Discussion Paper No. 02-73

Measuring the Impact of Innovation on Firm Value: A New Approach

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Non-technical Summary

Most of the existing studies concerning the effect of innovative activity on firm value use the evaluation of the firm by the stock market. The advantage is the evaluation of the firm's potential by many participants and therefore a bundling of information. The disadvantage is that this method works only for joint-stock companies which is a small and not representative subsample of all companies in an economy. The second, but less popular method is to calculate the relation between R&D, patents or innovations and profits. The advantage here is that exact information on the return is used. The disadantage is that long lags are necessary and accounting data on the financial situation is needed. Most firms are not obliged to publish such data.

We propose an alternative method: The calculation of the relation between innovative activity and credit ratings. We use three different measures of innovative activity: R&D, the patent stock and sales with recently developed products. We estimate Ordered Probit models: first, with the three measures separately and then with all included in one equation. The measures of innovation are significantly influencing the credit rating in all cases. We find a non-linear relationship: some innovative acitivity raises the credit rating, but too much innovativeness has a negtativ impact. Most likely the risk involved with any innovative activity is the cause for this result. Hence, in our view optimal innovative activity has to find the best compromise between the risk of failure and growth potential. A "moderate" level of innovative activity is optimal for firms future prospects and therefore also for the firm value.

Tests with alternative econometric specifications support the results. The control variables have the expected effect and have usually significant coefficients. Younger firms have worse ratings and rating improves with firm size.

Measuring the Impact of Innovation on Firm Value: A New Approach[1]

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November 2002

Abstract

Most of the existing empirical literature on the relationship of firm value and knowledge capital is based on the stock market valuation of companies. However, the assets of many firms are not publicly traded, and hence the calculation of market value is limited to a subsample of firms. We suggest to use a credit rating score instead and present an empirical analysis. It turns out that innovative firms, i.e. those with a reasonable knowledge stock, have a better credit rating and thus, as we propose, a higher value. However, too much of innovative activities is seen as risky and the firm value decreases.

Keywords: Firm Value, Credit Rating, Innovation, Intellectual Property Discrete Regression Models

JEL-Classification: C25, O31, O33

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[1] We would like to thank Bronwyn H. Hall, Georg Licht and Christian Rammer for helpful comments. Moreover, we are grateful to the MIP-Team for providing the survey data, to Jürgen Moka for extracting information from the Creditreform database and to Thorsten Doherr for processing the data on patent counts.

1 Introduction

Since many years, the relationship between innovation and economic return is frequently discussed in economic literature. Among others, one approach is to relate the valuation by financial markets on a firm's assets to measures of innovation (see Hall, 2000, for a survey). This approach has some advantages over the analysis of profits or productivity growth. First, the financial market valuation avoids problems of time lags between cost and revenues. Second, it is capable of forward looking evaluation and, finally, one can compare the economic impact of various measures of innovation.

The disadvantage of the market approach is that it is "[...] intrinsically limited in scope, because it can be used only for private firms and only where these firms are traded on a well functioning financial market [...]" (Hall, 2000, p. 177). The majority of companies is not publicly traded at the stock market and additionally this sample is hardly representative because usually only large firms are joint-stock companies. Therefore, we propose a complementary approach to the evaluation by the stock market: the evaluation by a leading credit rating company. Credit ratings are clearly important for all firms in an economy and therefore the number of firms which could be analyzed is much larger than if only joint-stock companies are considered and it is also representative for the economy as a whole. On the background of the New Basel Capital Accord[2], the relevance of such ratings will even increase in the future. We explore the effect of different innovation measures on the credit rating of the largest rating agency in Germany.

2 Theory

A popular approach to measure the effect of innovativeness on the present value of firms' future profits is to estimate the market value of the firm via stock market data (see Griliches, 1981 as the seminal paper for this strand of literature, Hall, 2000, for a survey or Toivanen et al. 2002 for a recent study). The advantage of the market value model is the evaluation by the stock market with many participants and therefore a bundling of information and expectations. A further advantage compared to data from annual accounts, e.g. profits, is that the problems of timing of costs and revenues and other effects of accounting rules and accounting policies do not matter.[3]

A second strand of literature estimates the returns to innovation directly. Mansfield et al. (1977), Jaffe (1986)[4], Geroski et al. (1993), estimate the effect of innovation on profits (with different approaches). The advantage is clearly that the economic effect can be quantified exactly. Disadvantages are that accountig data have to be used and that the long lag structure of R&D, for example, makes such a quantification rather complicated.

[2] Cf. e.g. Secretariat of the Basel Committee on Banking Supervision (2001).

[3] See Fisher and McGowan (1983) for problems associated with the use of accounting data.

[4] Jaffee (1986) uses both profits and Tobin’s q.

We propose another assessment of firm values as a complement to existing approaches: The credit rating of companies. The obvious advantage is that almost every firm which is looking for either bank loans or supplier credits is rated. The data basis is much broader and a selectivity effect, if still present at all, is clearly smaller than if only stock companies are considered. Similarly to the studies based on stock market evaluation of firm values, accounting practices do not distort the rating and lags are of minor importance.[5] The disadvantage is that not thousands of participants evaluate a firm's value as in the stockmarket, but a single credit rating company. However, due to the New Basel Capital Accord ratings become standardized worldwide.

The firm value is expected to reflect the value of both tangible assets and intangible assets, in particular the stock of innovative knowledge, i.e. the intangible assets created by R&D activity. The effect of innovative activity on the credit rating of a firm might be ambigous. A rating takes into account business and financial risks, like industry characteristics, competitive position, management, productivity, profitability, liquidity as well as financial policy and flexibility. Thus a rating reflects both currently observable firm characteristics and expectations on future developments.

The statement that innovative activity is a risky undertaking is close to a triviality. Risk is expected to affect the credit rating negatively, as the lender faces a higher probability of failure (of the whole firm). On the other hand, innovation is a driving force for economic success of a company and therefore an innovative firm may achieve a good credit rating. There might well be an internal optimum which means that “some“ R&D expenditures are useful, but too much innovative activities are not maximizing the discounted present firm value. Thus a 'moderately' successfully innovating firm is expected to have high revenues and a good financial performance. The credit rating will probably respond stronger to the result of innovative activity than to the input. Although innovation measures do not influence the rating directly, a credit rating agency could indirectly react to innovative activity because of the economic success (or failure).

One aim of this paper is the separation of different stages in the innovation process: We differentiate between investment in uncertain research projects (R&D expenditures), the intermediate output of research projects (stock of patents) and the success of new products at the market (share of sales with newly developed products).

3 Empirical Study

The data basis for our research is the Mannheim Innovation Panel (MIP) which is an annual German innovation survey conducted by the Centre for European Economic Research (ZEW) since 1992 on behalf of the Federal Ministry of Eduction and Research (BMBF). We use data from 1992 to 1998 of the manufacturing sector. The sample is restricted to Western German firms.

[5] We explain below why we use a one-period lead of the rating, but in principle, if it reacts at all, the rating should measure the firm value but not only present profits.

The information from the MIP is merged with the database of "Creditreform" which is the largest German credit rating agency. This database contains a credit rating of most firms in Germany. However, the credit rating is not regularly renewed, e.g. annually, but the agency enquires 'on demand', especially in case of small firms. Therefore, we cannot use all observations of the MIP, but only those, for which a credit rating is available in the corresponding year. The resulting sample after merging the two databases comprises of 5,305 observations at the firm level. The credit rating is an ordered variable with 5 categories:

1) not sufficient, 2) weak, 3) average, 4) good, 5) very good.

The dependent variable takes values from zero to four and is specified as a one-period lead. On one hand, the lead is used to ensure that the causality is running from innovativness to the rating, i.e. firm value. On the other hand, the rating agency will presumably need some time to react on changes in firm activities. Our innovation measures are calculated as follows:

- R&D intensity (R&D expenditure divided by total sales volume): In other studies, a knowledge stock is usually considered as stock of R&D calculated by the perpetual inventory method from a time series of annual expenditures. In our case, we do not have the required information to do so. Therefore, we only consider present R&D expenditure in relation to sales. Due to the high adjustment cost of R&D activities, the current expenditure is expected to represent a good proxy-variable for the R&D stock.
- The stock of patents (divided by sales) as an indicator of knowledge stock: In contrast to R&D, we have long time series for patent applications. These information are taken from the database of the German Patent Office and are merged with the MIP. The stock is calculated by the perpetual inventory method from the time series of the number of patent applications, where we assume a 15% rate of depreciation for the knowledge stock (cf. Hall 1990 for further details). The initial values of the patent stock are set to zero in 1980 for all firms. As our observations on firms begin in 1992, the bias emerging from this assumption is negligible. If two or more applicants did jointly file a patent, we count the application for each of them, because the measure should reflect the knowledge stock. We assume that the knowledge behind a patent is available for all applicants. Recently, Hall et al. (2001) have also used patent citations as weight for the economic value of different patents. They show that using a citation-weighted patent stock performs better in regressions than the mere counts. However, patent citations are not available for our data (yet).
- Sales with newly developed products divided by total sales volume ("newly" means introduced to the market during the three recent years): This measure reflects the innovative output of the knowledge stock which has led to new products evaluated by the market.

We have experimented with quadratic functional forms of these innovation measures because there might well be an internal optimum for innovative activity. Firms attempt to maximize their present value but not innovativeness. Like many other activities, innovative activity has possibly decreasing returns opposed to constant costs per “unit of innovation“. If this is true, an optimal rate of innovation can in principle be determined and identified by the non-linear specification.

Of course, the rating is affected by other factors besides inovativeness. We include several control variables, which reflect the basic characteristics of a firm: total sales volume and its squared value (in Billion DM) to control for size effects. Sales are used instead of physical assets, because this is in line with the construction of the rating, in our case. Firm age (specified as the inverse of the firms age to allow for a nonlinear relationship) is an important variable as, for very young firms, the credit rating may also indicate the likelihood of survival but not only economic wealth. Moreover, lacking track history may yield worse ratings. The value added per employee (in Mio. DM) should control for productivity differences among firms. We have also experimented with different liability limiting legal forms. The only significant effect has the joint-stock company form, for which we include a dummy variable. Twenty-three industry dummies capture sectoral differences and six time dummies shift intertemporal changes. Descriptive statistics of the variables used (except time and industry dummies) are given in Table 1.

Table 1:
Descriptive statistics (5,305 observations)

	Mean	Std. Dev.	Min.	Max.
Credit Rating (one-period lead)	2.518	.679	0	4
Total Sales (in Billion DM)	.253	1.794	$6 \cdot 10^{-5}$	54.493
Value Added / No. of Employees	.135	.069	.008	.589
Age	47.071	40.483	0	198
Dummy for Joint-Stock Companies	.062	.242	0	1
R&D Expenditure / Sales (in Mio. DM)	.018	.037	0	.443
Patent Stock / Sales (in Mio. DM)	.081	.206	0	2.004
Share of Sales with New Products	.306	.258	0	1

First, we use the three measures of innovation separately because multicollinearity may pose a problem. Afterwards, all three different innovation measures are used simultaneously. The results of Ordered Probit estimations are presented in Table 2. When the measures of innovation are used separately, all three have a significant effect on the credit rating. In all cases, the squared values are also significantly different from zero and yield an inversely u-shaped relationship. In Model I, it turns out that the highest rating is achieved at about 14% of R&D intensity. The estimated optimal level of patent stock to sales is about 0.7 (Model II), but this number is difficult to interpret. The share with new products yields the best rating at 60% (Model III). A very high share of sales due to new products may be the result of an unsuccessful product portfolio, because the consumers do not buy the firm's older products. The control variables have the expected signs and are all significantly different from zero: sales have a positive but decreasing effect. A higher value added per employee yields a better credit rating and younger firms have worse ratings than others. Both time and industry dummies are (jointly) different from zero.

Table 2:
Results of Ordered Probit Estimations[a)] (5,305 observations)

Explanatory Variables:	Dependent Variable: Credit Rating (one-period lead) Model I	Model II	Model III	Model IV
Total Sales in Billion DM	.199*** (7.63)	.215*** (8.32)	.208*** (8.04)	.202*** (7.76)
(Total Sales in Billion DM)^2	-.004*** (-6.05)	-.004*** (-6.60)	-.004*** (-6.35)	-.004*** (-6.15)
Value Added in Mio. DM / Employees	2.914*** (11.73)	2.926*** (11.77)	2.874*** (11.55)	2.882*** (11.57)
1 / Age	-2.823*** (-13.37)	-2.769*** (-13.09)	-2.812*** (-13.31)	-2.781*** (-13.13)
Dummy for Joint-Stock Companies	.645*** (9.25)	.637*** (9.14)	.650*** (9.33)	.632*** (9.05)
R&D Expenditures / Sales	4.594*** (4.81)	/	/	2.795*** (2.72)
(R&D Expenditures / Sales)^2	-16.421*** (-3.96)	/	/	-10.950*** (-2.54)
Patent Stock / Sales	/	.823*** (4.63)	/	.635*** (3.47)
(Patent Stock / Sales)^2	/	-.563*** (-4.15)	/	-.462*** (-3.35)
Share of New Products	/	/	.833*** (4.66)	.668*** (3.64)
(Share of New Products)^2	/	/	-.696*** (-3.35)	-.580*** (-2.77)
Pseudo-R^2	.0965	.0964	.0971	.0993

a) All estimations include 23 industry dummies, 6 time dummies and 4 threshold parameters.
t-values in parentheses. *** (**,*) indicate a 1% (5, 10%) level of significance.

It might be argued that all three measures for innovation are correlated with each other and that the separate consideration is of limited use as there is a possible omitted variable bias. If, for example, R&D is positively correlated with the share of sales due to new products, but only R&D is included in the equation, a positive and significant coefficient might be estimated, although the credit rating possibly only reacts to the sales share. Therefore, in the second step all three measures as well as their squared values are used. The estimation results are given in Table 2, Model IV. The results of the separate regressions are confirmed: all measures are significantly different from zero and the optima are almost the same. In the appendix, we present some additional estimations: We provide the true values of the four threshold parameters instead of estimating those and we allow for heteroscedasticity. However, the results do not change.

4 Conclusion

This paper reports the results of an empirical study concerning the effects of innovative activity on credit ratings of firms. Previously, the effects of innovativeness have often been investigated by market valuation of firms present at the stock market, which is a small subsample of firms in the population. In constrast to this, the credit rating approach can be applied to almost all firms in the economy.

We consider three different measures of innovative activity: R&D, patent stock and the share of sales with newly developed products. All three measures have a significant impact on the credit rating. We find an inversely u-shaped relationship for all three variables with internal optima. The optima show that credit ratings increase until a rather high level of innovation is reached (i.e. 14% of R&D intensity; 0.7 patents per 1 million DM of sales; 60% sales-share with new products). However, too much innovation is regarded as being negative to the rating, because innovative activities are always subject to possible failures. But most innovating firms have better ratings and therefore better access to credit markets. This seems to be an interesting result in itself but also with respect to the discussion on credit rationing and on the New Basel Capital Accord.

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Appendix: Additional Econometric Estimates

The estimations presented in the paper are the results of ordered probit models (see e.g. Greene, 2000, p. 875-877). Let the latent model be

$$y_i^* = x_i^{'} b + e_i\,, \quad \text{with } i = 1, \ldots, N\,. \tag{1}$$

y_i^* is the unobserved dependent variable, x_i the set of regressors and e_i the error term. The observed credit rating is

$$y_i = \begin{cases} 0 \ \text{ if } \ y_i^* \le m_0, \\ 1 \ \text{ if } \ m_0 < y_i^* \le m_{1,} \\ 2 \ \text{ if } \ m_1 < y_i^* \le m_{2,} \\ 3 \ \text{ if } \ m_2 < y_i^* \le m_{3,} \\ 4 \ \text{ if } \ y_i^* > m_{3.} \end{cases} \tag{2}$$

m_k (k=0,...,3) are usually unknown threshold values which have to be estimated. Assuming that the errors are normally distributed yields following probabilities

$$\begin{aligned} P(y_i = 0) &= \Phi\left(\frac{m_0 - x_i^{'} b}{s}\right), \\ P(y_i = 1) &= \Phi\left(\frac{m_1 - x_i^{'} b}{s}\right) - \Phi\left(\frac{m_0 - x_i^{'} b}{s}\right) \\ P(y_i = 2) &= \Phi\left(\frac{m_2 - x_i^{'} b}{s}\right) - \Phi\left(\frac{m_1 - x_i^{'} b}{s}\right) \\ P(y_i = 3) &= \Phi\left(\frac{m_3 - x_i^{'} b}{s}\right) - \Phi\left(\frac{m_2 - x_i^{'} b}{s}\right) \\ P(y_i = 4) &= 1 - \Phi\left(\frac{m_3 - x_i^{'} b}{s}\right) \end{aligned} \tag{3}$$

The joint likelihood function of these probalities can be estimated with the familiar Maximum Likelihood technique. In the estimations presented in the text, the standard deviation s is – as usual in Probit models – not identified. All estimated coefficients are scaled by s . In this case, however, we are in a situation, where we know the threshold values m_k. Recall that the credit rating is an index between 0 and 500 which is only categorized for better interpretation. Using the true threshold values, allows us to identify the variance (and the constant term) and reduces the parameters to be estimated. Thus, the coefficients can directly be interpreted as marginal effects in the "true" latent model (i.e. correctly scaled by the standard deviation). The regressions using this additional information are presented in Table 3 and do confirm the previous results.

Table 3:
Results of Ordered Probit Estimations with Known Threshold Values[a)] (5,305 obs.)

	Dependent Variable: Credit Rating (one-period lead)			
Explanatory Variables:	Model I	Model II	Model III	Model IV
Total Sales	8.670*** (7.06)	9.415*** (7.74)	9.094*** (7.47)	8.768*** (7.18)
(Total Sales)^2	-.168*** (-5.60)	-.183*** (-6.13)	-.176*** (-5.89)	-.170*** (-5.67)
Value Added in Mio. DM / Employees	132.082*** (11.38)	132.777*** (11.43)	130.311*** (11.21)	130.401*** (11.24)
1 / Age	-130.320*** (-13.16)	-127.828*** (-12.88)	-129.755*** (-13.10)	-128.004*** (-12.92)
Dummy for Joint-Stock Companies	26.911*** (8.26)	26.661*** (8.17)	27.162*** (8.34)	26.294*** (8.07)
R&D Intensity	207.047*** (4.59)	/	/	130.515*** (2.70)
(R&D Intensity)^2	-726.494*** (-3.71)	/	/	-492.138** (-2.43)
Patent Stock / Sales	/	36.006*** (4.30)	/	27.226*** (3.16)
(Patent Stock / Sales)^2	/	-25.862*** (-4.04)	/	-21.159*** (-3.27)
Share of New Products	/	/	36.138*** (4.29)	28.491*** (3.30)
(Share of New Products)^2	/	/	-29.906*** (-3.06)	-24.508** (-2.49)
Constant term	356.223*** (81.50)	356.358*** (81.51)	349.018*** (74.49)	350.040*** (74.69)
$\hat{s}$	47.918*** (82.53)	47.936*** (82.55)	47.906*** (82.55)	47.790*** (82.53)
Log likelihood	-5,084.158	-5,085.469	-5,082.20	-5,071.393

a) All estimations include 23 industry dummies and 6 time dummies. The true threshold values were included in the regressions. t-values are in parentheses. *** (**,*) indicate a 1% (5, 10%) level of significance.

Finally, we test for heteroscedasticity in the models, where the variance is allowed to vary over industries and firm size. Firm size is specified as seven size classes categorized by the number of employees. The homoscedastic standard deviation $\hat{s}$ is replaced by $\hat{s}_i$ as

$$s_i = \exp\left(s + w_i'a\right) \tag{4}$$

where a are the additional parameters to be estimated and w_i are the variables which are considered to model the heteroscedasticity (without a constant term). Although likelihood ratio tests do reject the hypothesis of homoscedasticity (compare log likelihood values of Table 3 and Table 4), the results concerning the innovation measures remain the same.

Table 4:
Results of Ordered Probit Estimations
with Known Threshold Values and Heteroscedasticity[a)] (5,305 obs.)

	Dependent Variable: Credit Rating (one-period lead)			
Explanatory Variables:	Model I	Model II	Model III	Model IV
Total Sales	9.815*** (6.99)	10.543*** (7.50)	10.233*** (7.28)	9.926*** (7.10)
(Total Sales)^2	-.193*** (-5.58)	-.208*** (-5.98)	-.200*** (-5.78)	-.195*** (-5.66)
Value Added in Mio. DM / Employees	124.737*** (11.28)	124.351*** (11.26)	123.272*** (11.16)	123.157*** (11.17)
1 / Age	-134.432*** (-13.61)	-132.428*** (-13.39)	-134.099*** (-13.59)	-132.204*** (-13.39)
Dummy for Joint-Stock Companies	26.433*** (7.98)	26.209*** (7.89)	26.784*** (8.07)	26.024*** (7.87)
R&D Intensity	173.535*** (3.97)	/	/	98.081** (2.11)
(R&D Intensity)^2	-616.315*** (-3.26)	/	/	-387.485** (-2.02)
Patent Stock / Sales	/	35.910*** (4.36)	/	28.860*** (3.42)
(Patent Stock / Sales)^2	/	-24.321*** (-3.83)	/	-20.490*** (-3.20)
Share of New Products	/	/	35.329*** (4.34)	28.981*** (3.48)
(Share of New Products)^2	/	/	-31.309*** (-3.30)	-26.933*** (-2.82)
Constant term	359.280*** (81.25)	359.488*** (81.32)	352.119*** (74.44)	353.055*** (74.57)
$\hat{s}$ (see equation 4; estimated a are not presented)	3.993*** (59.24)	3.991*** (59.16)	3.994*** (59.31)	3.991*** (59.27)
Log likelihood	-5,001.17	-4,999.62	-4,997.52	-4,987.89

a) All estimations include 23 industry dummies and 6 time dummies. The true threshold values were included in the regressions. t-values are in parentheses. The heteroscedasticity is modeled by six size dummies for the number of employees and the 23 industry dummies. *** (**,*) indicate a 1% (5, 10%) level of significance.