Does Innovation Success breed Innovation Success?

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Abstract: The theoretical literature provides different arguments of why and how innovation success may substantiate further success. Using an innovation panel data set on German manufacturing firms covering the period 1994–2005, this paper investigates the hypothesis whether success breeds success. The econometric results, based on a dynamic pooled and random effects tobit model and a new estimator recently proposed by Wooldrigde (2005), confirm the hypothesis that past innovation success is an important key for subsequent success. First, successful product innovators are more likely to introduce new products in the future and second, they achieve a higher share of sales with these product novelties.

Keywords: innovation, success breeds success, persistence, state dependence, dynamic random effects tobit model

JEL Classification: O31, C23, C25, L20

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Any errors remain those of the author.

1 Introduction

Recent empirical evidence indicates that firm performance in terms of productivity is highly skewed and that this heterogeneity is persistent over time (see Dosi et al. 1995 or Bottazzi et al. 2001). Since innovation is seen as a major determinant of firm's growth, one hypothesis is that the permanent asymmetry in productivity is due to permanent differences in innovation success. However, little is known so far about the dynamics in firms' innovation success. Cases like Toyota in the automobile industry or Intel demonstrate that successful innovators are able to sustain their market positions through permanent subsequent innovations, and hence support a view that innovation success breeds innovation success. On the other hand, there is also case evidence that successful innovators fail to keep pace with the technological progress as time goes by[1], that successful innovators can face great difficulties when trying to do something radically different from their past experience or that even failed innovation experience substantiates further success.

This paper analyses the dynamics in firms' innovation success. In particular, it focuses upon the following two research questions: First, are successful product innovators more likely to introduce new products in the future? And second, given that they subsequently innovate, are they more successful than previous non–innovators or less successful innovators? Or is innovation success driven by other (observable or unobservable) firm–specific factors other than previous innovation success?

Large scale empirical evidence on the development of innovation success at the firm-level is rare. There are a few patent–based studies which have mainly focused on the question whether innovation persistence exists, irrespective of its origin. Malerba and Orsenigo (1999), Cefis and Orsenigo (2001) and Cefis (2003) studied innovation persistence using EPO patent application data of manufacturing firms from six countries (France, Germany, Italy, Japan, USA and the UK). Their results showed that only a small fraction of firms were able to patent permanently. These firms became rather large innovators (in terms of the number of patents) over time, resulting in the fact that persistent innovators, although small in absolute numbers, accounted for an important part of all patents. The result that patent activities among patenting firms exhibited only a little degree of persistence, was also confirmed by Geroski et al. (1997) using data of UK manufacturing firms which had at least one patent granted in the US between 1969 and 1988. It is well-known that patents are not a perfect indicator of innovation success: Not all inventions are patentable and even if they are they do not necessarily lead to patents. Instead of patents firms might choose other measures to protect their inventions, like secrecy or complex designs. Furthermore, not all patents lead to new products or pro-

[1] See, for instance, Ford in the automobile industry or in recent times the development of Yahoo.

cesses, and the value of patents is highly skewed. In the context of persistence analysis, patents have an additional drawback, because in this kind of winner–takes–all contest, to be classified as permanent innovators firms have to win the patent race continuously (Kamien and Schwartz 1975).

Due to the development of a common definition of innovation and several new innovation indicators by the OECD and EUROSTAT (Oslo-manual, first published 1992) as well as the release of European–wide harmonized innovation surveys (known as Community Innovation Surveys CIS), researchers have recently started to analyze this question using innovation data. Most of the previous studies done so far measured innovation success as the introduction of at least one (product and/or process) innovation, and therefore investigated the persistence of innovation success by means of a simple binary indicator (Flaig and Stadler 1994 and 1998, Duguet and Monjon 2004 or Peters 2005). These studies confirm that previous innovators are more likely to innovate again. In contrast to that, this paper applies a quantitative indicator to measure innovation success. The firm's success of offering innovative products to its customers is measured by the share of sales due to these new or significantly improved products. This indicator is recommended by the Oslo manual as product innovation output indicator (see OECD and Eurostat 2005), and it can be interpreted as a sales weighted innovation count. Hence, this study is similar in nature to the recent work of Raymond et al. (2006) who first applied this quantitative innovation measure to investigate state dependence effects for Dutch manufacturing firms. They set up an econometric framework in which the decision to innovate in new products or processes depends on the preceding innovation status which is a binary indicator. Condition on the introduction of a (product or process) innovation, the product innovation outcome then depends on the lagged innovation outcome. Surprisingly, Raymond et al. could not ascertain persistence in the occurrence of innovations for Dutch manufacturing firms, but pointed out that among continuous innovators the innovation success had a positive impact on future success. In addition to the distinct data set, there are three main differences: First, this paper focuses solely on product innovation decisions, since the innovation outcome relates only to product innovations. Second, the framework I use in this paper takes into account that the decision to innovate might not only depend on the previous innovation status (binary indicator), but also on the level of the innovation success itself. That is, more successful innovators might be more likely to develop and launch new products. Third, the econometric estimation allows the unobserved firm-specific heterogeneity to correlate with the observed firm characteristics.

The analysis is based on panel data from the German innovation survey covering firms' innovation activities during the period 1994–2005. The descriptive analysis reveals that at the firm–level the introduction of product innovations show a high degree of persistence over time. Likewise evident, but less pronounced is the perseverance in innovation success. The question which factors drive this pattern – previous innovation success, other observed firm characteristics or unobserved firm-specific heterogeneity (see Heckman 1981a,b) – is then analysed and identified by means of a dynamic pooled and random effects tobit model.

The outline of the paper is as follows. Section 2 explores the theoretical arguments in favour of state dependence in innovation success. The construction of the panel data set is described in Section 3 and Section 4 depicts some first descriptive results about the persistence of product innovation occurrence and success. Section 5 presents the econometric model and its empirical implementation. It further explores the estimation method used and sets forth the econometric results. The final section contains some concluding remarks.

2 Related Theoretical Literature

The view that 'innovation success breeds innovation success' is actually based on different arguments in the literature. Economic theory provides at least three potential explanations of why innovation success might demonstrate state dependence over time.

First, successful innovations positively affect the conditions for subsequent innovations via an *increasing permanent market power* of prosperous innovators. In contrast to Schumpeter, who assumed that the increasing market power is a temporary phenomenon and is eroded by the entry of imitators or innovators, Phillips (1971) argued that success favours growing barriers to entry that eventually allow a few increasingly successful firms to permanently dominate an industry.

Second, successful innovations broaden the firm's technological opportunities which make subsequent innovation success more likely as was emphasised by Mansfield (1968) or Stoneman (1983). Based on this idea of dynamic intra–firm spill–overs, Flaig and Stadler (1994) developed a stochastic optimisation model in which firms maximise their expected present value of profits over an infinite time horizon by simultaneously choosing optimal sequences of both product and process innovations. Both were shown to be dynamically interrelated in this model.

A third line of reasoning is the existence of constraints in financing innovation projects (see Nelson and Winter 1982). Usually, information asymmetries about the risk and the failure probability of an innovation project exist between the innovator and external financial investors. This leads to adverse selection and moral hazard problems which usually force firms to finance innovation projects by means of internal funds (Stiglitz and Weiss 1981). Successful innovations provide firms with increased internal funding and hence can be used to finance further innovation projects. The larger the previous innovation success, the more likely it is, that the firm will carry out either (i) one larger and more important innovation project or (ii) a larger number of smaller innovation projects. Both strategies make the occurrence of future innovations not only more likely but also increase the expected innovation success.

Another theory which is closely related to the 'success breeds success' hypothesis is the theory of "dynamic competencies" (Winter 1987 and Teece and Pisano 1994). The theory states that firms' technological capabilities are a decisive factor in explaining innovation. Firms' innovative capabilities in turn are primarily determined by human capital, i.e., by the knowledge, skills and creativity of their employees. Experience in innovation is assumed to be associated with dynamic increasing returns in the form of learning–by–doing and learning–to–learn effects. That is, with innovation experience firms acquire technological competencies and accumulate technological capabilities which enhance knowledge stocks and, therefore, the probability of future innovations. Learning can be related to a better understanding of the pure technological context but also to improved knowledge of how to commercialize new products. Since a firm's absorptive capacity – i.e. its ability to recognise and to assimilate the value of new external information – is likewise a function of the level of knowledge, learning in one period will furthermore permit a more efficient accumulation of external knowledge in subsequent periods (Cohen and Levinthal 1990). The cumulative nature of knowledge should therefore induce state dependence in innovation (see, e.g., Nelson and Winter 1982 and Malerba and Orsenigo 1993). Theories which focus on how firms accumulate technological capabilities may also be considered as 'success breeds success' theories since technological capabilities might substantiate sustained competitive advantages (Teece and Pisano 1994). On the other hand learning can also occur as a result of unsuccessful innovations and the phenomenom that firms learn from their mistakes or flops is called 'failure breeds success'. Furthermore, in contrast to their innovation input firms can not necessarily control their innovation outcome because serendipity might play an important role in the innovation process (Kamien and Schwartz 1982).

Common to all various 'success breeds success' arguments is the notion that a firm can gain some kind of locked–in advantage over other firms due to successful innovations (Simons 1995). Based on these arguments, the following two hypotheses will be tested in the empirical analysis:

H1: Prior product innovation success make a firm more likely for subsequent product innovations.

H2: Prior product innovation success increase the firm's subsequent innovation outcome measured by the share of sales with new products.

3 Construction of the Data Set

The data set used is the Mannheim Innovation Panel (MIP), covering firms from manufacturing, mining, energy/water supply and construction. The MIP is based on innovation surveys carried out by the ZEW on behalf of the German Federal Ministry of Education and Research. The surveys are drawn as stratified random samples and are representative of the corresponding target population. The target population spans all legally independent enterprises with 5 or more employees and their headquarters located in Germany.[2] Firm size, industry and region serve as stratifying variables. The survey started in 1993.[3] Every fourth year the survey is the German contribution to the European–wide harmonized Community Innovation Surveys (CIS). While in most other European countries innovation surveys take place every 4 years, they are conducted annually in Germany. The survey methodology and definitions of innovation indicators comply with the OSLO-Manual (OECD and Eurostat 1997), thereby yielding internationally comparable data. The MIP is designed as a panel. As in many other European countries participation is voluntary in Germany. About 2000 to 2500 manufacturing enterprises fill out the questionnaire each year, implying a response rate of between 20 to 25 %.[4] A detailed description of the MIP is provided by Janz et al. (2002) or Peters (2006).

Although we have a yearly and hence fairly long panel data set at hand, its full exploitation is impeded by three facts: The first one is related to an important characteristic of the CIS data. Since the time needed to develop an innovation is often more than one year and innovation is therefore a multi–period activity, the indicator whether a firm has introduced a product innovation is related to a 3–year period. As an example, in the 2005 CIS survey a firm is defined as a product innovator if it has introduced at least one new or significantly improved product in the period 2004–2002, in the 2004 survey this indicator is related to 2003–2001. The innovation success is measured by the share of sales in a given year k due to product innovations introduced in the years k-2 to k. Though this indicator is measured on a yearly base, admittedly it implies that a new product introduced for example in 2002 counts for the share of sales with new products

[2]An enterprise in the survey is defined as the smallest combination of legal units that is an organisational unit producing goods or services. An enterprise carries out one or more activities at one or more locations. An enterprise may be a sole legal unit. In the following, I will use the expressions enterprise and firm interchangeable.

[3]Two years later the service sector was included. While in manufacturing the innovation output indicator – share of sales due to new products – was included right at the start of the survey, it was asked in the service sectors 1998 for the first time. Hence, I decided to focus on the industry sector.

[4]The low response rates are in line with those of comparable voluntary surveys of German firms. In order to control for a response bias in the net sample, non-response analyses are carried out each year, covering a similar number of firms of the net sample and collecting information on product and process innovations by the means of telephone interviews. They come up with the result that the share of innovators is only slightly underestimated in the net sample.

in 2002, 2003 and 2004. Hence, it is likely that this measure show a high persistence on a year-to-year basis and in the extreme case it might just reflect a stable market position of the same new product.[5] From a theoretical point of view, however, the 'success breeds success' hypothesis is related to the introduction of further innovations and the question whether firms can sustain their innovation outcome with their subsequent innovations. To avoid embracing the same product innovations, the panel sample used only includes every third wave.[6]

Table 1: Characteristics of the Panel

	Panel A	Panel B
Time Periods	1994–1996, 1997–1999, 2000–2002	1994–1996, 1997–1999, 2000–2002, 2003–2005
Number of observations	1401	972
Number of firms	467	243
Number of consecutive obs. per firm	3	4

The second difficulty is related to the fact that for analysing the firms' innovation success in a dynamic random effects tobit model, a balanced panel of only those firms which have consecutively answered in at least three waves is required. Although the survey is designed as a panel study, it has to be asserted that the main part of the firms participated only once or twice.[7] Furthermore, two major refreshments of the panel took place in the 1995 and 2004 surveys. Balancing the need (i) to investigate the dynamics in the innovation behaviour for a large number of enterprises, and (ii) to examine it for a long time period – to ensure that we can observe firms' innovation success over different phases of the business cycle and over an observation period that is also longer than the average product life cycle in an industry, lead me to the construction of two different samples. Panel A comprises 467 German manufacturing firms which we observe for three waves covering the time periods 1994–1996, 1997–1999 and 2000–2002. Panel B consists of the smaller set of 231 firms for which innovation activities are available for four waves spanning the period 1994–2005. Table 1 summarises the main characteristics of both samples. For both balanced panels the distributional characteristics with respect to firm size, region, industry and innovative activity have been compared with the ones

[5] Due to data restrictions, the study of Raymond et al. (2006) in part suffer from this overlapping of time periods problem.

[6] An alternative strategy is to use a panel with yearly observations and include a three-year-lagged dependent variable. The results are nearly unaltered and not reported here, but available upon request from the author.

[7] Peters (2005) provides more information on the individual participation behaviour of the sampled firms.

of the corresponding unbalanced panel. It turned out that both panels still reflect total–sample distributional characteristics quite well, though the share of product innovators are slightly lower in the balanced panels.

4 Descriptive Analysis

Before turning to the econometric results, I first provide a brief descriptive analysis of the data. Though evidence is provided for both panels, the interpretation of the results will be mainly based on panel A.

The variable PD indicates whether firm i has offered a product innovation in period t whereas the innovation success of firm i in the period t (SUCCESS) is measured as the share of sales in year k with new products introduced in the period t, i.e. the last three years k,, $k-1$ and $k-2$. Note that in the following t is used as an index for the period, k indicates a year. For more details on the variable definitions see Table 11 in the Appendix. In total, the share of product innovators is about 48% in the panel A and 45 % in panel B. A more interesting question though is that of "How persistently do firms innovate?". Table 2 and Table 3 report the transition probabilities for the introduction of new products for the whole period and differentiated by periods.

Table 2: Transition Probabilities in Product Innovation (0/1), Whole Period

	Innovation status in $t+1$					
	Panel A			Panel B		
Innovation status in t	Non–Inno	Inno	Total	Non–Inno	Inno	Total
Non–Inno	85.3	14.7	100.0	84.9	15.1	100.0
Inno	21.4	78.6	100.0	23.3	76.7	100.0

Table 2 indicates that innovation is permanent at the firm-level to a very large extent. Nearly 79% of product innovators in manufacturing in one period persisted in product innovation activities in the subsequent period while 21% did not succeed in introducing at least one new product. The persistence is even higher among non–product innovators, with a share of about 85% of them remaining non– product innovators in the following period.[8] Only 15% of previous non-product innovators offered new products in the subsequent period. The probability of introducing a new product in period $t+1$ was about 64 percentage points (hereafter: PP) higher for innovators than for non-innovators in t which can be interpreted as a measure of state dependence.

[8] Of course, this figure does not allow to distinguish whether previous non–product innovators didn't start to innovate at all or whether they didn't succeed in introducing new products.

Table 3: Transition Probabilities in Product Innovation (0/1), by Period

Innovation Status		Period		
Period t	Period $t+1$	94–96/97–99	97–99/00-02	00–02/03–05
Panel A				
Non–Inno	Non–Inno	79.5	91.7	–
	Inno	20.5	8.3	–
Inno	Non–Inno	12.3	29.7	–
	Inno	87.7	70.3	–
Panel B				
Non–Inno	Non–Inno	76.2	91.2	87.7
	Inno	23.8	8.9	12.3
Inno	Non–Inno	14.5	33.1	20.6
	Inno	85.5	66.9	79.4

Table 3 shows that these transition probabilities vary over time. The drop out of as well as entry into product innovation activities was particularly high for the period 1998–2000. This period marked a boom phase in the the German economy. This result is astonishing since it contradicts the demand-pull theory which predicts pro–cyclical effects to occur because the cash–flow as an important source of financing innovations is positively correlated with economic activity, see Himmelberg and Petersen (1994). Moreover, Judd (1985) argued that markets have a limited capacity for absorbing new products and thus firms are more likely to introduce new products in prosperous market conditions.

Table 4: Number of Entries into and Exits from Product Innovation

	Panel A			Panel B		
Number of changes	Total	Non–Inno in $t=0$	Inno in $t=0$	Total	Non–Inno in $t=0$	Inno in $t=0$
0	72.8	74.0	70.6	61.3	65.1	57.3
1	18.2	10.5	26.3	21.8	11.9	32.5
2	9.0	14.6	3.1	15.6	21.4	9.4
3	–	–	–	1.2	1.6	0.9
Total	100	100	100	100	100	100

Notes: Figures are calculated as share of total firms, initial non–product innovators and product innovators, respectively. Sample: Balanced Panel.

Looking at the innovative history of firms, Table 4 reports the number of (re–)entry into and (re–)exit from product innovation activities. 71% of the initial ($t = 0$) product innovators were continuously engaged in introducing new products throughout all three periods in panel A. This implies that 34.5% of all firms can be classified as permanent product innovators during the period 1994-2002. In panel B the share is somewhat lower, but still 57% of the initial product innovators kept in introducing new products in all following three periods. On the other hand, in panel A about 74% of the initial non–product innovators kept out of introducing new products in all following periods. This implies that 38% of all firms didn't launch any new products during the period 1994-2002.

Table 5 and 6 shed light into the dynamics of the innovation success with new products. Table 5 depict the innovation success in period t by its preceding product innovation status. On average, product innovators earn 42% of their sales in year k with new products launched in the period t. Differentiating by their preceding innovation status, it turns out that product innovators which have also introduced new products in the period $t-1$ achieve a share of sales with new products that is about 8 percentage points higher than that of prior non-product innovators. A mean difference test shows that this difference is significant at the 5 percent level.

Table 5: Innovation Success by Preceding Product Innovation Status, Panel A

Group	Mean	St.dev. Overall	St.dev. Between	St.dev. Within	Min	Max	Obs	n	ttest
$PD_t = 1$	0.420	0.293	0.252	0.172	0	1	670	288	
$PD_t = 1$ & $PD_{t-1} = 0$	0.311	0.300			0	1	67	67	
$PD_t = 1$ & $PD_{t-1} = 0$	0.393	0.283			0	1	375	214	0.016

Notes: t is an index for the period. *Obs* denotes the number of observations, n the number of firms. ttest is the p–value of a one–tailed t–test on equal means in both groups (the variances are allowed to be unequal between both groups). Note, the fact that the overall mean for $PD_t = 1$ is larger than for the subsamples is due to the fact that differentiating by prior innovation status reduces the number of periods by one.

Table 6: Transition Probabilities in Product Innovation Success, Panel A

	Innovation success category in $t+1$				
Innovation success category in t	0	1	2	3	4
0	85.4	4.5	5.2	1.7	3.2
1	22.7	34.0	27.8	12.4	3.1
2	21.7	11.7	30.8	26.7	9.2
3	21.0	6.5	18.6	31.5	22.6
4	19.7	3.9	8.7	18.9	48.8

Finally, the innovation success in each period was divided into 5 categories and Table 6 shows the one–period movements between the different categories. To take into account that the share of sales with new products varies over time, the success categories are not defined in absolute terms but on a relative base. That is, the categorial variable in a period t takes on the value 0 if the firm has not introduced any product innovations in t.

It equals 1 if the share of sales with new products is positive and is lower than the first quartile of the distribution (calculated for all firms with product innovations in period t). The values 2, 3 and 4 means the innovation success lies between the first quartile and the median, the median and the second quartile, and above the second quartile. Bases on the 'success breeds success' hypothesis we would expect a movement to higher innovation success classes. For each category the highest value can be found on the diagonal and the second highest value for the categories directly above the diagonal. That is, firms have the highest probability of sustaining their innovation success or even slightly improving their position. Interestingly enough nearly every second firm which belongs to the most successful innovators in period t, can sustain its outstanding position in the following period.

Though interesting, transition rates only depict the degree of persistence in the innovation success, but don't offer a clue to the causes of this phenomenon since it is not controlled for observed and unobserved individual characteristics. This is taken into account in the following econometric analysis.

5 Econometric Analysis

5.1 Econometric Model and Estimation Method

To examine the first research question whether successful product innovators are more likely to introduce new products in the future, a standard random effects probit model of the following form is specified (see Wooldridge 2002):

$$z_{it} = I\left[\theta\, y_{i,t-1} + w_{it}\,\delta + \eta_i + \nu_{it} > 0\right] \qquad i = 1, \ldots, N, \qquad t = 1, \ldots, T \tag{1}$$

where z_{it} is the observed binary indicator taking the value 0 for non–product innovators and 1 for firms introducing new products in period t and I denotes the indicator function. $y_{i,t-1}$ is the previous innovation success, row vector w_{it} includes further observable variables explaining the decision to launch new products, η_i captures unobservable time–constant individual effects, and ν_{it} is an idiosyncratic error term. Hypothesis H1 is supported if $\theta > 0$.

In a second step Hypothesis H2 which states that prior innovation success has a positive impact on future innovation success is tested.[9] I start on the assumption that the innovation success y_{it} of firm i in period t depends on its previous innovation success $y_{i,t-1}$, on some observable explanatory variables summarised in the l–dimensional row vector

[9] At this stage both questions are analysed in two steps. In the future they should be analysed in an integrated framework.

x_{it} and on unobservable factors u_{it}. The innovation success, however, is only observed if the firm introduces a new product and is 0 otherwise (corner solution problem). We therefore model the innovation success by the following equation:

$$y_{it} \;=\; max[0, \gamma\, y_{i,t-1} + x_{it}\,\beta + u_{it}] \qquad i = 1,\ldots,N, \qquad t = 1,\ldots,T \tag{2}$$

The 'success breed success' hypothesis implies that $\gamma > 0$. For the unobservable factors u_{it} I allow for two different assumptions. Assumption 1 is that of a pooled tobit model: $u_{it}|x_{it} \sim N(0, \sigma_u^2)$. This implies that u_{it} is independent of x_{it}, but that the relationship between u_{it} and x_{is} is unspecified for $s \neq t$. Hence it does not impose a strict exogeneity assumption of the x_{it} (see Wooldridge 2002). On the other hand, if the innovation success is influenced by firm–specific unobserved factors, a pooled tobit estimation leads to biased results. The second estimation strategy therefore allows for unobserved individual heterogeneity by assuming that

$$u_{it} \;=\; \mu_i + \varepsilon_{it} \tag{3}$$

μ_i captures time-constant firm-specific effects. The effect of other time–varying unobservable determinants is summarized in the idiosyncratic error ε_{it}. It is assumed that $\varepsilon_{it}|y_{i0},\ldots,y_{i,t-1},x_i,\mu_i$ is *i.i.d.* as $N(0,\sigma_\varepsilon^2)$ and that $\varepsilon_{it} \perp (y_{i0}, x_i, \mu_i)$ where $x_i = (x_{i1},\ldots,x_{iT})$.

One important problem in parametric estimation of dynamic non–linear models refers to the handling of the initial condition y_{i0}. I follow the conditional ML approach recently proposed by Wooldridge (2005). The idea is to assume that the individual heterogeneity depends on the initial innovation success and the strictly exogenous variables in the following way:

$$\mu_i \;=\; \alpha_0 + \alpha_1\, y_{i0} + \bar{x}_i\, \alpha_2 + a_i, \tag{4}$$

where $\bar{x}_i = T^{-1}\sum_{t=1}^{T} x_{it}$ denotes the time–averages of x_{it}.[10] Adding the means of the explanatory variables as a set of controls for unobserved heterogeneity is intuitive in the sense that we are estimating the effect of changing x_{it} but holding the time average fixed. For the error term a_i we assume that $a_i \sim i.i.d.\, N(0,\sigma_a^2)$ and $a_i \perp (y_{i0}, \bar{x}_i)$ and thus $\mu_i|y_{i0},\bar{x}_i$ follows a $N(\alpha_0+\alpha_1 y_{i0}+\bar{x}_i\,\alpha_2, \sigma_a^2)$ distribution. Having specified the distribution of μ_i in this way, Wooldridge (2005) showed that the likelihood of this dynamic random effects tobit model is the same as in the standard random tobit model, except that the explanatory variables are given by x_{it}, $y_{i,t-1}$, y_{i0} and $\bar{x}_i$. Identification of the $\beta' s$ requires

[10] Instead of $\bar{x}_i$ the original estimator used $x_i = (x_{i1},\ldots,x_{iT})$ in equation (4), but time–averages are allowed to reduce the number of explanatory variables (see Wooldridge 2005).

that the exogenous variables vary across time. If the structural model contains time–invariant regressors like industry dummies, one can include them in the regression to increase explanatory power. However, it is not possible to separate out the direct effect and the indirect effect via the heterogeneity equation. Time dummies which are the same for all i are excluded from $\bar{x}_i$.

5.2 Empirical Model Specification

The two dependent variables used are PD (research question 1) and SUCCESS (research question 2). Besides own previous innovation success (SUCCESS_{-1}), the theoretical literature has identified a bunch of other potential success factors and most of them have been confirmed to have a positive impact on the success of product innovations in previous cross–sectional studies, among others: R&D and innovation input (see, for instance, Crépon et al. 1998, Lööf and Heshmati 2001, Love and Roper 2001 or Janz et al. 2004), technological opportunities (see Cohen and Levinthal 1989), technological capabilities (see, e.g., Dosi 1997 or König and Felder 1994, Love and Roper 2001), absorptive capacity (see, e.g., Becker and Peters 2000, Raymond et al. 2006), appropriability conditions, market demand (see, e.g., Crépon et al. 1998), degree of international competition, network relationships, especially with customers (see, e.g., Hippel 1988) or corporate governance structure (manager-led companies perform better than owner-led companies, see Czarnitzki and Kraft 2004).

The following econometric analysis accounts for most of these factors and I allow them to be the same in both regressions. The innovation input (INPUT) is measured by the innovation intensity, that is the ratio of the innovation expenditure to sales. The innovation output equation is also specified as a function of technological capabilities. In addition to innovation experience, technological capabilities are mainly determined by the skills of employees. Hence, I operationalise this construct by means of three variables: the share of employees with a university degree (HIGH), a dummy variable equaling 1 if a firm has not invested in training its employees in the previous period (NOTRAIN) and the amount of training expenditure per employee (TRAINEXP). As in many previous studies, absorptive capacities are proxied by a dummy variable indicating whether the firm carries out R&D activities (R&D). The degree of international competition is measured by the export intensity (EXPORT). All these explanatory variables are measured by their value at the end of the period prior to the introduction of the new products accounted for by the dependent variable, that is in year $k-3$, to reduce potential endogeneity problems.

The regression further controls for firm size, ex ante market structure and availability of financial resources. Firm size is measured by the log number of employees (SIZE) and the market structure is captured by the Herschmann–Herfindahl index (HHI). The availability of financial resources is proxied by an index of creditworthiness (RATING). Note that we expect a negative coefficient of this variable, since the index ranges from 1 (best rating) to 6 (worst rating) and thus a higher value of RATING implies that less external funding is available and that it is more costly due to higher interest rates, making fewer innovation projects profitable and feasible. Again, all variables refer to the end of the period $t-1$, i.e. the year $k-3$.

In addition, firm–specific variables reflecting whether a firm has received public funding in the previous period (PUBLIC), firm age (AGE), location (EAST), whether the firm is part of an enterprise group (GROUP) and whether the group's headquarter is located abroad (FOREIGN) are included. The estimation also controls for ownership structure by distinguishing between public limited companies (PLC), private limited liability companies (LTD) and private partnerships (PRIVPART). One argument stressed by the principal agency theory is that managers prefer to carry out less risky investment and innovation projects than owners because managers are more closely related to the company and they will be threatened with the loss of their job if the investment fails while owners can spread their risk by diversification strategies (Jensen and Meckling 1976). On the other hand, the managers' income (as well as prestige) are often related to the firm's realised profits or sales. Hence, managers may pursue more innovation activities as it will have an impact on the development of new products and this in turn will lead to a larger sales volume (Czarnitzki and Kraft 2004).

Industry characteristics – alone or in combination with firm–specific features – may also breed firms' innovation success. In particular, technological opportunities and effective appropriability conditions are expected to play a significant role. The concept of technological opportunities can be summarised by the fact that the prevailing technological dynamics (basic inventions, spillover potentials of new technologies) in some industries spur innovation stronger than in other industries. Effective appropriability conditions are important in that they allow innovators to receive the returns on their innovation activities. Due to the lack of a good measurement for both concepts, industry dummies are intended to account for them.

Finally, time dummies are included in the regression.

5.3 Econometric Results

Estimation results for the probability of introducing a product novelty can be found in Table 7. Table 8 and Table 9 show the estimation results for the innovation success based on the pooled tobit model and on the RE effects tobit model for Panel A, respectively.

Estimation results for Panel B, though not shown here, overwhelmingly supports the results found for Panel A and are available upon request.

Table 7: Random Effects Probit Estimations, Panel A

Regression	1	2	3
	$P(PD=1)$	$P(PD=1)$	$P(PD=1)$
SUCCESS_{-1}	0.939***	0.798***	0.528***
	(0.089)	(0.092)	(0.098)
SIZE	—	0.095***	0.091***
		(0.026)	(0.025)
HERFIN	—	0.065	0.056
		(0.062)	(0.061)
RATING	—	0.007	0.007
		(0.044)	(0.043)
AGE	—	0.038	0.028
		(0.044)	(0.043)
GROUP	—	0.164***	0.145***
		(0.057)	(0.056)
EXPORT	—	0.332**	0.300**
		(0.138)	(0.135)
HIGH	—	0.405	0.243
		(0.265)	(0.261)
NOTRAIN	—	-0.432***	-0.417***
		(0.112)	(0.116)
TRAINEXP	—	0.030	0.030
		(0.022)	(0.021)
PUBLIC	—	—	0.249***
			(0.070)
FOREIGN	—	-0.215**	-0.191**
		(0.087)	(0.089)
EAST	—	-0.005	-0.092
		(0.071)	(0.071)
PLC	—	-0.128	-0.114
		(0.139)	(0.137)
PRIVPART	—	-0.102	-0.108
		(0.094)	(0.091)
INPUT	—	—	0.502***
			(0.252)
σ_η	0.831	0.713	0.634
	(0.385)	(0.164)	(0.164)
ρ	0.409	0.337	0.287
	(0.093)	(0.103)	(0.106)
$\ln L$	-461.5	-411.1	-401.3
LR	0.000	0.000	0.000
R^2_{MF}	0.168	0.259	0.276
W_{TIME}	0.000	0.000	0.000
W_{IND}	0.007	0.023	0.030
Obs	934	934	934

Notes: $***$, $**$ and $*$ indicate significance on a 1%, 5% and 10% level, respectively. Marginal effects are reported. Time and industry dummies are included in each regression. W_{IND} and W_{TIME} test for the null hypothesis that the industry and time dummies are jointly equal to zero.

In all three tables marginal effects are reported, i.e. in Table 7 the change in the probability of having product innovations is reported. In both tables of Table 8 and Table 9 the second column of each regression contain the marginal effect for the expected value of the innovation success conditional on observing a positive innovation success. The first column of each regression additionally reports the marginal effects for the probability of observing a positive innovation success.[11] All marginal effects are calculated at the sample means of the observable variables and in the RE models under the additional assumption that the unobserved heterogeneity takes its average value.

One limitation of the RE tobit estimator is the fact it assumes strict exogeneity of the explanatory variables. Hence, feedback effects from the innovation success on future values of the explanatory variables are ruled out. This strong assumption in the RE tobit model seems to be contestable at least for some of the explanatory variables. It is particularly crucial for the innovation input or the R&D variable, since it likely that shocks in the innovation outcome equation will have an impact on firms' subsequent innovation input behaviour. To assess the impact on the estimated state dependence effect by including variables, which potentially fail the strict exogeneity assumption, I apply a stepwise procedure. That is, I start estimating an extremely parsimonious specification including only industry and time dummies as strictly exogenous variables. Then additional explanatory variables are included which might fail this assumption. To compare the results I apply the same procedure for the RE probit model and the pooled tobit model.

It turns out more successful innovators have a higher probability of launching new products in the subsequent period. An increase in the prior innovation success by one percentage point (for instance from the average value of 24.6% to 25.6%) raises the probability of new products by roughly 0.5 percentage points (regression 3). This effect is significant at the one per cent level and is robust to the inclusion of additional variables. Even after accounting for the innovation input the effect remains highly significant though the estimated marginal effect decreases (from 0.8 to roughly 0.5). This indicates that the innovation output variable in regression 2 picks up part of the effect of the innovation input. Hypothesis H1 is thus clearly supported by the data for German manufacturing firms.

Estimates of the pooled tobit model additionally show a highly significant impact of previous innovation success on the actual innovation success. This result is seen in the very parsimonious specification and is again robust to including additional explanatory variables. Remember that strict exogeneity is not required for the pooled model. These

[11] Note that almost all product innovators demonstrate a positive share of sales with new products.

results would corroborate the 'success breeds hypothesis' H2. However, the pooled model does not control for unobserved heterogeneity. It might be the case that the lagged dependent variable just picks up the effect of time–constant firm specific characteristics not controlled for in the regression. The estimates of the dynamic RE tobit model show that even after controlling for individual effects, the lagged dependent variable is still significant at the 5% level. The marginal effects though are somewhat smaller than in the pooled model. Given the firm has introduced a new product, an increase in prior innovation success of one percentage point lead to an actual innovation success that is about 0.15 (pooled) to 0.09 (RE) percentage points higher. This effect still holds and is nearly unaltered after controlling for innovation input and absorptive capacities which themselves enter significantly.[12] This result points to the fact that firms gain a competitive advantage due to prior innovation success that cannot be copied by other firms investing for instance the same amount in innovation input and being equal with respect to all other observable variables as well. All in all, the estimates provide convincing evidence that innovation success breeds innovation success.

In addition to prior innovation success, innovation input and absorptive capacity, skills, age, foreign ownership and unobserved heterogeneity are crucial to the innovation success. The results found for age, for instance, indicate that firms with a lower average age in the period under consideration demonstrate a smaller innovation success, but with increasing age their innovation success steps up. Foreign owned enterprises show a significantly worse innovation performance that domestic enterprises. This is line with the 'liabilities of foreignness' hypothesis (see Zaheer 1995). The importance of unobserved heterogeneity can be gauged from $\rho = \sigma_a^2/(\sigma_\varepsilon^2 + \sigma_a^2)$. Unobserved heterogeneity still explains between 25 and 18% of the variation in the dependent variable in manufacturing depending on the specification of μ_i.

[12] Since the R&D indicator variable shows only little variation over time, only the firm-specific time-averaged value was included.

Table 8: Dynamic Pooled Tobit Estimations, Panel A

Regression	1		2		3	
	$P(y>0)$	$E(y\|y>0)$	$P(y>0)$	$E(y\|y>0)$	$P(y>0)$	$E(y\|y>0)$
SUCCESS_{-1}	0.934***	0.280***	0.836***	0.234***	0.589***	0.146***
	(0.053)	(0.015)	(0.057)	(0.015)	(0.061)	(0.015)
SIZE	—	—	0.053***	0.015***	0.024*	0.006*
			(0.014)	(0.004)	(0.015)	(0.004)
HERFIN	—	—	0.058*	0.016*	0.055*	0.014*
			(0.032)	(0.009)	(0.033)	(0.008)
RATING	—	—	0.011	0.003	0.009	0.002
			(0.028)	(0.008)	(0.028)	(0.007)
AGE	—	—	0.002	0.0004	-0.001	-0.0002
			(0.026)	(0.007)	(0.026)	(0.007)
GROUP	—	—	0.068*	0.019	0.033	0.008
			(0.036)	(0.010)	(0.037)	(0.009)
EXPORT	—	—	0.116	0.032	-0.023	-0.006
			(0.079)	(0.022)	(0.083)	(0.021)
HIGH	—	—	0.360**	0.101**	0.152	0.038
			(0.147)	(0.041)	(0.155)	(0.038)
NOTRAIN	—	—	-0.334***	-0.088***	-0.193*	-0.045*
			(0.090)	(0.024)	(0.110)	(0.025)
TRAINEXP	—	—	0.016	0.004	0.001	0.0003
			(0.014)	(0.003)	(0.014)	(0.004)
PUBLIC	—	—	—	—	0.072*	0.018*
					(0.043)	(0.011)
FOREIGN	—	—	-0.172***	-0.045***	-0.082	-0.020
			(0.056)	(0.014)	(0.063)	(0.015)
EAST	—	—	0.005	0.001	-0.030	-0.007
			(0.042)	(0.012)	(0.045)	(0.011)
PLC	—	—	-0.058	-0.017	0.032	0.008
			(0.088)	(0.023)	(0.094)	(0.024)
PRIVPART	—	—	-0.010	-0.003	0.031	0.008
			(0.062)	(0.017)	(0.065)	(0.017)
INPUT	—	—	—	—	1.302***	0.322***
					(0.252)	(0.062)
R&D	—	—	—	—	0.454***	0.128***
					(0.036)	(0.012)
σ_u	0.338		0.323		0.290	
	(0.012)		(0.012)		(0.010)	
$\ln L$	-391.5		-349.8		-249.2	
LR	0.000		0.000		0.000	
R^2_{MF}	0.389		0.454		0.611	
W_{TIME}	0.000		0.000		0.000	
W_{IND}	0.003		0.004		0.028	
Obs	934		934		934	
Cens	497		497		497	
Uncen	437		437		437	

Notes: $***$, $**$ and $*$ indicate significance on a 1%, 5% and 10% level, respectively. Marginal effects are reported. Time and industry dummies are included in each regression. W_{IND} and W_{TIME} test for the null hypothesis that the industry and time dummies are jointly equal to zero. LR is a the p-value of a likelihood ratio test comparing the model with the constant-only-model. R^2_{MF} denotes MacFadden R^2.

Table 9: Dynamic RE Tobit Estimations, Panel A

Regression	1		2		3	
	$P(y=1)$	$E(y\|y>0)$	$P(y=1)$	$E(y\|y>0)$	$P(y=1)$	$E(y\|y>0)$
Structural Equation						
SUCCESS_{-1}	0.080	0.025	0.296**	0.080**	0.330**	0.086**
	(0.111)	(0.033)	(0.146)	(0.039)	(0.158)	(0.041)
SIZE	—	—	0.064***	0.017***	0.042**	0.011**
			(0.017)	(0.004)	(0.017)	(0.004)
HERFIN	—	—	0.093*	0.025*	0.102*	0.027**
			(0.050)	(0.014)	(0.052)	(0.014)
RATING	—	—	-0.068	-0.018	-0.079	-0.021
			(0.078)	(0.021)	(0.081)	(0.021)
AGE	—	—	0.201**	0.054**	0.219**	0.057**
			(0.084)	(0.023)	(0.086)	(0.022)
GROUP	—	—	0.046	0.013	0.045	0.012
			(0.053)	(0.015)	(0.056)	(0.015)
EXPORT	—	—	0.008	0.002	-0.003	0.001
			(0.220)	(0.060)	(0.229)	(0.060)
HIGH	—	—	0.117	0.042	0.107	0.028
			(0.318)	(0.086)	(0.335)	(0.088)
NOTRAIN	—	—	-0.048*	-0.013**	-0.049*	-0.013*
			(0.025)	(0.007)	(0.026)	(0.007)
TRAINEXP	—	—	0.218	0.067	0.2228	0.068
			(0.218)	(0.077)	(0.228)	(0.079)
PUBLIC	—	—	-0.125**	-0.033**	-0.138**	-0.035**
			(0.058)	(0.014)	(0.062)	(0.015)
INPUT	—	—	—	—	0.414	0.109
					(0282)	(0.073)
Individual Heterogeneity						
SUCCESS_0	0.833***	0.256***	0.476***	0.129***	0.275**	0.072**
	(0.103)	(0.034)	(0.128)	(0.036)	(0.133)	(0.035)
M_HERFIN	—	—	-0.057	-0.015	-0.053	-0.014
			(0.062)	(0.017)	(0.064)	(0.017)
M_RATING	—	—	0.091	0.025	0.102	0.027
			(0.083)	(0.022)	(0.086)	(0.022)
M_AGE	—	—	-0.231***	-0.062***	-0.260***	-0.068***
			(0.089)	(0.024)	(0.091)	(0.024)
M_GROUP	—	—	0.015	0.004	-0.001	-0.003
			(0.073)	(0.020)	(0.074)	(0.020)
M_EXPORT	—	—	0.050	0.013	-0.001	-0.0002
			(0.237)	(0.064)	(0.245)	(0.064)
M_HIGH	—	—	0.120	0.033	0.077	0.020
			(0.363)	(0.098)	(0.376)	(0.099)
M_NOTRAIN	—	—	-0.773***	-0.209***	-0.608**	-0.159**
			(0.275)	(0.074)	(0.284)	(0.074)
M_TRAINEXP	—	—	0.086***	0.024***	0.073**	0.019**
			(0.031)	(0.009)	(0.031)	(0.008)
M_PUBLIC	—	—	0.415***	0.112***	0.278***	0.073***
			(0.084)	(0.022)	(0.088)	(0.023)

Table 9 – *continued from previous page*

Regression	1		2		3	
	$P(S=1)$	$E(S\|S>0)$	$P(S=1)$	$E(S\|S>0)$	$P(S=1)$	$E(S\|S>0)$
FOREIGN	—	—	-0.165***	-0.042***	-0.151**	-0.037***
			(0.060)	(0.015)	(0.061)	(0.015)
EAST	—	—	-0.101**	-0.027**	-0.081	-0.021
			(0.050)	(0.014)	(0.051)	(0.013)
PLC	—	—	-0.064	-0.017	0.010	0.003
			(0.097)	(0.025)	(0.099)	(0.026)
PRIVPART	—	—	0.027	0.007	0.062	0.017
			(0.068)	(0.019)	(0.068)	(0.019)
M_R&D	—	—	—	—	0.370***	0.097***
					(0.060)	(0.016)
σ_a	0.239		0.159		0.133	
	(0.028)		(0.037)		(0.044)	
ρ	0.454		0.254		0.187	
	(0.080)		(0.108)		(0.118)	
ln L	-371.0		-313.2		-291.0	
LR	0.000		0.000		0.000	
R^2_{MF}	0.350		0.451		0.490	
W_{TIME}	0.000		0.000		0.000	
W_{IND}	0.011		0.033		0.071	

Notes: $***$, $**$ and $*$ indicate significance on a 1%, 5% and 10% level, respectively. Marginal effects are reported. Time and industry dummies are included in each regression. W_{IND} and W_{TIME} test for the null hypothesis that the industry and time dummies are jointly equal to zero. LR reports the p-value of a likelihood ratio test comparing the model with the constant-only-model. R^2_{MF} denotes MacFadden R^2.

6 Conclusion

This paper has investigated the persistence of innovation success at the firm level and whether preceding innovation performance substantiates further innovation success. Evidence is based on data form German manufacturing firms during the period 1994-2005.

The econometric results confirm the 'success breeds success' hypothesis. First, successful product innovators are more likely to introduce new products in the future and second, they achieve a higher share of sales with these product novelties. These results hold even after controlling for unobserved heterogeneity across firms.

An essential element of the "dynamic competence" approach to the theory of the firm concerns the cumulative nature of firms' competencies implying that firms tend to improve gradually following rather rigid directions. As a consequence, they can face great difficulties when trying to do something radically different from their past experience Malerba et al. (2001). In this study innovation success is measured by means of products that are new to the firm, not necessarily new to the market. One obvious question for further research is whether the success breeds success hypothesis applies equally to both kinds of innovation.

Another interesting question for further research is to analyse if the persistence in firms' innovation success carry over to an asymmetric performance across firms over time.

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Appendix: Tables

Table 10: Branches of Industry

Branches of Industry	NACE
Mining	10 – 14
Manufacturing	
Food	15 – 16
Textile	17 – 19
Wood/paper/printing	20 – 22
Chemicals	23 – 24
Plastic/rubber	25
Glass/ceramics	26
Metals	27 – 28
Machinery	29
Electrical engineering	30 – 32
MPO instruments	33
Vehicles	34 – 35
Furniture/recycling	36 – 37
Energy/water	40 – 41
Construction	45

Notes: The industry definition is based on the classification system NACE Rev.1, using 2–digit or 3–digit levels. MPO: Medical, precision and optical instruments.

Table 11: Variable Definition

Variable	Type	Definition
Endogenous variable		
PD	0/1	1 if firm i has introduced a product innovation in period t. A product innovation is defined as a good or service which is new or significantly improved with respect to its fundamental characteristics, technical specifications, incorporated software or other immaterial components, intended uses, or user friendliness. The product innovation should be new to the enterprise; it has not necessarily to be new to the market.
SUCCESS	0-1	Innovation success in period t measured as share of sales in year k with new products introduced in the years $k-2$ to k.
Explanatory variables varying across individuals and time		
SIZE	c	Number of employees at the end of period $t-1$, i.e. in year $k-3$ (in log).
RATING	c	Credit rating index at the end of period $t-1$, i.e. in year $k-3$, ranging between 1 (highest) and 6 (worst creditworthiness).
AGE	c	Age at the end of period t (in log).
GROUP	0/1	1 if firm i belongs to a group at the end of period t.
NOTRAIN	0/1	1 if firm i has no training expenditure in period $t-1$, i.e. in year $k-3$.
TRAINEXP	c	Training expenditure per employee at the end of period $t-1$, i.e. in year $k-3$ if NOTRAIN=0 (in log), otherwise 0.
HIGH	c	Share of employees with a university or college degree at the end of period $t-1$, i.e. in year $k-3$.
EXPORT	c	Export intensity defined as exports/sales at the end of period $t-1$, i.e. in year $k-3$.
PUBLIC	0/1	1 if firm i received public funding for innovation at the end of period $t-1$, i.e. in year $k-3$.
INPUT	c	Innovation intensity which is defined as the ratio of innovation expenditure to sales at the end of period $t-1$, i.e. in year $k-3$. Innovation expenditure includes expenditure for intra– and extramural R&D, acquisition of external knowledge, machines and equipment, training, market introduction, design and other preparations for product and/or process innovations.
R&D	0/1	1 if firm i carries out R&D in year $k-3$.

Continued on next page.

Table 11 – *continued from previous page*

Variable	Type	Definition
Explanatory variables varying across industries and time		
HERFIN	c	Hirschman–Herfindahl Index in year $k-3$, on a 3–digit NACE level, divided by 100.
Time–constant individual–specific explanatory variables		
FOREIGN	0/1	1 if firm i is a subsidiary of a foreign company.
EAST	0/1	1 if firm i is located in Eastern Germany.
PLC	0/1	1 if firm i is a public limited company.
LTD	0/1	1 if firm i is a private limited liability company.
PRIVPART	0/1	1 if firm i is a private partnership.
IND	0/1	System of 15 industry dummies, see Table 10.
Time–varying individual–constant explanatory variables		
TIME	0/1	System of time dummies for each period.

Notes: c denotes a continuous variable.