a new product but its success in terms of sales is still to come. Although these zeros are "true" zeros referring to

[4] The credit rating indicator is taken from Creditreform, Germany's largest credit rating agency.

[5] Possible reasons are entries and exits from the panel sample and irregular responses of the participating firms.

a true failure of success (see Greene, 2012) we perform robustness checks using RE Tobit models to adjust for potential selectivity issues. One major criticism of the estimations of latent variable random effects models is the assumption of strict exogeneity (see e.g. Wooldridge, 2010; Greene, 2012). For that reason, Mundlak (1978) defines the time-invariant individual heterogeneity to be a function of a constant parameter, the time means of the time-varying variables and an i.i.d. error term with zero-mean that is uncorrelated with the explanatory variables.[6] In so doing, the assumption of strict exogeneity is "created". We apply the approach developed by Mundlak (1978) and include the time means of the time-varying variables as additional controls in our RE Tobit estimations. Since some firms have even changed their industry (primary sales market), we included the time means of the industry dummies as well.[7]

5. Estimation Results

Table 5-1 presents the results of the FE estimations. We run three different models: (i) one for the sales share of market novelties (market), (ii) one for the sales share of product imitations (imit) and (iii) one for the sum of both, i.e. the sales share of new products (new). Each estimated model includes interaction terms of the companies' innovation budgeting decisions (D_intensity_t|t-1) and business cycle indicators each of them covering high-growth, medium-growth and low-growth periods.

The one-year lag of a firm's innovation intensity does not show any statistically significant effects. This insignificance is basically due to the way the individual heterogeneity is adjusted for by FE regressions as the robustness checks disclose strong significant effects for the firm means of the lagged innovation intensity (see Table 5-2).[8] Our key variables – the interaction terms – show consistent results regarding the effects on the sales share of product imitations across the different business cycle indicators and growth phases. Accordingly, increased (decreased) innovation budgets do not affect the innovation success with product imitations, whether or not strict (10 / 90 percent) or tolerant (25 / 75 percent) thresholds of the industry-level indicators are underlying or GDP growth is used as the business cycle indicator. Thus, not even a (positive) crisis adjustment in the innovation budgets had any significant effects on product imitation success.

In contrast to product imitations, firms gain from greater sales shares of market novelties when increasing their annual innovation budgets. This relationship holds for medium-growth phases, independent of the business cycle indicator and underlying thresholds. This means

[6] A more general approach can be found in Chamberlain (1980).

[7] The estimation results do not change when leaving out the mean values of the industry dummies.

[8] Pooled OLS regressions (not presented in the paper) also show strong significant effects of intensity_t-1.

that if the economy or the firm's target industry are moderately growing it seems to be beneficiary for a firm to increase its innovation expenditures. Moreover, when considering a tolerant threshold and the GDP growth indicator, firms specifically have an incentive to channel more financial means to the introduction of market novelties during periods of high growth. Both findings support our hypothesis H1 of expansive innovation budgeting being a successful strategy during economically stable conditions. This implies that firms should combine an increase in innovation expenditures with a strong focus on the implementation of market novelties during medium- and high-growth periods since greater investment in product imitations do not pay off in the short-term. Indeed, the effects on market novelties are not significant in low-growth periods implying the strategy of greater investments in more ambitious projects not always to be superior to a greater investment in product imitations. However, the coefficients are always higher for the effects on market novelties than for the effects on product imitations. We thus fail to reject our hypothesis H3. Intuitively it makes sense as market novelties depict rather radical new products compared to product imitations. On average, market novelties require more monetary effort but they are also more promising in terms of sales. This implies that market novelties most likely sell best if the innovator was not financially constrained, which is usually the case during medium- and high-growth periods.

Table 5-1: Effect of a change in the innovation budget on innovation success considering the business cycle, FE model

Thresholds	**10 / 90** percent			**25 / 75** percent			**real GDP-growth**		
Sales share of	*new*	*market*	*imit*	*new*	*market*	*imit*	*new*	*market*	*imit*
Intensity (t-1)	0.041 (0.066)	0.027 (0.059)	0.014 (0.064)	0.053 (0.067)	0.045 (0.067)	0.008 (0.068)	0.059 (0.066)	0.036 (0.062)	0.022 (0.064)
D_intensity_t|t-1 during:									
High growth	0.020 (0.076)	0.092 (0.061)	-0.072 (0.069)	0.115 (0.086)	**0.188**** (0.080)	-0.073 (0.061)	**0.104*** (0.053)	**0.084**** (0.036)	0.020 (0.046)
Medium growth	**0.121***** (0.046)	**0.098***** (0.029)	0.023 (0.037)	**0.109**** (0.046)	**0.074**** (0.030)	0.035 (0.035)	**0.112*** (0.064)	**0.108**** (0.053)	0.003 (0.036)
Low growth	0.024 (0.109)	0.051 (0.069)	-0.027 (0.117)	0.113 (0.095)	0.094 (0.063)	0.018 (0.103)	0.159 (0.112)	**0.131*** (0.075)	0.028 (0.109)

Note: *** p<0.01, ** p<0.05, * p<0.1; standard errors – in parentheses – are clustered at the firm level; for full information on estimation results see Table A-2; authors' own calculations.

With regard to the effects of expansive innovation budgeting during a crisis period (low-growth period), Table 5-1 shows some mixed results. On the one hand, there is no significant effect when considering the business cycle indicators on an industry level. On the other hand, increasing innovation expenditures during a crisis period measured by GDP growth significantly drives innovation success with market novelties, which supports H3. Remember, low growth measured by GDP growth only appeared in 2009, i.e. in the severest crisis year.[9] This means that, independent of the firm's industry situation, companies that have counter-cyclically shifted more financial resources to the introduction of market novelties in 2009 compared to 2008 could gain from a greater innovation success in the following upswing period. That effect is even stronger than in medium-growth and high-growth periods, though it is less significant.

This is a critical result since no counter-cyclical adjustment effects could be found for the industry-level indicators. It hence does not seem to be a promising strategy for a firm to expand its innovation budget when demand in its primary sales market is falling. As mentioned in section 2, a main rationale for pursuing a counter-cyclical innovation strategy is lower opportunity costs of innovative efforts compared to capital investment during recessions. The insignificant effect for the industry level implies that opportunity costs are not low enough during a (sales market) crisis for a firm to benefit from a crisis adjustment. However, opportunity costs may be low enough when the whole economy suffers from a crisis, i.e. if real GDP declines. In such a situation, labour, capital and raw material markets will be affected by the economic decline. (High-skilled) labour and industrial inputs (from raw materials to equipment) will become more affordable and interest rates fall, favouring investment in general, and innovation expenditure in particular. Such effects are likely to be more pronounced if the crisis catches the entire world economy as it happened in 2009. In that case, firms can gain e.g. from lower oil prices, lower costs for new equipment, increased cross-border mobility of (high-skilled) labour and excess supply of cheap financial capital. As a result, we would expect the positive effect on market novelty success for the negative GDP growth dummy to be mainly driven by firms whose primary sales markets were less strongly affected by the 2009 crisis. These firms were able to fully exploit the strength/robustness of their primary sales market and the relatively low opportunity costs. We have to reject hypothesis H2 when we link a crisis to a firm's sales market but we fail to reject H2 if we take on a broader view by considering also developments on other markets.

Table 5-2 presents the results of various robustness checks. We performed RE Tobit estimations by using the Mundlak (1978) approach that requires the estimation of the time means of the time-varying variables to account for individual heterogeneity. Controlling for that, we obtain similar results as with the FE results presented in Table 5-1. The sales share of product imitations is not affected by an increased innovation budget, independent of the underlying thresholds, indicators and regarded growth periods. Furthermore, expansive

[9] This effect also holds when dropping the time dummies from the estimations that include GDP growth dummies.

innovation budgeting during medium- and high-growth periods can significantly increase the subsequent success of new products and market novelties. These positive effects support our hypotheses H1 and H3. However, they are less strong and less significant for new products as compared with the FE estimations. The positive crisis adjustment effect found in Table 5-1 is not only stronger than in Table 5-2 but also appears in the industry-level indicator with tolerant growth thresholds. This strengthens the finding that a positive crisis adjustment of the firms' innovation budgets can be a promising strategy to increase post-crisis innovation success. While the effect is only weakly significant for the industry-level indicator it is even more significant for the GDP growth indicator. According to the results of our robustness checks, we would fail to reject hypothesis H2.

Table 5-2: Robustness check – RE Tobit model

Thresholds	**10%; 90%**			**25%; 75%**			**GDP-growth**		
Sales share of	*new*	*market*	*imit*	*new*	*market*	*imit*	*new*	*market*	*imit*
Intensity (t-1)	0.029	0.051	-0.008	0.013	0.066	-0.026	0.042	0.041	0.023
	(0.070)	(0.062)	(0.075)	(0.071)	(0.063)	(0.077)	(0.069)	(0.061)	(0.074)
D_intensity_t|t-1 during:									
High growth	-0.038	**0.249****	-0.118	0.073	**0.300*****	-0.090	0.057	**0.101*****	0.009
	(0.108)	(0.124)	(0.114)	(0.070)	(0.064)	(0.076)	(0.045)	(0.039)	(0.048)
Medium growth	**0.072***	**0.117*****	-0.015	0.065	**0.083****	0.000	0.094	**0.127*****	-0.010
	(0.041)	(0.035)	(0.044)	(0.044)	(0.038)	(0.047)	(0.059)	(0.049)	(0.064)
Low growth	-0.052	0.180	-0.125	-0.047	**0.144***	-0.118	0.028	**0.190****	-0.058
	(0.126)	(0.116)	(0.135)	(0.083)	(0.075)	(0.088)	(0.099)	(0.092)	(0.105)
Individual heterogeneity:									
M_intensity (t-1)	**0.335*****	**0.181****	**0.254*****	**0.349*****	**0.173****	**0.260*****	**0.317*****	**0.183****	**0.222****
	(0.087)	(0.076)	(0.090)	(0.087)	(0.076)	(0.091)	(0.086)	(0.075)	(0.089)
M_High	**0.144****	**0.162*****	-0.107	**0.137****	**0.153*****	-0.081	**0.158*****	**0.138*****	-0.005
	(0.062)	(0.049)	(0.104)	(0.060)	(0.048)	(0.082)	(0.056)	(0.045)	(0.061)
M_Medium	**0.199****	0.034	**0.179****	**0.244****	0.125	0.151	**0.298***	**0.305****	-0.002
	(0.090)	(0.076)	(0.090)	(0.113)	(0.095)	(0.112)	(0.180)	(0.145)	(0.177)
M_low	**0.525***	0.124	0.435	**0.428****	-0.114	**0.477*****	0.289	-0.195	0.356
	(0.316)	(0.275)	(0.313)	(0.175)	(0.154)	(0.178)	(0.214)	(0.192)	(0.220)

Note: *** p<0.01, ** p<0.05, * p<0.1; standard errors – in parentheses – are clustered at the firm level; for full information on estimation results see Table A-3; authors' own calculations.

6. Conclusion

This paper looked at the effects of changes in innovation budgets during the recent economic crisis on firms' post-crisis innovation performance. We used firm-level panel data from Germany covering pre-crisis, crisis and post-crisis periods (2006-2012). In order to properly account for the economic crisis, we considered the firms' target markets since not all markets were equally affected by the shock in 2008/2009. Our business cycle indicators thus refer to annual industry-level sales growth. We additionally used the annual real GDP growth rates of Germany to further check the validity of our results.

The change in innovation budgets for the respective growth period was constructed as interaction terms of the change in the ratio of innovation expenditures over sales and binary dummies capturing high-growth, medium-growth and low-growth periods. We estimated FE panel models and find that expansive innovation budgeting increases innovation success only during high-growth and medium-growth periods. A positive crisis adjustment effect could only be found for more ambitious innovations (products new to the market) and when referring to GDP growth as the business cycle indicator. This means that expansive innovation budgeting in 2009 increased the post-crisis innovation performance for market novelties across all industries, on average.

Neglecting the industry perspective, the positive effect of expansive innovation budgeting during the crisis on the post-crisis sales share of more ambitious innovations suggests that maintaining a higher level of innovation expenditures despite a deteriorating macroeconomic environment could give firms a head start over its competitors in the following upswing period in case the competitors refrained from following this strategy. Firms with relatively greater innovation expenditures during the crisis can profit from a larger new product portfolio and more thoroughly developed new products. This allows them to offer new products to the market earlier, at a better quality or better targeted to user needs than their competitors when demand for new products rises in the post-crisis period.

Conditioning on the fact that not all industries have been affected by the 2008/2009 crisis leaves a crisis adjustment in the innovation budget without leverage. In case the primary sales market of a firm suffers from (severely) declining sales an expansive innovation strategy does not seem to be an effective way to boost post-crisis innovation performance. The discrepancy between the findings for industry-level and GDP growth indicators could be due to ancillary effects resulting from industry and national level perspectives. While the industry level represents a firm's primary sales market only, the GDP additionally considers changes in labour, capital and supply markets. Hence, a crisis appearing on a firm's sales market may cut the opportunity costs of innovative efforts not strong enough to increase post-crisis innovation success, while it seems to be the case for a crisis measure that considers the situation in the entire economy.

A main limitation of this study is its short-term perspective. We only look at effects of budgeting decisions on innovation performance in the following year. Many innovations, particularly the more radical ones, produce high returns only some years after market introduction. In order to analyse these effects, longer time series data at the firm level would be needed. Since we do not have such data at hand (yet), we must leave this important aspect to future research.

7. References

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A. Appendix

Table A-1: Variable definitions and basic descriptive statistics

Variables	Description	Mean	Std.dev..
Dependent variables			
new	Sales share of new products in year t+1	0.178	0.223
market	Sales share of market novelties in year t+1	0.043	0.107
imit	Sales share of product imitations in year t+1	0.135	0.192
Explanatory variables			
Intensity_t-1	(Innovation expenditures / firm sales) in year t-1	0.081	0.136
D_intensity_t|t-1	(Innovation expenditures_t - innovation expenditures_t-1) / firm sales_t-1	0.009	0.132
Threshold: 10 / 90 percent			
High growth	Value of D_intensity_t|t-1 in high growth periods between t & t-1	0.001	0.030
Medium growth	Value of D_intensity_t|t-1 in medium growth periods between t & t-1	0.008	0.125
Low growth	Value of D_intensity_t|t-1 in low growth periods between t & t-1	0.000	0.032
Threshold: 25 / 75 percent			
High growth	Value of D_intensity_t|t-1 in high growth periods between t & t-1	0.003	0.055
Medium growth	Value of D_intensity_t|t-1 in medium growth periods between t & t-1	0.006	0.096
Low growth	Value of D_intensity_t|t-1 in low growth periods between t & t-1	0.000	0.073
Threshold: GDP-growth			
High growth	Value of D_intensity_t|t-1 in high growth periods between t & t-1	0.008	0.097
Medium growth	Value of D_intensity_t|t-1 in medium growth periods between t & t-1	0.001	0.062
Low growth	Value of D_intensity_t|t-1 in low growth periods between t & t-1	0.000	0.065
Control variables			
Salesgrowth	(Firm sales_t - firm sales_t-1) / firm sales_t-1	0.089	0.370
Credrat	Credit rating indicator ranging from 1 (excellent) to 6 (dismal)	2.150	0.606
Capitalint	Ratio of tangible assets over employees	0.120	0.430
Age	Firm age	38.171	42.704
Group	The firm has been part of a group in t - (0/1)	0.465	0.499
Pc	The firm has introduced a process innovation between t|t-2 - (0/1)	0.590	0.492
Rnd	The firm has conducted in-house R&D in t- (0/1)	0.773	0.419
Export	The firm has been an exporter in t - (0/1)	0.740	0.439
Employee dummies			
<20	The firm employed less than 20 employees - (0/1)	0.231	0.421
20_99	The firm employed between 20 and 99 employees - (0/1)	0.297	0.457
100_249	The firm employed between 100 and 249 employees - (0/1)	0.138	0.345
250_499	The firm employed between 250 and 499 employees - (0/1)	0.081	0.273
>499	The firm employed at least 500 employees - (0/1)	0.254	0.435
Individual heterogneity			
M_Intensity_t-1	Mean value of Intensity_t-1	0.081	0.120
M_D_intensity_t|t-1	Mean value of D_intensity_t|t-1	0.006	0.093
Thresholds: 10 / 90 percent			

M_High	Mean value of High growth	0.002	0.071
M_Medium	Mean value of Medium growth	0.005	0.062
M_Low	Mean value of Low growth	-0.001	0.017
Thresholds: 25 / 75 percent			
M_High	Mean value of High growth	0.003	0.075
M_Medium	Mean value of Medium growth	0.004	0.049
M_Low	Mean value of Low growth	-0.001	0.037
Thresholds: GDP-growth			
M_High	Mean value of High growth	0.006	0.086
M_Medium	Mean value of Medium growth	0.000	0.032
M_Low	Mean value of Low growth	-0.001	0.033
M_Salesgrowth	Mean value of Sales growth	0.088	0.183
M_Credrat	Mean value of Credrat	2.154	0.576
M_Capitalint	Mean value of Capitalint	0.119	0.416
M_Age	Mean value of Age	38.226	42.697
M_Group	Mean value of Group	0.466	0.470
M_Pc	Mean value of Pc	0.563	0.376
M_Rnd	Mean value of Rnd	0.730	0.363
M_Export	Mean value of Export	0.736	0.415
M_<20	Mean value of <20 employees	0.229	0.407
M_20_99	Mean value of > 19 & < 100 employees	0.299	0.436
M_100_249	Mean value of > 99 & < 250 employees	0.137	0.324
M_250_499	Mean value of > 249 & < 500 employees	0.081	0.254
M_>499	Mean value of > 499 employees	0.254	0.430

Number of observations: 4,238.
Note: For convenience, we left out the information on age squared.
Source: ZEW, Mannheim Innovation Panel and Destatis; authors' own calculation.

Table A-2: Full results of Table 5-1

Thresholds	10 / 90 percent			25 / 75 percent			real GDP-growth		
Sales share of	*new*	*market*	*imit*	*new*	*market*	*imit*	*new*	*market*	*imit*
Intensity_t-1	0.041	0.027	0.014	0.053	0.045	0.008	0.059	0.036	0.022
	(0.066)	(0.059)	(0.064)	(0.067)	(0.067)	(0.068)	(0.066)	(0.062)	(0.064)
D_intensity_t|t-1 during									
High growth	0.020	0.092	-0.072	0.115	**0.188****	-0.073	**0.104***	**0.084****	0.020
	(0.076)	(0.061)	(0.069)	(0.086)	(0.080)	(0.061)	(0.053)	(0.036)	(0.046)
Medium growth	**0.121*****	**0.098*****	0.023	**0.109****	**0.074****	0.035	**0.112***	**0.108****	0.003
	(0.046)	(0.029)	(0.037)	(0.046)	(0.030)	(0.035)	(0.064)	(0.053)	(0.036)
Low growth	0.024	0.051	-0.027	0.113	0.094	0.018	0.159	**0.131***	0.028
	(0.109)	(0.069)	(0.117)	(0.095)	(0.063)	(0.103)	(0.112)	(0.075)	(0.109)
Control variables									
Salesgrowth	-0.013	-0.007	-0.006	-0.014	-0.007	-0.007	-0.014	-0.007	-0.006
	(0.011)	(0.006)	(0.010)	(0.012)	(0.007)	(0.010)	(0.011)	(0.006)	(0.010)
Credrat	0.006	0.004	0.001	0.006	0.004	0.002	0.006	0.004	0.001
	(0.020)	(0.008)	(0.018)	(0.020)	(0.008)	(0.018)	(0.020)	(0.008)	(0.018)
Capitalint	0.026	0.027	-0.001	0.026	0.026	-0.000	0.026	0.026	-0.001
	(0.028)	(0.018)	(0.013)	(0.028)	(0.018)	(0.013)	(0.028)	(0.018)	(0.013)
Age	**0.018*****	**-0.006****	**0.012*****	**0.018*****	**-0.006****	**0.013*****	**0.018*****	**-0.006****	**0.012*****
	(0.004)	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)
Age^2	**0.000****	**0.000*****	0.000	**0.000****	**0.000*****	0.000	**0.000****	**0.000*****	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Group	-0.016	0.003	-0.019	-0.015	0.004	-0.019	-0.015	0.003	-0.018
	(0.018)	(0.009)	(0.016)	(0.018)	(0.009)	(0.016)	(0.018)	(0.009)	(0.016)
Pc	-0.010	-0.004	-0.006	-0.010	-0.003	-0.006	-0.010	-0.004	-0.006
	(0.010)	(0.005)	(0.010)	(0.010)	(0.005)	(0.010)	(0.010)	(0.005)	(0.010)
RnD	0.012	0.005	0.007	0.013	0.005	0.007	0.013	0.005	0.008
	(0.012)	(0.005)	(0.012)	(0.012)	(0.005)	(0.012)	(0.012)	(0.005)	(0.012)
Export	0.004	0.015	-0.010	0.005	0.016	-0.011	0.005	0.015	-0.010
	(0.022)	(0.010)	(0.021)	(0.022)	(0.010)	(0.021)	(0.022)	(0.010)	(0.021)
Employee dummies									
<20	0.002	-0.016	0.018	0.001	-0.015	0.016	0.001	-0.017	0.018
	(0.104)	(0.073)	(0.082)	(0.104)	(0.073)	(0.081)	(0.104)	(0.073)	(0.082)
20_99	0.042	-0.034	0.076	0.042	-0.032	0.074	0.041	-0.034	0.076
	(0.085)	(0.054)	(0.067)	(0.086)	(0.055)	(0.067)	(0.085)	(0.054)	(0.067)
100_249	-0.020	-0.041	0.022	-0.019	-0.041	0.022	-0.020	-0.041	0.022
	(0.074)	(0.051)	(0.056)	(0.074)	(0.051)	(0.056)	(0.074)	(0.051)	(0.056)
250_499	0.013	0.014	-0.001	0.013	0.014	-0.001	0.013	0.013	-0.001
	(0.063)	(0.038)	(0.047)	(0.062)	(0.037)	(0.047)	(0.062)	(0.038)	(0.047)
Constant	**0.581*****	0.078	**0.503*****	**0.580*****	0.069	**0.511*****	**0.581*****	0.077	**0.503*****
	(0.178)	(0.088)	(0.173)	(0.179)	(0.089)	(0.174)	(0.178)	(0.089)	(0.174)
Observations	4,238	4,238	4,238	4,238	4,238	4,238	4,238	4,238	4,238
Rho	0.912	0.836	0.903	0.913	0.837	0.905	0.913	0.835	0.904
F-test									
Time dummies	**9.640*****	0.96	**8.910*****	**9.910*****	1.130	**8.750*****	**10.04*****	0.980	**8.950*****
Industry dummies	**75.77*****	**25.47*****	**64.72*****	**66.89*****	**25.16*****	**56.65*****	**74.45*****	**25.14*****	**63.13*****

Note: *** p<0.01, ** p<0.05, * p<0.1; standard errors – in parentheses – are clustered at the firm level; authors' calculations.

Table A-3: Full results of Table 5-2

Thresholds	**10 / 90 percent**			**25 / 75 percent**			**real GDP-growth**		
Sales share of	*new*	*market*	*imit*	*new*	*market*	*imit*	*new*	*market*	*imit*
Intensity_t-1	0.029	0.051	-0.008	0.013	0.066	-0.026	0.042	0.041	0.023
	(0.070)	(0.062)	(0.075)	(0.071)	(0.063)	(0.077)	(0.069)	(0.061)	(0.074)
D_intensity_t|t-1 during									
High growth	-0.038	**0.249****	-0.118	0.073	**0.300*****	-0.090	0.057	**0.101*****	0.009
	(0.108)	(0.124)	(0.114)	(0.070)	(0.064)	(0.076)	(0.045)	(0.039)	(0.048)
Medium growth	**0.072***	**0.117*****	-0.015	0.065	**0.083****	0.000	0.094	**0.127*****	-0.010
	(0.041)	(0.035)	(0.044)	(0.044)	(0.038)	(0.047)	(0.059)	(0.049)	(0.064)
Low growth	-0.052	0.180	-0.125	-0.047	**0.144***	-0.118	0.028	**0.190****	-0.058
	(0.126)	(0.116)	(0.135)	(0.083)	(0.075)	(0.088)	(0.099)	(0.092)	(0.105)
Control variables									
Salesgrowth	-0.005	-0.016	0.005	-0.005	-0.014	0.005	-0.005	-0.015	0.004
	(0.012)	(0.011)	(0.013)	(0.012)	(0.011)	(0.012)	(0.012)	(0.011)	(0.013)
Credrat	0.014	0.017	0.005	0.014	0.016	0.006	0.014	0.017	0.005
	(0.018)	(0.017)	(0.020)	(0.018)	(0.017)	(0.020)	(0.018)	(0.017)	(0.020)
Capitalint	0.045	0.041	0.015	0.045	0.039	0.016	0.044	0.040	0.015
	(0.032)	(0.029)	(0.034)	(0.032)	(0.029)	(0.034)	(0.032)	(0.029)	(0.034)
Age	0.062	-0.467	0.643	0.087	-0.434	0.649	0.055	-0.418	0.596
	(0.688)	(0.558)	(0.705)	(0.688)	(0.559)	(0.704)	(0.687)	(0.558)	(0.702)
Age^2	**0.000***	**0.000****	0.000	**0.000***	**0.000****	0.000	**0.000***	**0.000****	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Group	-0.015	0.021	-0.026	-0.014	0.023	-0.026	-0.015	0.022	-0.026
	(0.021)	(0.020)	(0.023)	(0.021)	(0.020)	(0.023)	(0.021)	(0.020)	(0.023)
Pc	**-0.020****	**-0.018***	-0.012	**-0.020****	**-0.018***	-0.011	**-0.020****	**-0.018***	-0.011
	(0.010)	(0.010)	(0.011)	(0.010)	(0.010)	(0.011)	(0.010)	(0.010)	(0.011)
RnD	**-0.034****	-0.019	**-0.038****	**-0.034****	-0.017	**-0.039****	**-0.034****	-0.018	**-0.039****
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Export	0.007	0.012	-0.007	0.006	0.014	-0.008	0.007	0.011	-0.006
	(0.025)	(0.025)	(0.026)	(0.025)	(0.025)	(0.026)	(0.025)	(0.025)	(0.026)
Employee dummies									
< 20	-0.050	-0.034	-0.030	-0.049	-0.032	-0.029	-0.049	-0.037	-0.028
	(0.088)	(0.081)	(0.095)	(0.088)	(0.081)	(0.095)	(0.088)	(0.081)	(0.095)
> 19 & < 100	0.017	-0.086	0.081	0.017	-0.082	0.081	0.017	-0.086	0.082
	(0.080)	(0.074)	(0.086)	(0.080)	(0.073)	(0.086)	(0.080)	(0.074)	(0.086)
> 99 & < 250	-0.026	-0.103	0.042	-0.026	-0.103	0.042	-0.025	-0.104	0.043
	(0.070)	(0.066)	(0.076)	(0.070)	(0.066)	(0.076)	(0.070)	(0.066)	(0.076)
> 249 & < 500	0.014	0.005	0.012	0.014	0.005	0.012	0.015	0.004	0.013
	(0.047)	(0.046)	(0.050)	(0.047)	(0.046)	(0.050)	(0.047)	(0.046)	(0.050)
Individual heterogeneity									
M_intensity_t-1	**0.335*****	**0.181****	**0.254*****	**0.349*****	**0.173****	**0.260*****	**0.317*****	**0.183****	**0.222****
	(0.087)	(0.076)	(0.090)	(0.087)	(0.076)	(0.091)	(0.086)	(0.075)	(0.089)
M_high	**0.144****	**0.162*****	-0.107	**0.137****	**0.153*****	-0.081	**0.158*****	**0.138*****	-0.005
	(0.062)	(0.049)	(0.104)	(0.060)	(0.048)	(0.082)	(0.056)	(0.045)	(0.061)
M_medium	**0.199****	0.034	**0.179****	**0.244****	0.125	0.151	**0.298***	0.305**	-0.002
	(0.090)	(0.076)	(0.090)	(0.113)	(0.095)	(0.112)	(0.180)	(0.145)	(0.177)
M_low	0.525*	0.124	0.435	**0.428****	-0.114	**0.477*****	0.289	-0.195	0.356
	(0.316)	(0.275)	(0.313)	(0.175)	(0.154)	(0.178)	(0.214)	(0.192)	(0.220)
M_salesgrowth	0.002	0.043	-0.014	0.001	0.041	-0.017	0.000	**0.046***	-0.020
	(0.032)	(0.028)	(0.032)	(0.032)	(0.028)	(0.032)	(0.032)	(0.028)	(0.032)
M_credrat	-0.017	-0.008	-0.008	-0.017	-0.007	-0.009	-0.017	-0.010	-0.007
	(0.021)	(0.019)	(0.022)	(0.021)	(0.019)	(0.022)	(0.021)	(0.019)	(0.022)

M_capitalint	**-0.080****	-0.047	-0.062	**-0.081****	-0.046	-0.064	**-0.081****	-0.047	-0.063
	(0.039)	(0.033)	(0.041)	(0.039)	(0.033)	(0.041)	(0.039)	(0.033)	(0.041)
M_age	-0.063	0.466	-0.643	-0.087	0.433	-0.649	-0.056	0.418	-0.596
	(0.688)	(0.558)	(0.705)	(0.688)	(0.559)	(0.704)	(0.687)	(0.558)	(0.702)
M_age^2	**-0.000***	**-0.000****	-0.000	**-0.000***	**-0.000****	-0.000	**-0.000***	**-0.000****	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
M_group	0.015	-0.031	0.022	0.013	-0.034	0.023	0.013	-0.032	0.022
	(0.027)	(0.024)	(0.028)	(0.027)	(0.024)	(0.027)	(0.027)	(0.024)	(0.028)
M_pc	**0.156*****	**0.096*****	**0.125*****	**0.156*****	**0.095*****	**0.126*****	**0.157*****	**0.096*****	**0.126*****
	(0.019)	(0.017)	(0.019)	(0.019)	(0.017)	(0.019)	(0.019)	(0.017)	(0.019)
M_rnd	**0.187*****	**0.188*****	**0.148*****	**0.186*****	**0.185*****	**0.149*****	**0.187*****	**0.186*****	**0.150*****
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
M_export	0.056*	0.051*	0.052*	0.057*	0.049*	0.054*	0.055*	0.052*	0.052*
	(0.030)	(0.030)	(0.031)	(0.030)	(0.030)	(0.031)	(0.030)	(0.030)	(0.031)
M_Employee Dummies									
M_<20	0.099	0.029	0.054	0.099	0.025	0.055	0.100	0.033	0.051
	(0.091)	(0.084)	(0.098)	(0.091)	(0.084)	(0.098)	(0.091)	(0.084)	(0.098)
M_20_99	-0.006	0.053	-0.076	-0.006	0.048	-0.075	-0.007	0.053	-0.078
	(0.083)	(0.076)	(0.089)	(0.083)	(0.076)	(0.089)	(0.083)	(0.076)	(0.089)
M_100_249	0.062	0.100	-0.013	0.062	0.100	-0.013	0.061	0.101	-0.014
	(0.074)	(0.068)	(0.079)	(0.074)	(0.068)	(0.079)	(0.074)	(0.068)	(0.079)
M_250_499	-0.028	-0.053	-0.018	-0.028	-0.052	-0.019	-0.028	-0.052	-0.019
	(0.054)	(0.051)	(0.056)	(0.054)	(0.051)	(0.056)	(0.054)	(0.051)	(0.056)
Constant	**0.262*****	**0.416*****	**0.218*****	**0.260*****	**0.416*****	**0.216*****	**0.259*****	**0.416*****	**0.216*****
	(0.068)	(0.062)	(0.067)	(0.068)	(0.062)	(0.067)	(0.068)	(0.062)	(0.067)
Observations	4,238	4,238	4,238	4,238	4,238	4,238	4,238	4,238	4,238
Log-Likelihood	-702.7	-513.2	-930.9	-702.5	-507.6	-928.9	-703.5	-511.9	-933.6
Rho	0.530	0.531	0.448	0.529	0.533	0.445	0.530	0.530	0.448
LR-rho	**687.4*****	**505.9*****	**472.9*****	**682.1*****	**508.9*****	**466.7*****	**683.6*****	**503.1*****	**470.9*****
Chi2									
Time dummies	**34.18*****	9.300	**30.32*****	**34.75*****	**9.650***	**30.30*****	**35.14*****	8.760	**30.67*****
Mean value	**14.10****	6.180	**15.42****	**14.10****	6.450	**15.11****	**14.31****	6.490	**15.29****
Industry dummies	**29.82***	18.56	**28.49**	**30.01***	18.14	**29.19***	**30.20***	18.66	**28.87***
Mean value	**41.03*****	28.47	**29.31***	**41.45*****	28.45	**29.54***	**40.91*****	28.63	**28.90***

Note: *** p<0.01, ** p<0.05, * p<0.1; standard errors – in parentheses – are clustered at the firm level; authors' calculations.