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Financing Conditions, the Concept of Innovation Capacity and the Innovative Activity of Firms

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Abstract

In this paper a novel survey dataset allows us to use a direct measure for credit constraints as well as a direct measure for the innovative activity of a firm to identify the effects of credit constraints on the innovation behaviour of firms. Furthermore, the design of the survey questions and the panel structure of the dataset allow us to avoid problems commonly difficult to solve such as the existence of forward looking adjustments in a world of expectations or mutual causation, and moreover to analyse potential asymmetries in the effects of above average and below average credit conditions. As opposed to many other papers we find clear evidence for a negative effect of credit constraints on the innovative activity of firms. In addition, we find that below average financing conditions restrict innovative activity, while above average financing conditions do not foster it. To explain this novel result we extend the usual theory of innovation activity by rigidities with respect to a firm's individual innovation capacity, which leads to a differentiation between a long run and a short run equilibrium in innovative output.

JEL-Code: C35, G31, O31.

Keywords: credit restrictions, innovative activity.

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1 Introduction

One of the most popular areas of research on credit restrictions is their effect on the innovative activity of firms. This field is of great importance as innovative activity is considered one of the main factors for economic growth and firm performance.

Due to the lack of appropriate data, earlier literature has mostly used indirect measures as indicators for credit constraints as well as innovative activity (Bhagat and Welch (1995), Harhoff (1998), Hall et al. (2001), Bond et al. (2006)).[1] However, the results concerning the existence as well as the degree of the effects of credit restrictions were far from clear cut. Moreover, the use of the indirect measures was questioned in recent years.[2] Due to better availability of data literature has been published which applies more direct measures (Binz and Czarnitzki (2008), Atzeni and Piga (2007), Hottenrott and Peters (2009), Savignac (2006)). Nonetheless, often a direct measure of only one of the variables of interest – either of the level of financing conditions or of the level of innovative activity – is available. Moreover, by investigating the effects of credit restrictions on the innovative activity of firms, it often is impossible to consider problems caused by the existence of forward looking adjustments in a world of expectations, unobserved heterogeneity, or mutual causation.

This paper contributes to the literature by using a novel dataset to solve these issues and moreover to analyse aspects which until now have not been taken into account. First, the dataset provides – unlike other datasets – both direct information on the existence of credit constraints as well as direct information on the beginning of an innovation activity. This helps to avoid the drawbacks we had until now by using indirect measures. Secondly, the design of the survey questions and the panel structure of the dataset give us the possibility of avoiding issues like unobserved heterogeneity or mutual

[1]Most prominent indirect measures are different cash flow ratios of a company as inverse proxies for the degree of the credit restrictions the firm is facing and the investment in R&D as proxy for the innovative activity of the firm.

[2]For example, R&D activities are only one input factor to the innovation process and all innovations do not necessarily stem from R&D. Furthermore and more severely, the measure on the degree of credit restrictions is also an indirect one. In this context especially the use of cash flow ratios as proxies for the financing condition of a firm is questioned the last years (see Kaplan and Zingales (1997), Alti (2003)).

causation between dependent and independent variables. Third, due to the availability of variables like the expectations of a firm concerning the future business situation we can also deal with problems usually difficult to solve such as forward looking adjustments in a world of expectations. Finally, the unique possibility to distinguish between "normal", "good" and "bad" credit conditions allows to analyse if there exist asymmetries in the effects of above average and below average credit conditions.

The results give – unlike those of many other papers – strong evidence that credit constraints restrict innovative activity. Moreover, the results provide evidence for asymmetries in the effects of above average and below average credit conditions. We show that bad credit conditions restrict innovative activity, whereas favourable conditions do not foster it. This novel result could support hypotheses, which state that a firm's innovation capacity plays an important role in its innovation behaviour. To strengthen this thesis we expand the usual theory of innovation activity by rigidities with respect to a firm's individual innovation capacity, which leads to a differentiation between a long run and a short run equilibrium in innovative output.

The remainder of the paper is organized as follows. Section 2 provides the conceptual framework for the analysis. Section 3 presents some information about the survey dataset used in the paper. Section 4 describes our empirical specification and methodology. Section 5 presents the estimation results. Section 6 concludes.

2 Conceptual Framework

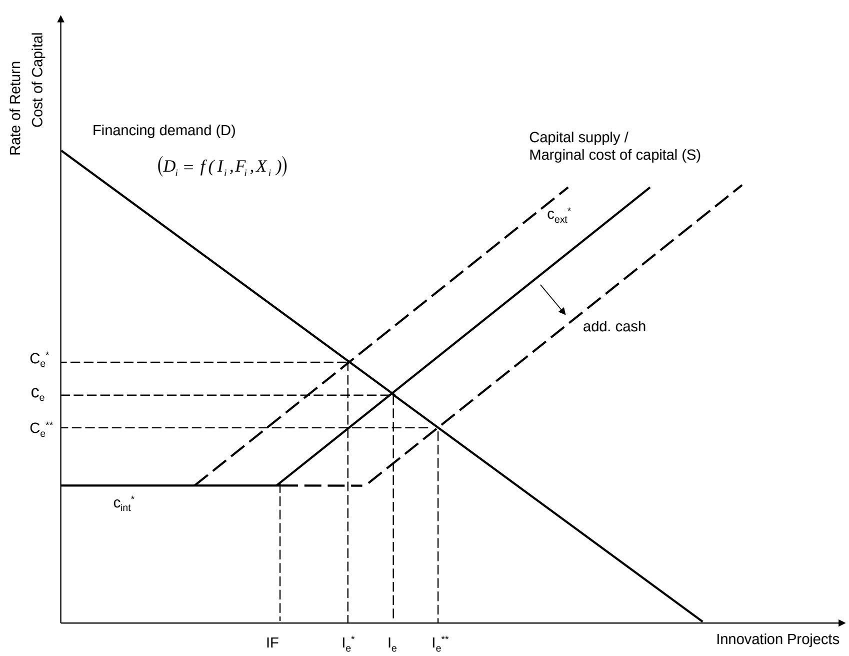
To relate our empirical investigations to theory we use a standard model, which analyses the effects of financing conditions on innovative activity.[3] Subsequently, the model is extended by taking into account the rigidities with respect to a firm's individual innovation capacity.

Figure 1 provides the standard model, which is hereafter referred to as "long run equilibrium model". D_i is the capital demand curve of the firm, representing the marginal revenues of capital depending on the level of innovative

[3]The model inter alia is used by Howe and Mc Fetridge (1976), Carpenter and Petersen (2002), and Hottenrott and Peters (2009).

output. The marginal revenues of capital depend on the level of innovation expenditures I_i, firm specific characteristics F_i and industry characteristics X_i. The capital demand curve therefore is defined as $D_i = f(I_i, F_i, X_i)$. S_i is the capital supply curve for the company, representing the marginal costs of capital depending on the level of innovative output. As there are two sources of capital supply – internal as well as external sources – we assume a pecking order. This means that the firms first will use their internal funds IF_i. Afterwards they will start to obtain external financing, with a positive relationship between the amount of capital and marginal costs. The intersection of the supply and the demand curves constitutes the equilibrium innovative output I_e. In this setting, a decrease in the financing conditions, represented by a shift of the supply curve to the left, will lead to higher marginal costs in equilibrium and lower innovative output. On the other hand, increasing financing conditions, represented by a shift of the supply curve to the right, will lead to lower marginal costs in equilibrium and higher innovative output.

Figure 1: Long Run Equilibrium

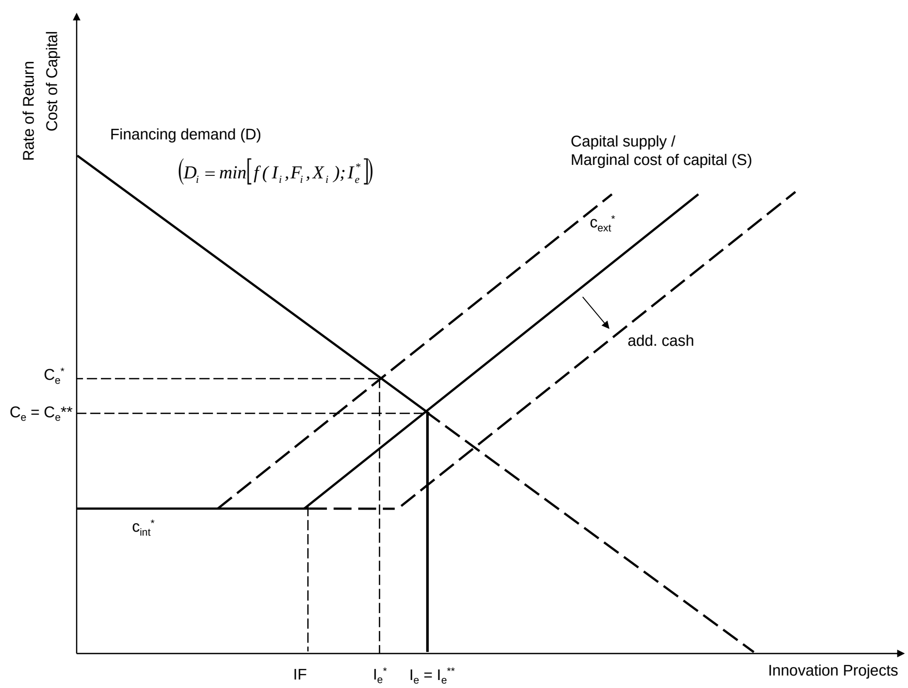


To underpin our novel findings at the empirical level – the existence of asymmetries in the effects of above average and below average financing conditions – we now distinguish between the long run equilibrium provided above and a short run equilibrium derived below. By this means we introduce the concept of innovation capacity and short term rigidities with respect to the adjustment of the level of input factors to R&D. The individual innovation capacity is defined as the number of potential innovative projects the firm is able to produce over a certain period. It may for example be determined by the amount of input factors to R&D – such as the number of researchers allocated to R&D, their level of know-how or the quality of the technical equipment related to R&D. How much of these input factors a company accumulates then again depends on the firm's individual capital costs and is determined in the long run equilibrium (see Figure 1). In the long run the firm will choose its level of input factors to R&D and accordingly its innovative capacity such that it can produce exactly I_e of potential innovation projects. If it produces on average less than I_e potential projects, this is inefficient as in the long run some projects with positive net marginal revenues cannot be undertaken. If it produces on average more than I_e potential projects, it is inefficient as in the long run not all these projects can be undertaken, because the financing costs are too high.

However, by introducing adjustment rigidities with respect to the input factors to R&D, the implications of the model differ from before. Specifically, and in contrast to the long run equilibrium model, the firms now are facing a demand function of $D_i = min[f(I_i, F_i, X_i]); I_e{}^*]$. This means that we now observe a demand curve, which is kinked at point I_e (see Figure 2). By this we take into account that – due to the presence of the adjustment rigidities introduced in the model – in the short run the innovative output cannot be increased above its maximum level (which is determined by the firm's innovative capacity, its long run equilibrium I_e). As one can see, a decrease in the financing conditions, represented by a shift of the supply curve to the left, again will lead to fewer potential innovation projects being undertaken. However, unlike in the previous example, an increase in financing conditions, represented by a shift of the supply curve to the right, now has no positive effect on the level of innovative output, as the maximum level of potential innovative projects is limited to I_e.

This leads to the result we find in our empirical investigations: a decrease in financing conditions decreases innovative activity, while an increase will not foster it (in the short run).

Figure 2: Short Run Equilibrium



3 Data

To perform our analysis we use data from two sources: the Ifo innovation survey and the Ifo business tendency survey for German manufacturing firms.[4] As the surveys include questions which are asked on different frequencies, we will transform all variables that are used to the lowest frequency (annual) where necessary.

[4]Both datasets are provided by the Economics & Business Data Center (EBDC), a combined platform for empirical research in business administration and economics of the Ludwig-Maximilian University of Munich (LMU) and the Ifo Institute for Economic Research.

The Ifo innovation survey is performed once a year. The survey inter alia asks the firms,[5] if they have "started or continued" an innovation process during the last year. As the survey additionally provides information as to whether the company has "finished" or "stopped" an innovation process, we can correct for years where the company only continued an innovation process.[6] Innovations are categorized as either product or process innovations. The resulting variables are *"productinnov"*, which is coded 1 if a product innovation has started in the corresponding year, and 0 otherwise, and *"processinnov"*, which is coded 1 if a process innovation has started in the corresponding year, and 0 otherwise.

The Ifo business tendency survey is carried out monthly and contains questions asked at different frequencies. One of these questions regards the financing conditions the firms are facing and is included in the survey biannually. The answers are coded as -1 ("favourable financing conditions"), 0 ("normal financing conditions"), and +1 ("reserved financing conditions"). This data is aggregated on a yearly base by taking the average of the values of the variable for every year. The variable *"credit"* resulting from this can be interpreted as the average credit condition over the year. It can take the values 1, 0.5, 0, -0.5, or -1. For example, 1 indicates that the company reported below average financing conditions at both inquiry dates of the year and -1 indicates that the company reported above average financing conditions at both inquiry dates of the year.[7]

[5] Note that each ID-number of the dataset is representing a single production entity for a single product of the firm rather than the whole firm. This aspect is a further advantage of the data set as it allows a more detailed analysis for multi-product firms. However, for simplicity, in the following we will refer to the particular unit of observation as "firm".

[6] To correct the original variable for values indicating only a continuation of an innovation process we proceed as follows. The value of the variable at time t will be converted from 1 to 0 (i.e. the value of 1 of the variable is indicating a continuation rather than the start of an innovation process), if there was a start or continuation of an innovation project in the preceding year (and no finish or stop of an innovation process), and concurrently no finish or stop of an innovation process in the current period (to prevent that a new innovation process was started after finishing or stopping another process within the same year). The possibility that there exist multiple product or process innovations at the same time is mostly prevented by the fact that each ID-number of the dataset represents a single production entity for a single product of the firm rather than the whole firm. However, the estimations using the data set without the correction provide qualitatively the same results (results available upon request).

[7] Furthermore, a value of 0.5 indicates that the corresponding firm reported a below

Furthermore, the Ifo business tendency service consists of questions on the overall business situation of the firm (*"situat"*) and on the overall expectations of the firm (*"expect"*)[8]. The answers to the question regarding the business situation of the firm are coded as -1 ("bad business situation"), 0 ("normal business situation"), and +1 ("good business situation"). The answers to the question regarding the firms' expectations are coded as -1 ("expectations worsen"), 0 ("expectations remain constant"), and +1 ("expectations increase"). As the questions on the business situation and the expectations of the companies are asked every month, they also have to be aggregated on a yearly base. We do this by again taking the average of the values of the variables for every year. Moreover, we can relate to the size of a company in terms of its market power (*"mkp"*), which is defined as the number of employees per firm divided by the number of employees in the firm's branch.

Additionally, each firm is allocated to one of the following 14 manufacturing subsectors: Food, Beverages and Tobacco; Textiles and Textile Products; Tanning and Dressing of Leather; Cork and Wood Products except Furniture; Pulp, Paper, Publishing and Printing; Refined Petroleum Products; Chemicals and Chemical Products; Rubber and Plastic Products; Other Nonmetallic Mineral Products; Basic and Fabricated Metal Products; Machinery and Equipment; Electrical and Optical Equipment; Transport Equipment; Furniture, Manufacture. Furthermore, each firm is allocated to one of the following regions in Germany: East Germany, West Germany, South Germany and North Germany.[9]

We use data for the period from 2003 to 2007. The dataset is organized as

average financing condition at one inquiry date of the year and normal financing conditions at the other inquiry date of the year. Correspondingly, a value of -0.5 indicates that the corresponding firm reported an above average financing condition at one inquiry date of the year and normal financing condition at the other inquiry date of the year. If the variable takes the value 0, the companies mostly have reported normal financing conditions at both inqiry dates. The situation that a company has reported above average financing conditions at one inquiry date of the year and below average financing conditions at the other inquiry date of the year, represented by a value of 1, accounts only for a small minority of cases (34 out of 2898 cases, representing 1.17% of the whole sample).

[8] The variable refers to the expectations the firms are facing with respect to the following 6 months.

[9] A more detailed overview about the questionnaire and the survey variables can be found in Becker and Wohlrabe (2008).

an unbalanced panel. The total number of observations is about 3,000.

4 The Model

4.1 Specification

To identify possible effects of credit restrictions on the innovative activity of firms we specify the latent variable y_{it} underlying this probit model as

$$y_{it}^* = \alpha_{it} + \beta_1 credit_{it} + \beta_2 expect_{it} + \beta_3 situat_{it} + \beta_4 mkp_{it} + \\ + \beta_5 exit_{it} + \beta_6 B_{it} + \beta_7 L_{it} + \beta_8 T_{it} + u_{it}.$$

In our first specification, y_{it} is a dummy variable with value 1, if firm i started an innovation project (product or process innovation) at time t, and 0 otherwise. In our second and third specifications we distinguish between product and process innovations. Specifically, we estimate a second model where y_{it} is a dummy variable with value 1, if firm i started a product innovation project at time t, and 0 otherwise. Similarly, we estimate a third model where y_{it} is a dummy variable with value 1, if firm i started a process innovation project at time t, and 0 otherwise.

The variable *"credit"* represents the financing conditions the firm is facing. The higher the value of the variable, the worse the financing conditions over the year. It is important to note that the innovation question in the survey refers to the start of an innovation activity rather than the achievement of an innovation. From this it follows that the variable is included contemporaneously, as it is highly likely that the timing of the financing of an innovation project is assigned closely to the actual beginning of an innovation activity. To identify any asymmetries in the effects of "worse than average" and "better than average" financing conditions, we provide alternative specifications where we split the variable *"credit"* into two dummy variables. In particular, we create one dummy variable which is coded 1 if the financing conditions over the year were worse than normal and 0 otherwise (*"creditdif"*). Likewise, we create a second dummy variable which is coded 1 if the financing conditions over the year were better than normal and 0 otherwise (*"crediteas"*).

Furthermore, a firm's decision to start an innovation project very likely is influenced by its expectations. As our dataset includes information about the firm's expectations, we have the almost unique possibility to control for this aspect. Consequently, the variable *"expect"* is introduced, representing the change in expectations of the firm over the year. The higher the value of the variable, the more the expectations of the company increased over the year. As the variable *"credit"*, the variable *"expect"* is included contemporaneously as a firm will take into account the actual rather than the past expectations when deciding to start an innovation project.

Moreover, to capture the effects of firm-specific developments we control for the actual business situation of the firm. The business situation of the firm is represented by the variable *"situat"*, which increases as the business situation over the year improves. Similarly to the two preceding variables *"credit"* and *"expect"*, the variable *"situat"* is included contemporaneously for the same reasons. Beside this, we introduce the variable *"mkp"*, which represents the size of the firm in terms of its relative number of employees compared to the competitors of its branch. This variable is of potential interest as the literature shows a clear positive relationship between the market power and the level of innovative activity of a firm.

In addition, we control for certain other firm characteristics. To account for a heterogeneous level of innovation activity between firms of different branches we include vector B_{it}, a set of 13 dummy variables which indicate the affiliation of the firm to a specific branch.[10] For similar reasons – heterogeneity in the innovation activity of companies of different regions – we include a further set of dummy variables, represented by vector L_{it}, which consists of 3 dummy variables indicating the region the company is allocated to.[11] Finally, to take account of possible changes of innovative behaviour over time due to major technological or structural developments, we introduce vector T_{it}, which consists of 4 time dummies representing the years 2004 to 2007.[12]

Finally, we have to address a possible sample selection bias due to attrition.[13] Some companies initially included in the survey were discharged from the sur-

[10] The baseline branch is the branch "Machinery and Equipment".
[11] The baseline region is North Germany.
[12] The baseline year is the year 2003.
[13] See Heckman (1979), Smolny (1998).

vey over time. The main reasons for discharge usually are that the company is no longer interested in taking part in the survey, that the company was taken over by another firm or that the company went bankrupt. If the exit of the companies is not random and there exist some common underlying reasons that the companies left the survey – e.g. bad overall performance – there could be some source of sample selection bias in our estimations. In order to ease this problem we include the dummy variable (*"exit"*), which indicates if a firm has left the survey or not, thereby capturing firm specific common characteristics of those firms which were discharged from the survey (see Smolny (1996)).

4.2 The Aspect of Endogeneity

As in most analyses, one major point to address is that of endogeneity in its various forms. This short section deals with this aspect. Specifically, it lists the different potentially relevant types of endogeneity, discusses how they are related to our analysis and how the analysis deals with these different types, if necessary.

The first source of endogeneity is unobserved heterogeneity. As our data is organized as a panel dataset we can control for this by applying a fixed effects or random effects panel estimator. In this context one has to note that the design of the questions in our survey is such that by nature of the questions firm fixed effects are eliminated.[14] This leaves α_{it}, representing the firm-specific effects, uncorrelated with our independent variables and leads us in our first regression to the use of a random effects model, thereby avoiding the incidental parameter problem commonly present when applying fixed effects estimators in short panels (Newman and Scott (1948), Hausman et al. (1984)).

The second source of endogeneity possibly relevant is simultaneity between the response variable and our explanatory variables. For example, it might

[14] The survey asks for the financing conditions and the business situation compared to their normal firm-specific levels (normal, better than normal, worse than normal), which by definition eliminates the firm fixed effects with respect to these variables (similarly to a within-transformation). Furthermore, the survey asks for the change in business expectations on an ordinal scale (increase/decrease/no change of business situation), which also rules out any firm fixed effects concerning this variable.

not only be possible that the firm's decision to innovate is influenced by the firm-specific financing conditions, but also that the firm-specific financing conditions are influenced by the firm's decision to innovate. We can control for this by again using the panel structure of our dataset. In particular, we apply a two stage least squares instrumental variable probit estimator, which allows us to instrument our explaining variables by their first lags.

Finally, when estimating our models for the start of process and product innovations separately, we have to consider the possible simultaneity of these two decisions. Specifically, there exists the possibility that the decision of starting a product innovation is made conditional on the decision of starting a process innovation and vice versa. To take into account this potential mutual dependency we additionally estimate a bivariate probit model when dealing with these variables.

5 Results

Table 1 provides the results of our random effects probit panel estimator. The estimations show how financing conditions relate to the probability of starting an innovation project (product or process innovation project) for a firm in the corresponding year.

First, when including our original measure of the credit situation in Specification 1 we can observe a clearly significant and negative relationship between worsening financing conditions and the probability that a firm will start an innovative activity. The worse the financing conditions (the higher the value of our variable *"credit"*), the smaller the probability that the firm will start an innovation project in the corresponding year.

Secondly, when splitting our financing conditions measure into above average (*"creditdif"*) and below average (*"crediteas"*) financing conditions and replacing our original variable on the financing conditions with these new variables, we can observe some asymmetries. The results, presented in Columns 2-4 of Table 1, show that financing conditions which were worse than normal (*"creditdif"*=1) indeed have some negative effect on the probability that a firm will start an innovative activity. In contrast, financing conditions which were better than normal (*"crediteas"*=1) apparently do not have a positive effect. This is in contrast to the standard theory, which suggests that a decrease in financing conditions decreases innovative activity and vice versa.

Table 1: Innovation

	Innov – Binary Panel Regression (1)	(2)	(3)	(4)
credit	-0.189 **	-	-	-
	(0.076)			
creditdif	-	-0.223 **	-	-0.214 **
		(0.084)		(0.085)
crediteas	-	-	0.125	0.066
			(0.122)	(0.124)
expect	0.187 *	0.190 *	0.183 *	0.188 *
	(0.107)	(0.106)	(0.107)	(0.107)
situat	0.293 ***	0.295 ***	0.328 ***	0.292 ***
	(0.086)	(0.085)	(0.085)	(0.086)
mkp	1.666 ***	1.698 ***	1.685 ***	1.702 ***
	(0.527)	(0.527)	(0.527)	(0.528)
branch	yes	yes	yes	yes
region	yes	yes	yes	yes
time	yes	yes	yes	yes
exit	yes	yes	yes	yes
Log-Lik.	-1580.86	-1580.43	-1583.44	-1580.29
Observ.	2898	2898	2898	2898

***: $p < 0.01$; **: $p < 0.05$; *: $p < 0.1$. Standard errors in paranthesis.

As discussed in Section 4, some potential bias due to an endogeneity problem still could be present. To prove that our results are not driven by this aspect we provide an instrumental variable estimation, where we tackle this issue. Specifically, we apply a two stage least squares probit instrumental variable estimator as an additional robustness check. Our potential endogenous variables, the variables on the financing conditions, the variable on the state of the business and the variable on the change in the expectations of the firm, are instrumented by their first lags. For all these instruments the first stage regressions indicate that they are significant and strong instruments.[15] The results of the second stage regression, presented in Table 2, support the findings of our preceding estimations.

In Column 1 of Table 2 we again can observe a clearly negative and significant effect of worsening financing conditions on the innovative activity of a firm.

[15]Results of the first stage regressions available upon request.

Furthermore, the results again provide clear evidence for the existence of asymmetries in the effects of above average and below average financing conditions on the innovative activity of a firm. As before we find that below average financing conditions do restrict innovative activity, whereas above average financing conditions do not foster it.

Table 2: Innovation

	Innov – Binary IV Regression			
	(1)	(2)	(3)	(4)
credit	-0.297 **	-	-	-
	(0.134)			
creditdif	-	-0.430 **	-	-0.494 **
		(0.174)		(0.213)
crediteas	-	-	0.002	-0.233
			(0.384)	(0.438)
expect	0.416 **	0.393 **	0.385 **	0.389 **
	(0.345)	(0.166)	(0.165)	(0.166)
situat	0.485	0.157	0.309 **	0.171
	(0.271)	(0.134)	(0.130)	(0.136)
mkp	1.094	0.875	0.778	0.865
	(0.848)	(0.588)	(0.580)	(0.590)
branch	yes	yes	yes	yes
region	yes	yes	yes	yes
time	yes	yes	yes	yes
exit	yes	yes	yes	yes
Log-Lik.	-764.19	-1580.43	-1583.44	-1580.29
Observ.	1489	1489	1489	1489

***: $p < 0.01$; **: $p < 0.05$; *: $p < 0.1$. Standard errors in paranthesis.

One further feature of our dataset is the possibility to distinguish between product and process innovations. This allows us to provide some additional robustness checks by performing our analysis for the two kinds of innovative activity separately. Specifically, we can examine if the previous results hold when distinguishing between process and product innovations. Table 3 provides the results of our random effects panel estimator for both kinds of innovative activity. Table 4 provides the results of our two stage instrumental variable estimator.[16] As already mentioned in Section 4, when distinguishing

[16] Again, also here the first stage regressions indicate our instruments are significant and strong instruments. As before, the results of the first stage regressions are available upon request.

between the decision to start a product innovation and the decision to start a process innovation, we have to consider in addition the possible simultaneity of the two decisions. Therefore, to account for the potential dependency of the two decisions, in Table 5 we provide the results of our bivariate probit estimator.

Columns 1-4 of each table provide the results regarding the probability to start a product innovation project, Columns 5-8 of each table provide the results regarding the probability to start a process innovation project. However, one can see that for both kinds of innovative activity the outcomes again support our previous findings. All estimations show a clearly significant and negative relationship between worsening financing conditions and the probability that the firm will start a product or process innovation project, respectively. Furthermore, the results show that below average financing conditions have a negative effect on the engagement in product as well as process innovation activity and that above average financing conditions do not foster it, thereby again supporting previous findings and conclusions.

Table 3: Product/Process Innovation

	Productinnov – Binary Panel Regression				Processinnov – Binary Panel Regression			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
credit	-0.229 ***	-	-	-	-0.190 **	-	-	-
	(0.076)				(0.075)			
creditdif	-	-0.244 ***	-	-0.233 ***	-	-0.187 **	-	-0.165 *
		(0.084)		(0.085)		(0.083)		(0.085)
crediteas	-	-	0.145	0.080	-	-	0.213 *	0.166
			(0.122)	(0.123)			(0.121)	(0.122)
expect	0.193 **	0.200 **	0.235 ***	0.196 **	0.298 ***	0.306 ***	0.328 ***	0.299 ***
	(0.085)	(0.084)	(0.084)	(0.085)	(0.084)	(0.084)	(0.083)	(0.084)
situat	0.272 **	0.275 **	0.265 **	0.273 **	0.033	0.036	0.028	0.031
	(0.107)	(0.107)	(0.108)	(0.107)	(0.105)	(0.105)	(0.105)	(0.105)
mkp	0.907 *	0.939 *	0.939 *	0.944 *	1.136 **	1.159 **	1.172 **	1.171 **
	(0.484)	(0.483)	(0.486)	(0.483)	(0.459)	(0.459)	(0.461)	(0.460)
branch	yes	yes	yes	yes	yes	yes	yes	yes
region	yes	yes	yes	yes	yes	yes	yes	yes
time	yes	yes	yes	yes	yes	yes	yes	yes
exit	yes	yes	yes	yes	yes	yes	yes	yes
Log-Lik.	-1501.75	-1502.08	-1501.87	-1505.58	-1376.95	-1377.63	-1378.58	-1376.71
Observ.	2898	2898	2898	2898	2898	2898	2898	2898

***: $p < 0.01$; **: $p < 0.05$; *: $p < 0.1$. Standard errors in paranthesis.

Table 4: Product/Process Innovation

	Productinnov – Binary IV Regression				Processinnov – Binary IV Regression			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
credit	-0.301 **	-	-	-	-0.425 ***	-	-	-
	(0.146)				(0.157)			
creditdif	-	-0.457 **	-	-0.448 **	-	-0.591 ***	-	-0.669 ***
		(0.177)		(0.217)		(0.190)		(0.234)
crediteas	-	-	0.245	0.033	-	-	0.032	-0.283
			(0.386)	(0.439)			(0.422)	(0.485)
expect	0.155	0.124	0.248 *	0.122	0.162	0.141	0.341 **	0.155
	(0.136)	(0.136)	(0.132)	(0.139)	(0.145)	(0.146)	(0.141)	(0.148)
situat	0.297 **	0.291 *	0.288 *	0.291 *	0.338	0.329 *	0.317 *	0.325 *
	(0.168)	(0.169)	(0.168)	(0.169)	(0.180)	(0.181)	(0.179)	(0.182)
mkp	-0.156	-0.102	-0.151	-0.100	1.062 *	1.140 *	0.999 **	1.136 *
	(0.654)	(0.658)	(0.647)	(0.659)	(0.591)	(0.596)	(0.585)	(0.600)
branch	yes	yes	yes	yes	yes	yes	yes	yes
region	yes	yes	yes	yes	yes	yes	yes	yes
time	yes	yes	yes	yes	yes	yes	yes	yes
exit	yes	yes	yes	yes	yes	yes	yes	yes
Observ.	1489	1489	1489	1489	1489	1489	1489	1489

***: $p < 0.01$; **: $p < 0.05$; *: $p < 0.1$. Standard errors in paranthesis.

Table 5: Product/Process Innovation

	Productinnov – Binary Bivariate Regression				Procesinnov – Binary Bivariate Regression			
	(1a)	(2a)	(3a)	(4a)	(1b)	(2b)	(3b)	(4b)
credit	-0.202 ***	-	-	-	-0.190 ***	-	-	-
	(0.051)				(0.053)			
creditdif	-	-0.234 ***	-	-0.231 ***	-	-0.222 ***	-	-0.215 ***
		(0.057)		(0.058)		(0.059)		(0.060)
crediteas	-	-	0.092	0.021	-	-	0.114	0.049
			(0.085)	(0.087)			(0.086)	(0.088)
expect	0.149 ***	0.153 ***	0.196 ***	0.151 ***	0.236 ***	0.240 ***	0.278 ***	0.236 ***
	(0.054)	(0.054)	(0.053)	(0.054)	(0.057)	(0.056)	(0.056)	(0.057)
situat	0.228 ***	0.229 ***	0.224 ***	0.229 ***	0.081	0.081	0.078	0.081
	(0.069)	(0.069)	(0.068)	(0.069)	(0.072)	(0.072)	(0.072)	(0.072)
mkp	0.740 **	0.763 **	0.763 **	0.765 **	0.826 ***	0.846 ***	0.849 ***	0.850 ***
	(0.326)	(0.329)	(0.323)	(0.329)	(0.315)	(0.312)	(0.317)	(0.312)
branch	yes	yes	yes	yes	yes	yes	yes	yes
region	yes	yes	yes	yes	yes	yes	yes	yes
time	yes	yes	yes	yes	yes	yes	yes	yes
exit	yes	yes	yes	yes	yes	yes	yes	yes
Log-Lik.	-2760.19	-2759.13	-2768.59	-2758.98	-2760.19	-2759.13	-2768.59	-2758.98
Observ.	2898	2898	2898	2898	2898	2898	2898	2898

***: $p < 0.01$; **: $p < 0.05$; *: $p < 0.1$. (Robust) standard errors in paranthesis.

6 Summary and Conclusion

In this paper we have analysed the effects of financing conditions on the innovative activity of firms. In contrast to other literature we were able to use direct measures for the innovative activity of the firms as well as for the financing conditions the firms were facing. By this means we were able to avoid problems of indirect measures like some cash flow ratios or R&D investments as proxies for these two variables. Furthermore, the dataset gave us the possibility to control for the business expectations of a firm – due to the existence of forward-looking adjustments in a world of expectations an important determinant of the innovative activity of the firm. In addition, the characteristics of the dataset and the design of the survey questions allowed us to avoid endogeneity issues caused by unobserved heterogeneity or mutual causation, which commonly are present in the literature. Moreover, the possibility to differentiate between "worse than average" and "better than average" financing conditions allowed us to analyse potential asymmetries in the effects of "below average" and "above average" financing conditions.

The results gave – as opposed to many other papers – strong evidence that credit constraints do restrict the innovative activity of firms. More interestingly, the results showed asymmetries in the effects of below average and above average financing conditions. We found that below average financing conditions restrict innovative activity, whereas above average financing conditions do not foster it. The novel second result on the existence of asymmetries has interesting implications. It gives strong evidence for considerations raised in more recent literature that the individual innovation capacity of a firm plays an important role in its innovation activity. To additionally support our findings we have extended the usual theory of innovation activity to take into account rigidities with respect to a firm's individual innovation capacity, which leads to a differentiation between a long run and a short run equilibrium in innovative output.

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