Market Structure and Innovation Races: An Empirical Assessment

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Abstract

Based on an extended game-theoretic innovation-race model, we derive some Schumpeterian hypotheses of the impact of technological rivalry, market power, technological opportunities and market size on the timing of product and process innovations. Using innovation data at the firm level in the German industrial sector, we estimate various versions of an econometric specification of the model with dichotomous innovation data by using a univariate binary probit model with qualitative regressor variables. Our empirical results are consistent with the derived hypotheses that intense rivalry, favorable technological opportunities and high demand expectations spur innovative activity, while the effect of market power is ambiguous.

Keywords: Innovation Races, Market Structure, Indirect Inference Estimation

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1 Introduction

Since Schumpeter's seminal conjectures about the importance of technological rivalry and market power for the dynamics of innovation processes, the relationship between market structure and innovative activity has attracted a great deal of theoretical and empirical research. Modern game-theoretic models in the Industrial Organization literature treat technological competition as a dynamic stochastic process. Firms are assumed to invest in R&D projects over time without being certain whether, or when, the projects will be successfully completed.

One of the most convincing approaches of modeling the innovation process is the game-theoretic innovation-race approach as originally introduced by Loury (1979), Dasgupta and Stiglitz (1980) and Lee and Wilde (1980). Especially the Lee and Wilde model is heavily used as a basic concept for multi-dimensional extensions in the Industrial Organization literature as well as in macroeconomic analyses of endogenous growth and trade. The model assumes that identical firms compete for a given innovation that, due to perfect patent protection, only yields profits to the first firm that introduces the new product or the new technology. While the winner of the race takes all, the losers get nothing and therefore suffer a loss given by the invested R&D expenditures which are cancelled as soon as the race is finished. From an empirical point of view, the standard innovation race relies on at least two inappropriate assumptions. Firstly, no firm participating in the race realizes flow profits in the pre-innovation market. Secondly, since innovations are considered as being drastic, the prize for the winner is not only exogenously given, but also independent of the post-innovation number of firms in the market. For the same reason, the losers cannot reap any profits which again implies that the number of firms does not influence profits in the post-innovation market.

For these reasons, we follow Delbono and Denicolo (1991) in assuming that firms realize profits during and after each innovtion race where, of course, the profits of the winner will increase and the profits of the losers will decrease. Hence, at any point in time, profits will depend on the number of firms in the oligopoly market. In their model with quantity-setting Cournot firms, Delbono and Denicolo (1991) show that the essential result derived by Lee and Wilde (1980), that an increase in the number of identical firms increases the Nash-equilibrium R&D activity, does not generally hold anymore. Instead, they derive conditions under which R&D efforts will decrease with a rising number of firms. To a certain extent, this theoretical ambiguity coincides which the empirical evidence on the relationship between market power and innovative activity. As the empirical surveys by Baldwin and Scott (1987), Cohen and Levin (1989) and Cohen (1995) show, the influence of rivalry on innovative activity is, more than 60 years after Schumpeter's conjectures, still an open question.

The objective of this paper is to theoretically and empirically reexamine the influence of technological rivalry, market power, technological opportunities, demand expectations and further possible explanatory factors on the timing of innovations. Using an available innovation data set at the firm level, we are able to provide some new insights about the importance of these variables in explaining the dynamics of innovations. We therefore develop an empirically motivated version of the standard innovation race model which departs from the Delbono and Denicolo (1991) scenario in three important ways and, hence, yields some novel theoretical results interesting in their own right. Firstly, we distinguish between the number of competitors in the pre-innovation market on the one hand and the number of technological rivals in the innovation race on the other hand. The distinction between these kinds of rivalry, which can be justified for example by financial constraints of some firms, is appropriate since our survey data show that these two variables usually do not coincide. Secondly, we prefer an oligopoly model of price competition in heterogeneous markets since homogeneous markets are rarely found in reality. This allows us thirdly to consider not only cost-reducing process innovations, but also demand-stimulating product innovations. Both types of innovation are included in our data set.

The remainder of the paper is organized as follows: In Section 2 we present our basic innovation-race model which is further specified in Section 3 to explain the expected timing of innovations in terms of technological rivalry, market power, technological opportunities and market size. In Section 4 we derive a tractable econometric specification which can be estimated using qualitative-dependent-variable models. A description of the data is given in Section 5. Section 6 presents the empirical results. Finally, Section 7 concludes.

2 The Innovation-Race Model

Following the game-theoretic innovation-race approach as suggested by Lee and Wilde (1980), we consider a given number of firms m, which compete for a product or process innovation. The date at which firm i's research project is completed is a random variable T_i which follows the exponential distribution

$$F_i(t) = 1 - e^{-h(x_i)t}.$$

The hazard rate $h(x_i) = \dot{F}_i(t)/(1 - F_i(t))$ defines the conditional probability of an innovation success in the marginal time interval $[t; t + dt]$ given that no success occured until this time. The hazard rate is assumed to be an increasing function of variable R&D expenditures x_i. Even if Lee and Wilde (1980) originally allowed for the possibility of initial increasing returns to R&D, we adopt the standard text book version of the model assuming a global concave function (see, e.g. Tirole 1988, Martin 1993). For concreteness, we specifiy the square root function

$$h(x_i) = 2\mu x_i^{0.5}, \tag{1}$$

where μ represents the productivity of R&D activities reflecting the technological opportunities in the innovation race. The expected time of completion of the innovation project can then be calculated as

$$E[T_i] = \int_0^\infty t h(x_i) e^{-h(x_i)t} dt = 1/h(x_i) = (1/2)\mu^{-1} x_i^{-0.5}. \tag{2}$$

The greater a firm's research effort, the sooner is the expected time of completion. In game-theoretic R&D models, research activities depend strategically on the activities of their rivals. To keep the model tractable, we follow Delbono and Denicolo (1991) by assuming that all firms realize an equal pre-innovation profit flow and that only one further innovation is considered. The expected discounted profits of a firm i, net of R&D expenditures, can then be written as

$$\begin{aligned} \Pi_i(x_i) &= \int_0^\infty e^{-(r+h_i+\hat{h}_i)t} \left[h_i \pi_W/r + \hat{h}_i \pi_L/r + \pi_0 - x_i \right] dt \\ &= \frac{h_i \pi_W/r + \hat{h}_i \pi_L/r + \pi_0 - x_i}{r + h_i + \hat{h}_i} \ , i = 1, \ldots, m, \end{aligned} \tag{3}$$

where π_0 is the profit flow of all symmetric incumbent firms in the pre-innovation market, π_W is the post-innovation profit flow accruing forever to the winner of the innovation race, π_L is the corresponding post-innovation profit flow of the non-participants and the losers in the race, $\hat{h}_i = \sum_{j \neq i} h(x_j)$ is the instantaneous probability that one of the $(m-1)$ rivals of firm i innovates and r is the constant interest rate. Maximizing the profit function (3) and using the hazard-rate function (1) yields the first-order conditions

$$\tilde{\mu}(2m-1)x^* - [2\tilde{\mu}^2(m-1)(\pi_W - \pi_L) - 1]x^{*0.5} - \tilde{\mu}(\pi_W - \pi_0) = 0 \tag{4}$$

in the symmetric Nash-equilibrium, where $\tilde{\mu} \equiv \mu/r$. Equation (4) determines the equilibrium $R\&D$ expenditures x^* as a function of the technological opportunities μ, the interest rate r, the intensity of technological rivalry m, and the flow profits $\pi_L < \pi_0 < \pi_W$. The term $(\pi_W - \pi_0)$ measures the pure "profit incentive", i.e., the incentive to invest in R&D in the absence of rivalry. The term $(\pi_W - \pi_L)$ reflects the "competitive threat" (Beath et al. 1989) in the innovation race. Each firm has to recognize that, should it fail to innovate, one of its rivals will succeed in realizing the innovation. In contrast to the Lee and Wilde (1980) model where there are no pre-innovation profits and no post-innovation profits of the losers, the presence of pre-innovation profits and the assumption that even the losers can realize profits in the post-innovation market induces firms to delay the expected date of innovation.

It can be shown that the symmetric equilibrium is unique and locally stable provided that $\partial N/\partial x^* < 0$, N denoting the left-hand side of (4), whereby this stability condition is generelly met for a wide class of hazard-rate functions including our specification (see Nti (1999). Thus, by implicitly differentiating (4), we derive the following unambiguous comparative-static effects on the equilibrium R&D expenditures and, taking (2) into account, the expected completion dates of the innovations $E[T_i]^*$:

Hypothesis 1: An increase in the technological opportunities μ or a decrease in the interest rate r will increase the equilibrium R&D effort and decrease the expected innovation dates of each firm $(\partial E[T_i]^*/\partial\tilde{\mu} < 0)$.

Hypothesis 2: An increase in the intensity of technological rivalry m will increase the equilibrium R&D effort and decrease the expected innovation date of each firm $(\partial E[T_i]^*/\partial m < 0)$.

As long as π_0, π_W and π_L do not depend on m, the derivatives of the competitive-threat and the profit-incentive terms with respect to m are zero and the market-structure effect is unambiguous. However, as Delbono and Denicolo (1991) have pointed out, if these flow profits also depend on m, the impact of rivalry on innovative efforts becomes ambiguous. To further analyze the model in this case, they derive reduced-form profit flows resulting from a Cournot oligopoly. In order to develop an empirically tractable version of the innovation-race model, we follow their modeling strategy but depart from some crucial assumptions in three ways: Firstly, we distinguish between the number of competitors n in the pre-innovation market and the number of technological rivals m in the innovation race and assume $m \leq n$. This extension is necessary to account for our survey data which show that these two explanatory variables usually do not coincide. Accordingly, the flow profits in the theoretical model depend on n but not on m. This can be theoretically justified for example by financial constraints which hinder some of the competitors in the pre-innovation market from participating in the race. Secondly, since all firms in our survey data set operate in more or less heterogeneous markets, we cannot deal with homogenous markets. Therefore, we present an empirically appropriate oligopoly model of price competition in heterogeneous markets which complements the Cournot model used by Delbono and Denicolo (1991). The extension to heterogeneous markets allows us thirdly to consider not only cost-reducing process innovations but also demand-stimulating product innovations accounting for the fact that both variables are included in our data set.

3 An Illustrative Model of Price Competition

To analyze the subgame-perfect equilibrium of the two-stage game where m firms participate in the R&D race in the first stage and n firms compete in prices in the second stage, we have to derive the reduced-form profit flows π_0, π_W and π_L. For reasons of simplicity and comparability, we assume linear demand functions $D_i(\boldsymbol{p}) = s_i - p_i + (1/(n-1)) \sum_{j \neq i} p_j, i, j = 1, ..., n, i \neq j$, and constant marginal (and average) production cost c_i, leading to flow profits

$$\pi_i = (p - c_i)(s_i - p_i + (1/(n-1)) \sum_{j \neq i} p_j). \qquad (5)$$

Within the symmetric structure of the pre-innovation market, where $c_i = c$ and $s_i = s \forall i$, we derive the reduced-form flow profits as

$$\pi_0 = s^2, \tag{6}$$

where the demand parameter s can be interpreted as an indicator of the size of the market. Since variables for product as well as process innovations are included in our data set, we consider two versions of the model. In the case of product innovations, we assume that the winner's demand parameter rises from s to s_W where $d_s \equiv s_W - s > 0$ represents the size of the product innovation. Since the extreme case of a drastic innovation is already covered in the standard patent race model, we assume that the product innovation is non-drastic. This implies that the losers as well as the non-participants of the race, while still facing the demand parameter s, will remain active in the post-innovation market. As a result, the flow profits of the winner and the loosers in the asymmetric equilibrium can be derived as

$$\pi_W = \left[s + \frac{n}{2n-1} d_s\right]^2, \ \pi_L = \left[s + \frac{1}{2n-1} d_s\right]^2. \tag{7}$$

In the alternative case of process innovations, we assume that the winner of the innovation race reduces its average production cost from c to c_W where $d_c \equiv c - c_W > 0$ represents the size of the process innovation. Again, we concentrate on non-drastic innovations. The corresponding flow profits can be derived as

$$\pi_W = \left[s + \frac{n-1}{2n-1} d_c\right]^2, \ \pi_L = \left[s - \frac{1}{2n-1} d_c\right]^2. \tag{8}$$

Since prices are strategic complements, a demand-stimulation product innovation makes the winner soft, while a cost-reducing process innovation makes him tough. In the first case, all prices and profits increase, of course those of the winner more than those of the rivals. Since $\partial(\pi_W - \pi_0)/\partial n < 0$ and $\partial(\pi_W - \pi_L)/\partial n > 0$, an increasing number of competitors in the market lowers the profit incentive but raises the competitive threat. In second case, the profits of the winner rise even if its price is reduced, but prices and profits of the rivals decline. The derivatives $\partial(\pi_W - \pi_0)/\partial n > 0$ and $\partial(\pi_W - \pi_L)/\partial n < 0$ are of the opposite signs compared to the case of product innovations, so that an increasing number of competitors in the market now raises the profit incentive but lowers the competitive threat. Thus, the reduced-form profit specifications in (7) and (8) enable us to additionally set up:

Hypothesis 3: The impact of an increase in the number of firms n in the pre-innovation market on the equilibrium R&D effort and the expected innovation date of each firm is ambiguous ($\partial E[T_i]^*/\partial n \gtrless 0$).

Implicitly differentiating (4) with respect to the market size s, making use of (7) and (8), finally yields:

Hypothesis 4: An increase in the size of the market s will increase the equilibrium R&D effort and decrease the expected innovation date of each firm ($\partial E[T_i]^*/\partial s < 0$).

The comparative statics indicate that the probability of an expected product or process innovation within a specific time interval from the present depends positively on the intensity of rivalry m, technological opportunities μ and market size s, while the influence of market power as measured by the (inverse) number of competitors n is ambiguous. All these hypotheses will now be econometrically tested with our data set.

4 Econometric Specification

According to the theoretical model, each firm decides on R&D expenditures and, hence, the expected innovation date $E[T_i]^* = 1/h(x_i^*)$. In our data set, these decisions cannot be observed directly. Instead, we can only observe whether or not a firm intends to introduce an innovation within the next two years, implying whether or not $E[T_i]^*$ falls into this given time interval. Therefore, we have to treat the expected innovation dates as continuous latent variables and define

$$T^D = \begin{cases} 1, \text{iff } E[T_i]^* \leq 2 \\ 0, \text{iff } E[T_i]^* > 2. \end{cases} \tag{9}$$

The structural equation for the latent variable is specified as

$$E[T_i]^* = \boldsymbol{\beta}'\boldsymbol{y}_i + \varepsilon_i, \tag{10}$$

where the exogenous variables are summarized in the vector $\boldsymbol{y}_i$ and the stochastic error term ε_i is added to account for random unobserved heterogeneities. For our econometric model this implies that a firm's probability of introducing an innovation within this given time period is a function of the explanatory variables μ, m, n, and s.

If we assume the error term ε to be independently and normally distributed, we obtain the conditional probabilities of the random variable T^D given the exogenous variables $\boldsymbol{y}$:

$$P(T^D = 1|\boldsymbol{y}, \boldsymbol{\beta}) = \Phi\left(\frac{2 - \boldsymbol{\beta}'\boldsymbol{y}}{\sigma}\right), \tag{11}$$

where Φ denotes the standard normal distribution function. To be able to identify the parameters, the variance σ^2 has to be restricted to unity. In addition, the threshold value and the constant term need to be combined so that

$$P(T^D = 1|\boldsymbol{y}, \boldsymbol{\beta}) = \Phi(-\boldsymbol{\beta}'\boldsymbol{y}). \tag{12}$$

With the available observations from individual firms on T^D and also on the regressor variables $\boldsymbol{y}$, we can formulate a likelihood function and maximize it with respect to the parameter vector $\boldsymbol{\beta}$. This is the standard probit model. As will be shown in the next section, some of the regressors are ordinally scaled. We deal with this problem in three different ways. Firstly, as is common practice in applied research, we transform these variables into dummy variables implying that they can be treated as nominally scaled variables. Secondly, we replace the ordinal coding of $y = 1, \ldots, y = l$ by $\mathrm{E}(y^*|y = 1), \ldots, \mathrm{E}(y^*|y = l)$ as suggested by Terza (1987). Thirdly, we follow an estimation procedure developed in Kukuk (2002) and applied in Kukuk and Stadler (2001) to account for the ordinal scale of the regressors. All results are presented to demonstrate the robustness of our results.

5 The Data

For our empirical analysis we use data from an innovation survey of German industrial firms. The survey was conducted by the Centre for European Economic

Research (ZEW), Mannheim, in cooperation with infas Sozialforschung, Bonn, in 1994 and is part of the European Community Innovation Survey (CIS) initiated by Eurostat. For a detailed description of the survey refer to Janz et al. (2001). The CIS frame questionnaire is closely related to the OECD recommendations for firm level innovation surveys summarized in the OSLO Manual (1992). Following the OSLO Manual recommendation, a postal survey was designed and the questionnaire was sent out to approximately 11,500 firms in the German industrial sector stratified by firm size groups and branches. On average, about 25% to 30% of the firms responded which is comparable to other national CIS innovation surveys. For the 1994 wave a sample of 3065 firms is obtained.

The approach is to ask at the firm level, for instance, whether or not a product and/or a process innovation is planned to be introduced within the next two years. Definitions for these types of innovations are given to help the respondents to classify themselves. In addition to these questions about innovative activities, each panel wave had at least one block of varying topics. We use the second wave (1994) conducted in 1995 since it is the only questionnaire asking for the number of competitors and for the development of the intensity of technological rivalry in the firms' relevant markets. It is the combination of innovation and market structure data which makes our available data set extremely appropriate to empirically investigate the relationship between rivalry and the timing of innovations. According to the number of competitors, which we interpret as an inverse measure of market power, the firms responded whether they had one to five competitors (category 1), six to ten (category 2), or more than ten (category 3). In addition, the firms were asked to appraise the intensity of technological rivalry for the future on a five-point Likert scale. We gather this information into three categories, according to whether firms face a reduced (category 1), an unchanged (category 2) or a strengthened (category 3) intensity of rivalry. As a first attempt, we record bivariate and conditional frequencies of technological rivalry and planned innovations in Table 1. Obviously, the firms in markets with a high intensity of rivalry (category 3) are more likely to plan to introduce an innovation within the next two years. This result will continue to hold in our econometric analysis in the next section.

Table 1: Relative Frequencies of Rivalry and Planned Innovations

Rivalry	Planned Innovations		Sum
	No	Yes	
category 1	1.98	2.56	4.53
	[43.61]	[56.39]	[100]
category 2	6.71	8.73	15.44
	[43.49]	[56.51]	[100]
category 3	23.21	56.82	80.03
	[29.00]	[71.00]	[100]
Sum	31.90	68.10	100

Note: Relative frequencies in % are recorded. N=2934.
Conditional relative frequencies in brackets.

6 Empirical Results

According to our theoretical model, we are interested in analyzing the effects of technological rivalry m, market power n, technological opportunities μ, and market size s on the planned dates of product and process innovations. Fortunately, the survey questions we use for our empirical work come close to the decisive variables in our innovation-race model.

As a first step, we explain planned innovations in Table 2 where we do not differentiate between product and process innovations. Starting with the common practice method, it can be seen that the third category of market power has a negative parameter which is only weakly significant. The market power variable is measured by three categories in the data set. The first category serves as the reference group. The parameter for the second group is smaller in absolute terms than the parameter of the third category underlining the ordinal nature of this variable and also the linear effect this variable has on the dependent variable. In the second approach using the conditional expected value for the truncated latent variable, the market power variable is still (weakly) significantly negative. However, in the indirect inference approach which is reported in the last column, market power is slightly positive but insignificant. This difference in estimates is due to the error-in-variables problem in the first two approaches.

With respect to technological rivalry, all three approaches find a strong positive effect on the planned timing of innovations reproducing the result of Table 1.

Table 2: Estimation Results for Planned Product and/or Process Innovations

Explanatory variables	Dummies Parameter (t-value)	Terza's method Parameter (t-value)	Indirect inf. Parameter (t-value)
C	-0.7773	0.33631	0.71980
	(-3.26)	(1.521)	(2.525)
Log(numb. of empl.)	0.11337	0.11427	0.02571
	(5.26)	(5.302)	(1.065)
Innovation in the past	1.38126	0.84865	0.92436
	(22.78)	(22.783)	(22.151)
Market size	-0.1107	0.12343	0.05559
	(-1.14)	(3.829)	(2.271)
	0.15267		
	(2.07)		
Market power	-0.02448	-0.05774	0.02487
	(-0.28)	(-1.650)	(0.638)
	-0.10226		
	(-1.36)		
Intensity of rivalry	-0.1065	0.11957	0.09741
	(-0.71)	(3.703)	(3.204)
	-0.2169		
	(2.66)		
East-Germany	-0.1270	-0.13994	-0.13485
	(-1.98)	(-2.176)	(-1.533)
Organizational Changes	0.2659	0.24922	0.23930
	(3.13)	(2.897)	(3.039)
Part of a trust	0.0066	0.00499	0.00261
	(0.10)	(0.073)	(0.034)
Dummies for branches included but not reported			
Number of observations	2775	2775	2775
Log-Likelihood	-1211.7	-1208.9	
R^2_{VZ}	0.485	0.486	

Note: R^2_{VZ} denotes a pseudo coefficient of determination (Veall and Zimmermann, 1996). In the dummies approach, reference groups are category 1 for market power and the unchanged categories for rivalry and market size, respectively.

The current innovation status as a measure for technological opportunities is highly significant and accounts for a large portion of the explanatory power of the estimation. Flaig and Stadler (1994, 1998) interpreted it as the *success breeds success* hypothesis. Compared to the services sector which is analyzed in Kukuk and Stadler (2001) the technological opportunities have a stronger impact in the industrial sector. There is also evidence for demand pull in all the different methods since the expected demand variable[1] shows the correct sign significantly. Surprisingly, the firm size measured by the (log of the) number of employees is not significant in the indirect estimation. An explanation is that the current innovation status already captures the firm size. Since we simulate the latent variable[2] of the ordinal innovation indicator, the log of the number of employees does not carry the appropriate firm size information to explain more than the latent innovation variable.

The dummy variable for East-German firms is negative in all three approaches indicating that even four years after reunification the technological opportunities of those firms were lagging behind. We also controlled for organizational changes. About 15% of firms had a major change in the firm structure. Our results indicate that these changes have a positive effect on the planned innovations. We also included dummy variables for 14 different branches accounting for sector specific innovation behavior, however to save space, we suppressed the results.

In a next step we differentiate between product and process innovations and analyze the determinants of the timing of their introduction. The results are recorded in Table 3. The dummy variable approach usually obtains the same results as Terza's method and is therefore omitted in the table. For both types of innovation we find an insignificant positive effect of market power using the indirect inference. Terza's method reveals that the negative effect is larger for product innovations. The log of number of employees is significant for process innovations whereas for product innovations it is insignificant which drives the combined estimate of Table 2. All the other results are similar in both innovation types. In the data set there are also variables for the past development of demand and technological rivalry. We included

[1] As the variable for technological rivalry, the market size variable is originally measured with five categories, too. We summarize them into variables with three categories although estimation results are very similar using the original variables.

[2] Strongly monotonic transformations of the latent variable lead to the same ordinal observations (Kukuk, 1994).

Table 3: Estimation results for Planned Innovations

Explanatory variables	Terza's method		Indirect inference	
	Parameter	t-value	Parameter	t-value
Dependent variable: Planned Process Innovation				
C	0.12961	0.622	0.46451	2.352
Log(numb. of empl.)	0.13213	6.700	0.05814	2.602
Innovation in the past	0.71141	19.828	0.77625	14.335
Market size	0.11574	3.917	0.05400	2.297
Market power	-0.04251	-1.330	0.02445	0.738
Intensity of rivalry	0.08898	2.968	0.07220	2.750
East-Germany	-0.08698	-1.455	-0.07817	-1.195
Organizational changes	0.25674	3.370	0.25177	3.362
Part of a trust	-0.06168	-1.001	-0.06505	-0.737
Dummies for branches included but not reported				
Number of observations	2775			
Log-Likelihood	-1471.8			
R^2_{VZ}	0.393			
Dependent variable: Planned Product Innovation				
C	-0.33401	-1.662	0.04245	0.162
Log(numb. of empl.)	0.09716	4.690	0.01139	0.378
Innovation in the past	0.82102	22.467	0.89455	22.387
Market size	0.12055	3.863	0.05439	2.208
Market power	-0.06248	-1.851	0.01734	0.483
Intensity of rivalry	0.11273	3.583	0.09504	3.155
East-Germany	-0.13037	-2.079	-0.12477	-1.486
Organizational changes	0.24000	2.941	0.23198	2.483
Part of a trust	0.03169	0.487	0.02832	0.446
Dummies for branches included but not reported				
Number of observations	2775			
Log-Likelihood	-1301.9			
R^2_{VZ}	0.478			

them in another specification to determine their effects although our model does not suggest their inclusion. With the exception of past demand having a slightly negative effect on process innovation these variable are insignificant.

The presented empirical results are consistent with the derived hypotheses that intense rivalry, favorable technological opportunities and high demand expectations spur innovative activity, while the effect of market power is ambiguous. Therefore, it is not the number of firms in the pre-innovation market but the number of technological rivals that significantly influences the innovative activities of firms.

7 Summary and Conclusion

The objective of this paper was to theoretically and empirically examine the influence of technological rivalry, market power, technological opportunities and demand expectations on the planned timing of innovations. Using an extended version of the game-theoretic innovation-race model, we derived an estimation function where the timing of innovations depends positively on technological rivalry, demand expectations and technological opportunities but where the influence of market power, measured by the number of firms in the relevant market, is ambiguous.

The derived econometric specification is estimated using 2775 firms in the German manufacturing sector. The empirical results, obtained with three conceptually different estimation procedures, show a significant positive effect of technological rivalry on the timing of innovations as suggested by our theoretical model. Further, our results confirm the technology-push and the demand-pull hypotheses since technological opportunities, measured by innovation successes in the past, and demand expectations also show the predicted signs. The market power effect which is ambiguous in our model also tends to spur the innovation process, however the effect is not significant throughout.

The derived results show that market structure is an important explanatory factor when it comes to analyzing innovation behavior. However, it is not the number of competitors in the pre-innovation market but the number of rivals, participating in the innovation race, that strongly influences the innovative activities of firms. This insight supports the empirical relevance of the extended innovation-race models which are heavily used in the Industrial Organization literature.

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