Persistence in Innovation Activities? Stylised Facts and Panel Data Evidence

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Abstract: This paper investigates whether innovation behaviour exhibits persistence at the firm-level using a long innovation panel data set of German manufacturing and service firms for the period 1994-2002. We find that innovation behaviour is permanent at the firm-level to a very large extent. Using a dynamic random effects discrete choice model and the estimator recently proposed by Wooldrigde (2005), we further shed some light on the driving forces for this phenomenon. The econometric results confirm the hypothesis of true state dependence for manufacturing as well as for service sector firms. In addition, unobserved individual heterogeneity as well as some observed firm characteristics have also found to be important factors in explaining innovation.

Keywords: Innovation, persistence, panel, transition, random effects dynamic model

JEL Classification:

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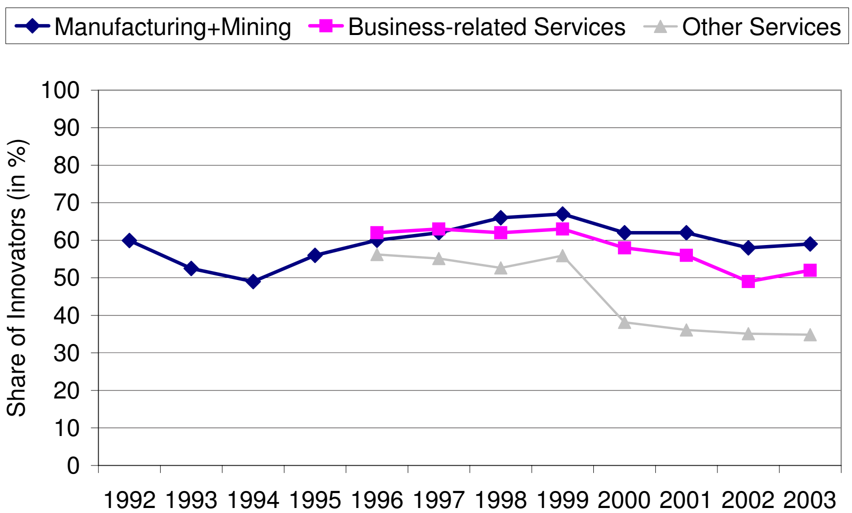
1 Introduction

Innovation is widely considered to be the long-term driving force for economic growth. In 1993, the first Community Innovation Surveys (CIS) started within the European countries to investigate firms' innovation activities. These rich and internationally harmonised data sets have served as the starting-point for plenty of empirical studies which have analysed various aspects of innovation activities. However, there is still very little evidence on the dynamics in firms' innovation behaviour. Looking for example at innovation performance indicators at the aggregate or industry level, we can identify high and quite stable shares of innovators in the manufacturing and the service sector in Germany over the last ten years, see Figure 1. One interesting question though cannot be answered by such macroeconomic numbers, that is, whether always the same firms set themselves at the cutting edge by introducing new products and processes or whether there is a steady entry into and exit from innovation activities at the firm level with the aggregate level remaining more or less stable over time?

Figure 1: Share of Innovators 1992-2003



Notes:
Business-related services includes telecommunication, financial intermediation, data processing, technical services, consultancies and other business-related services. Wholesale, retail, transport, real estate and renting are summarized to other services. All figures are expanded to the target population which covers all German firms with 5 or more employees.
Comparison of figures for other services before and after 2000 is reduced due to a slight change of wording in the innovation definition.
Source: Rammer et al. (2004).

This paper analyses the dynamics in firms' innovation behaviour. In particular, it is focused upon the following two research questions: Does innovation reflect persistence at the firm-level? Persistence occurs when a firm which has innovated in one period, innovates once again in the subsequent period. And if persistence is prevalent, what drives this phenomenon?

In principle, there are various potential sources for persistent behaviour, see Heckman (1981a,b): First, it might be caused by true state dependence. This means that a causal effect exists, in the sense that the decision to innovate in one period itself enhances the probability to innovate in the subsequent period. The theoretical literature delivers some potential explanations for such state dependence. The most prominent ones relate to sunk costs especially in building up R&D departments (see Sutton 1991 or Manez Castillejo et al. 2004), the hypothesis that success breeds success (see Mansfield 1968), or the hypothesis that innovations involve dynamic increasing returns (learning-by-doing or learning-to-learn) which enhance the innovative capabilities of firms and thus the probability of future innovations (see Nelson and Winter 1982 and Malerba and Orsenigo 1993). Second, firms may possess certain characteristics which make them particularly "innovation-prone". Such firm-specific characteristics can be classified into observable characteristics[1], like firm size or competition, and unobservable ones. Typically technological opportunities, managerial abilities or risk attitudes are important for the firms' decision to innovate, but are not observed. To the extent that these characteristics themselves show persistence over time, they will also increase the innovation probability of future periods, creating a spurious relationship between current and future innovation (see also Biewen 2004). In contrast to true state dependence this phenomenon is called spurios state dependence. Third, serial correlation in exogenous shocks to the innovation decision can cause persistent behaviour over time.

The answers to both research questions are important for several reasons. First, it is interesting from a theoretical point of view. Endogenous growth models for example differ in the underlying assumptions about the innovation frequency of firms. While Romer (1990) assumes that the innovation behaviour is persistent at the firm level to a very large extent, the process of creative destruction leads to a perpetual renewal of innovators in the model of Aghion and Howitt (1992). Thus, empirical knowledge about the dynamics in firms' innovation behaviour is a tool to assess different endogenous growth models. Furthermore, it constitutes an important piece of evidence for finding and improving current theories of industrial dynamics, where some forms of dynamic increasing returns play a major role in determining degrees

[1] Observable characteristics means known to the econometrician.

of concentration, the evolution of market shares and their stability over time, see Geroski (1995). Second, from a managerial point of view permanent innovation activities are seen as a crucial factor for strengthening competitiveness. And last but not least, the distinction between permanent innovation activities due to firm-inherent factors as opposed to true state dependence has important implications for the technology and innovation policy. If the innovation performance shows true state dependence, then innovation-stimulating policy measures such as governmental supporting programmes are supposed to have a more profound effect, because they do not only affect the current innovation activities but are likely to induce a permanent change in favour of innovation. If, on the contrary, individual heterogeneity induces persistent behaviour, long-lasting effects of supporting programmes are unlikely and economic policy should concentrate on measures which have the potential to improve firm-specific factors.

To answer the first question, the paper presents some stylised facts of how permanently German firms did innovate in the period 1994-2002. While in most of the other European countries the innovation survey takes place every 4 years, it is conducted annually in Germany. This provides us with a long panel data set which is appropriate to study whether the innovation behaviour is persistent at the firm-level. This part ties on the literature about innovation persistence effects using patents (see Geroski et al. 1997, Malerba and Orsenigo 1999 and Cefis 2003) and R&D indicators (see Manez Castillejo et al. 2004).

To answer the question on causal effects, I apply a dynamic random effects binary choice model. The same model was chosen by Manez Castillejo et al. (2004) for R&D indicators. This panel data approach allows us to control for individual heterogeneity, a potential source of bias which was not taken into account in the study of Duguet and Monjon (2002) due to data restrictions.

The paper contributes to the existing literature in that it is one of the first which investigates firm-level persistence using innovation data (see section 5.2) and that we are able to exploit international comparable data from a unique long innovation panel data set. Furthermore, we applied a new estimation method recently proposed by Wooldridge (2005) and we analyse this topic not only for manufacturing but also for service sector firms, the latter gaining increasing importance over the last fifteen years in many industrialised countries. Looking at the potential theoretical explanations for true state dependence, especially the first one is strongly related to R&D, the latter being less important and less spread in the service sectors. Thus, one hypothesis is that innovation activities are less permanent in this sector compared to the manufacturing.

The outline of the paper is as follows. Section ?? presents some related theoretical literature which predicts that the innovation behaviour at the firm-level should be persistent. Section ?? summarises the main empirical firm-level results so far. The panel data set underlying this study and the relevant variables are explored in section 2. The following section 4 come up with some stylised facts about the entry into and exit from innovation activities at the firm-level during the period 1994-2002. Section 5 presents the econometric model and its empirical implementation. It further explores the estimation methods used and set forth the econometric results. Section 6 draws some conclusions on the persistence of firm-level innovation activities and discusses the results.

2 Data Set

In Germany, the Centre for European Economic Research (ZEW) runs two different, but complementary innovation surveys on behalf of the German Federal Ministry of Education and Research. The first one covers industry firms, i.e., firms from the manufacturing, mining, energy, water and construction sector. The second one is the counterpart for the service sector, comprising not the whole service sector, but retail, wholesale, transport, real estate and renting, financial intermediation, computer services and telecommunications, technical services, consultancies and other business related services.[2] Both surveys formed the Mannheim Innovation Panel (MIP). The survey methodology and definitions of innovation indicators are strongly related to the recommendations on innovation surveys manifested in the OSLO-Manual, see OECD and EUROSTAT (1997) or Janz et al. (2001), thereby yielding international comparable data on innovation activities of German firms. In 1993 (CIS1), 1997 (CIS2) and 2001 (CIS3) the surveys have been the German contribution to the European-wide harmonised Community Innovation Surveys.

While in most of the other European countries the innovation surveys take place every 4 years, it is conducted annually in Germany. In manufacturing, it started in 1993. However, due to a major refreshment and enlargement of the initial sample in 1995 and the need to construct a balanced panel for estimation purposes, I decided to discard the first two waves in manufacturing. In the service sector, the first usable wave was that of 1997.[3] The last surveys taken into account are those of 2003, thus,

[2] For a detailed definition, see Table 14 in the appendix.

[3] Actually, the first survey in the service sector took place in 1995, but with a break in 1996. Thus, the first usable wave was that of 1997.

up to now 9 waves in manufacturing and 7 in services are available. The data of each survey refers to the previous year, hence we focus on the period 1994–2002 in manufacturing and 1996–2002 in the service sector. This relatively long period ensures that we can observe firms' innovation behaviour over different phases of the business cycle and it is also longer than the average product life cycle in industry.

The target population spans all legally independent firms with 5 or more employees. Both samples are drawn as stratified random samples. Firm size (8 size classes according to the number of employees), branches of industries and region (East and West Germany) serve as stratifying variables. The samples are constructed as panels and about 10,000 firms in manufacturing and 12,000 service firms are questioned each year. But, participation is voluntary and the response rates vary between 20 to 25 per cent[4] and although the survey is designed as a panel study, we have to detect that the main part of the firms participated only once or twice.[5] Furthermore, for analysing econometrically the dynamics in firms' innovation behaviour, only those firms which have answered consecutively can be taken into account. Therefore, in the following we distinguish between two panels: Panel U is an unbalanced panel comprising all firms for which at least 4 successive observations (3 after constructing lagged values) are available and Panel B is the balanced sub–sample. The latter one is needed for estimation purposes (see section 5.2).

Table 1 summarises the main characteristics of both samples. Given our interest to analyse the persistence behaviour of firms and the need to estimate a dynamic specification with a lagged endogenous variable, I have chosen the time dimension of the panel as long as possible. As a result, in manufacturing as well as in the service sector these selection criteria lead to a perceptibly reduction of the number of observations and the resulting panels might not be representative of the far larger total sample. To check the representativeness of both samples, the Tables 2 and 3 compare the distribution of firms by industry, size class, region and innovation status in the total sample of all observations, the unbalanced panel of all firms with at least four successive observations and the balanced sub–sample. It turns out,

[4] The low response rates are in line with those of comparable voluntary surveys among German firms. In order to control for a response bias in the net sample, non-response analyses have been carried out. They come up with the result, that the share of innovators is only slightly underestimated in the net sample.

[5] Table 15 in the appendix sheds some light on the individual participation behaviour of the sampled firms. But note, that the number of observations actually used in this study is higher than the one which would arise from the participation pattern. This can be explained by the fact that since 1998 the survey is sent only to a sub-sample of firms in even years due to cost reasons. However, to maintain the panel structure with yearly waves, the most relevant variables are asked retrospectively for the preceding year in odd years.

Table 1: Characteristics of the Unbalanced and Balanced Panel

	Manufacturing	Services
Panel U: Unbalanced Panel		
Number of observations	13558	7901
Number of firms	2256	1528
Minimum number of consecutive obs. per firm	4	4
Average number of consecutive obs. per firm	6.0	5.2
Panel B: Balanced Panel		
Number of observations	3933	1974
Number of firms	437	282
Number of consecutive obs. per firm	9	7
Time Period	1994–2002	1996–2002

Source: Own calculations.

that in manufacturing large firms with 100 or more employees are slightly over–represented in the unbalanced and balanced panel compared to the total sample, while the opposite applies to the service sector. Moreover, the share of East German firms is slightly higher in both panels in manufacturing as well as in the service sector. The tables further demonstrate that the share of innovators is lower in both panels used. But, while the difference for instance between the balanced panel and the total sample is rather small in manufacturing, it amounts to 8.5 percentages points in the service sector. That is, the service firms in our sample are less likely to engage in innovation activities. Based on these comparisons, we argue that by and large the panels still reflect total–sample distributional characteristics quite well in manufacturing and don't give any obvious cause for selectivity concerns. Admittedly, in the service sector selectivity might be a more severe problem in the resulting panels since innovators are less represented.

Table 2: Distribution of the Unbalanced and Balanced Panel in Manufacturing

Distribution by:	Panel[a)]			Difference		Distribution by:	Panel[a)]			Difference	
	T	U	B	B-T	B-U		T	U	B	B-T	B-U
Industry[b)]						**Size**[b)]					
Mining	2.0	2.1	1.7	−0.3	−0.4	0-4	2.7	1.8	1.6	−1.2	−0.3
Food	6.3	6.0	5.5	−0.8	−0.5	5-9	6.9	6.5	5.5	−1.3	−1.0
Textile	5.2	4.9	4.9	−0.3	−0.0	10-19	12.1	11.6	10.2	−1.8	−1.4
Wood/printing	6.7	6.5	6.4	−0.3	−0.0	20-49	17.8	18.2	19.7	+1.9	+1.5
Chemicals	6.6	6.8	8.7	+2.1	+1.9	50-99	15.2	15.7	14.3	−0.8	−1.3
Plastic/rubber	6.8	7.7	8.4	+1.6	+0.8	100-199	13.0	13.7	13.8	+0.8	+0.2
Glass/ceramics	4.7	5.0	5.5	+0.8	+0.6	200-499	15.5	16.4	17.5	+2.0	+1.1
Metals	13.2	13.4	11.5	−1.6	−1.8	500-999	7.6	8.0	8.3	+0.7	+0.3
Machinery	14.3	14.5	13.0	−1.3	−1.5	1000+	8.9	8.2	9.1	+0.3	+1.0
Electrical engineering	8.0	7.8	7.8	−0.2	+0.0						
Medical instr.	6.5	6.8	7.8	+1.3	+1.1	**Region**[b)]					
Vehicles	4.6	4.5	4.4	−0.2	−0.1	West	68.2	66.8	65.7	−2.6	−1.1
Furniture/recycling	4.2	3.6	3.8	−0.4	+0.2	East	31.8	33.2	34.3	+2.6	+1.1
Energy/water	4.4	4.8	5.9	+1.5	+1.1						
Construction	6.6	5.9	4.6	−2.0	−1.3	**Innovators**[b)]	59.3	57.8	55.1	−4.2	−2.7
Total Obs	27116	13558	3933				27116	13558	3933		

Notes:
[a)] T: Unbalanced panel of all firms within the period 1994–2002. U: Unbalanced panel of firms with at least 4 consecutive observations within 1994–2002.
B: Balanced panel of firms within 1994–2002.
[b)] Calculated as share of total number of observations (in %).
Source: Own calculations.

Table 3: Distribution of the Unbalanced and Balanced Panel in the Service Sector

Distribution by:	Panel[a]			Difference		Distribution by:	Panel[a]			Difference	
	T	U	B	B-T	B-U		T	U	B	B-T	B-U
Industry[b]						**Size**[b]					
Wholesale	11.4	12.0	10.7	−0.7	−1.2	0-4	7.3	7.2	9.4	+2.1	+2.1
Retail	10.4	12.8	11.9	+1.5	−0.8	5-9	13.9	15.4	14.2	+0.3	+1.1
Transport	15.4	18.8	18.8	+3.4	+0.0	10-19	17.7	19.5	19.1	+1.4	+0.4
Bank/insurance	11.1	10.0	9.2	−1.8	−0.8	20-49	19.5	22.2	20.0	+0.4	−2.2
Computer	8.3	6.8	7.1	−1.1	+0.3	50-99	11.3	12.1	12.9	+1.6	+0.8
Technical serv.	14.4	13.5	11.5	−2.9	−2.0	100-199	9.6	9.8	11.0	+1.4	+1.2
Consultancies	7.8	6.7	8.2	+0.4	+1.5	200-499	8.0	7.0	6.5	−1.5	−0.5
Other BRS	13.8	12.0	12.8	−1.0	+0.8	500-999	4.5	2.8	1.8	−2.7	−0.9
Real estate/renting	6.7	7.5	9.7	+3.0	+2.2	1000+	7.9	4.1	5.2	−2.7	+1.1
						Region[b]					
						West	62.5	57.4	57.9	−4.6	+0.5
						East	37.5	42.6	42.1	+4.6	−0.5
						Innovators[b]	44.5	37.6	35.8	−8.6	−1.8
Total Obs	20493	7901	1974				20493	7901	1974		

Notes:
[a] T: Unbalanced panel of all firms within the period 1996–2002. U: Unbalanced panel of firms with at least 4 consecutive observations within 1996–2002.
B: Balanced panel of firms within 1996–2002.
[b] Calculated as share of total number of observations (in %).
Source: Own calculations.

3 Measurement Issues

In what follows we want to give an answer to the first research question of "How persistently do firms innovate?". In a broader sense this part ties on the literature about innovation persistence effects using patents (see Geroski et al. 1997, Malerba and Orsenigo 1999 and Cefis 2003) and R&D indicators (see Manez Castillejo et al. 2004). It is well known that patents have been heavily criticised as being a poor indicator of innovative outcomes, see Griliches (1990). In the context of persistence analysis patents have an additional drawback, because in this kind of winner-take-all contests to be classified as permanent innovators firms have to win continuously the patent race, see Kamien and Schwartz (1975). This means that patent data measure the persistence of innovative leadership rather than the persistence of innovation, as was stressed by Duguet and Monjon (2002). On the other hand, R&D is an important input to innovation, but it does not capture all aspects pertinent to innovation. Innovation activities close to the market are not captured by the concept of R&D; such activities of small and medium-sized as well as service sector firms are particularly heavily underestimated. Like Duguet and Monjon (2002) for French or Raymond et al. (2005) for Dutch manufacturing firms we concentrate on innovation indicators as defined by the OSLO Manual.

One problem in studying state dependence effects in innovation behaviour with CIS data is the fact that the indicator whether a firm has introduced an innovation is related to a 3–year–period, that is, using this indicator for yearly waves would induce an artificial high persistence due to overlapping time periods and double counting.[6] Both studies of Duguet and Monjon (2002) or Raymond et al. (2005) suffer from this overlapping time periods problem in their dependent variable. However, information on innovation expenditure is available on a yearly base. Innovation expenditure include expenditure for intramural and extramural R&D, acquisition of external knowledge, machines and equipment, training, market introduction, design and other preparations for product and/or process innovations in a given year.[7] Therefore and in contrast to the previous mentioned studies, we define an innovator as a firm which decides to engage in innovation activities and exhibits positive innovation expenditure in a given year. This implies that we analyse the persistence in innovation input rather than in innovation outcome behaviour. From a theoret-

[6] As an example, in the survey 2001 a firm is defined as an innovator if it has introduced an innovation in the period 1998–2000, in the survey 2002 this indicator is related to 1999-2001.

[7] R&D expenditure accounted for 50–55 per cent of innovation expenditure in the period under consideration, see Gottschalk et al. (2002).

ical point of view it is not unambiguous whether state dependence in innovation behaviour should be tested in terms of an input or an output measure. The literature on sunk costs usually models the decision to invest in R&D by a rational profit–maximising firm, so that an input measure seems advisable, see e.g. the two-stage game model of Sutton (1991) or the model applied by Manez Castillejo et al. (2004). In contrast, Flaig and Stadler (1994,1998) 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. By stressing the accumulative nature of innovation and the importance of learning effects in the innovation process, the evolutionary theory is likewise rather outcome-oriented since the process of learning involves successful implementation rather than just spending some resources to innovation projects, see Blundell et al. (1993). Econometric evidence shows that on average innovation output is significantly determined by innovation input (see e.g. Crepon et al. 1998, Lööf and Heshmati 2001, Love and Roper 2001 or Janz et al. 2004), implying that input persistence should converted into output persistence to a certain degree. However, often more than one period is needed to translate innovation effort into new products or processes and furthermore firms can not necessarily control their innovation outcome because serendipity might play an important role in the innovation process, see Kamien and Schwartz (1982) or Flaig and Stadler (1998).[8]

4 Stylised Facts

To investigate whether innovation behaviour is persistent at the firm level, transition probabilities are an appropriate method. Tables 4 and 5 show corresponding figures for the whole period and differentiated by years. First of all, it turns out that there are hardly any differences between our much larger unbalanced panel and the smaller balanced panel which has to be used for estimation purposes. Table 4 clearly indicates that innovation behaviour is permanent at the firm-level to a very large extent. In the period 1994–2002, nearly 89 per cent of innovating firms in manufacturing in one period persisted in innovation activities in the subsequent period while 11 per cent stopped their engagement. Similarly, about 84 per cent of non–innovators maintained this status in the following period while at least 16 per

[8] Alternatively, I checked the robustness of my results by applying the output-oriented 3–period innovation indicator and taking only every third survey information into account. This strategy led to a larger reduction of the number of observations. However, the main result of significant true state dependence presented in the next section also showed up in this setting. Results are not presented here, but are available upon request.

Table 4: Transition Probability, Whole Period[a)]

	Innovation status in $t+1$					
	Unbalanced Panel			Balanced Panel		
Innovation status in t	Non–Inno	Inno	Total	Non–Inno	Inno	Total
Manufacturing						
Non–Inno	83.6	16.4	100.0	85.3	14.7	100.0
Inno	11.2	88.8	100.0	11.2	88.8	100.0
Total	41.9	58.1	100.0	44.5	55.5	100.0
Services						
Non–Inno	82.9	17.1	100.0	83.9	16.1	100.0
Inno	29.2	70.8	100.0	30.2	69.8	100.0
Total	62.6	37.4	100.0	64.0	36.0	100.0

Notes:
[a)] Manufacturing: 1994–2002, service sector: 1996–2002.
Source: Own calculations.

cent entered into innovation activities. That also means that the probability of being innovative in period $t+1$ was about 72 percentage points higher for innovators than for non-innovators in t which can be interpreted as a measure of state dependence. Against the background of the sunk costs hypothesis, it is interestingly enough that using the narrower concept of R&D expenditure, Manez Castillejo et al. (2004) even found little higher exit rates in Spanish manufacturing for the period 1990–2000, while maybe not surprisingly the entry into R&D activities is much less frequent than into innovation activities.[9]

In services persistence effects are also well observable, though less prevailing than in manufacturing. Non–innovative service firms had pretty much the same propensity to enter into innovation activities than manufacturing firms. However, in any given year the probability of an innovative service firm to remain in innovation activities in the subsequent year was significantly lower (70 per cent) than for a manufacturing firm. This implies that the state dependence effect in the service sector was clearly lower with approximate 54 percentage points. Several arguments could explain this finding, one being the fact the sunk cost hypothesis is strongly related to R&D investments, however, R&D is less important and less spread in most of the service sectors compared to manufacturing. Alternatively, individual

[9]Manez Castillejo et al. (2004) reported only transition rates for small and large firms. Using a weighted average, one would get an exit rate of about 17 per cent and an entry probability of 8 per cent.

or industry heterogeneity for example in the technological opportunities or in the demand for new innovations might explain this difference.

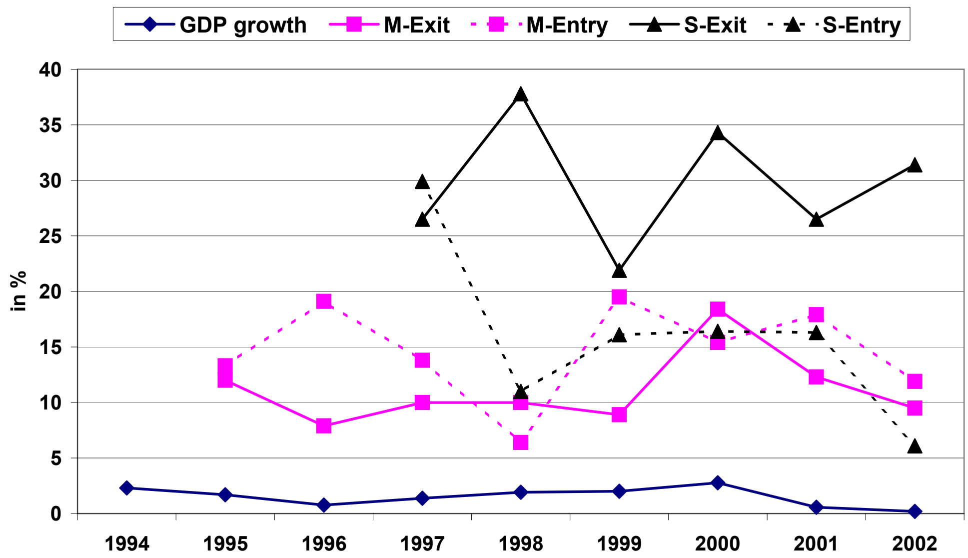
Table 5: Transition Probability by Year

Innovation Status		Years							
Year t	Year $t+1$	94–95	95–96	96–97	97–98	98–99	99–00	00–01	01–02
Manufacturing[a)]									
Non–Inno	Non–Inno	86.7	81.0	86.2	93.6	80.5	84.6	82.1	88.1
	Inno	13.3	19.1	13.8	6.4	19.5	15.4	17.9	11.9
Inno	Non–Inno	12.0	7.9	10.0	10.0	8.9	18.4	12.3	9.5
	Inno	88.1	92.1	90.0	90.0	91.1	81.6	87.7	90.5
Services[a)]									
Non–Inno	Non–Inno	–	–	70.1	89.0	83.9	83.6	83.7	93.9
	Inno	–	–	29.9	11.0	16.1	16.4	16.3	6.1
Inno	Non–Inno	–	–	26.5	37.8	21.9	34.3	26.5	31.4
	Inno	–	–	73.5	62.2	78.1	65.7	73.5	68.6

Notes:
[a)] Sample: Balanced Panel.
Source: Own calculations.

There is a related strand of literature investigating the interrelationship between business cycles and innovation activity. According to the technology-push argument science and technology are a major driver for innovation and entrepreneurial activities and consequently the business cycle, see e.g. Schumpeter (1939) or Kleinknecht (1990) for an empirical assessment. In contrast, the demand-pull hypothesis states that innovation behaviour depends on demand conditions and thus on the level of economic activity, see Schmookler (1966). Within this literature, arguments for both, a pro- as well as a counter–cyclical relationship can be found. Pro–cyclical effects are expected to occur because cash–flow as an important source to finance innovations is positively correlated with the economic activity, see Himmelberg and Petersen (1994). Furthermore, Judd (1985) argued that markets have a limited capacity for absorbing new products and thus firms' are more likely to introduce new products in prospering market conditions. In contrast, Aghion and Saint-Paul (1998) showed that firms tend to invest more in productivity growth during recessions, since the opportunity cost in terms of forgone profits of investing capital in technological improvements is lower during recessions. During the period 1994–2002 the German economy underwent different business cycles. 1993 was characterised by a deep recession, followed by an upswing in 1994-1995 which has nearly stopped in 1996. Since 1997 economic growth steadily increased again, reaching its peak in 2000. Since 2001 the German economy had got into a significant cyclical slump again. Table 5 shows that despite different business cycles, the propensity to remain innovative and correspondingly the exit rates were quite stable over time in manufacturing, with one remarkable exception in the peak period 2000 where the flow out of innovating sharply increased.[10] At the same time, the entry rate was more volatile across the periods in manufacturing. In the service sector, the propensity to remain innovative was not only lower but also exhibited a higher variance across time.[11] However, contrasting both exit and entry rates with the annual GDP growth rate, no clear pro– or counter–cyclical link to the level of economic activity can be found.

Figure 2: Entry and Exit Rates and Economic Growth



Notes:
M and S denotes manufacturing and services, respectively.
Source: GDP growth rates: Sachverständigenrat (2004). Own calculation.

The following Table 6 and Figure 3 give some information on innovation persistence by size class and industry. As expected, behaviour was more stable in larger firms, though also relatively high in small firms. This result holds for manufacturing and by and large likewise for service firms. The propensity to remain innovative increased with firm size, but at the same time the propensity for non–innovators to

[10] This results chimes with the plain decline in the share of innovators at the aggregate level, see Figure 1.

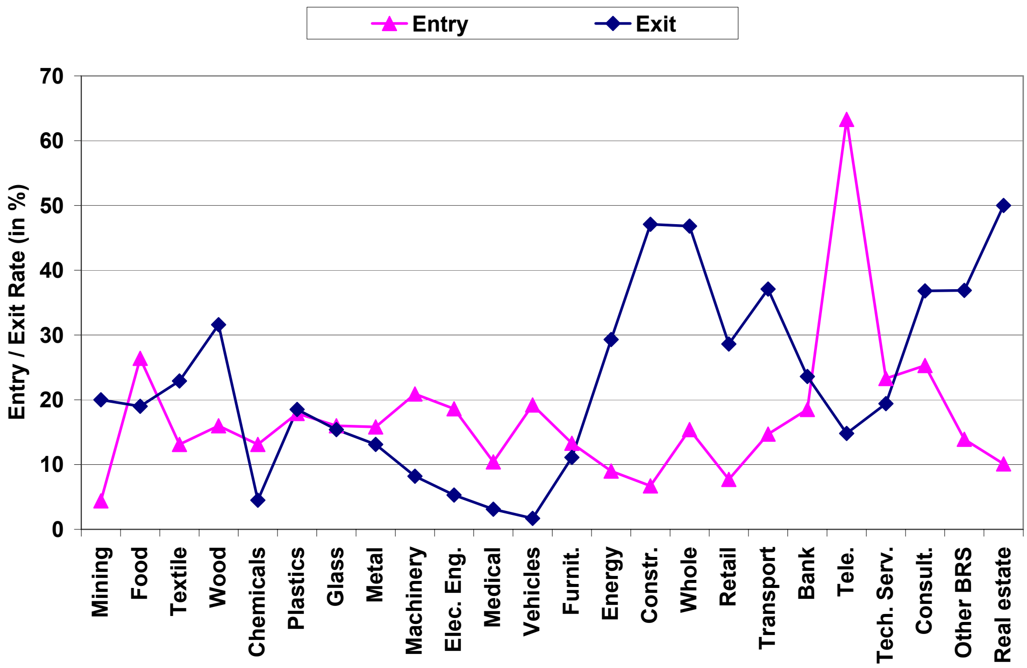
[11] The standard deviation of exit and entry rates is 3.3 and 4.4 in manufacturing and 5.8 and 8.0 in the service sector.

Table 6: Transition Probability by Size Class

Innovation Status		Years					
Year t	Year $t+1$	< 10	10–19	20–49	50–99	100–499	>=500
Manufacturing[a)]							
Non–Inno	Non–Inno	93.8	88.3	87.6	84.6	79.4	81.5
	Inno	6.2	11.7	12.4	15.4	20.6	18.5
Inno	Non–Inno	35.1	20.4	16.9	16.3	8.4	3.8
	Inno	64.9	79.6	84.2	83.7	91.6	96.2
Services[a)]							
Non–Inno	Non–Inno	86.4	81.0	85.3	83.2	82.2	77.8
	Inno	13.6	19.0	14.7	16.8	17.8	22.2
Inno	Non–Inno	38.5	54.9	29.6	20.3	28.7	11.5
	Inno	61.5	45.1	70.4	79.8	71.3	88.5

Notes:
[a)] Sample: Balanced Panel.
Source: Own calculations.

Figure 3: Entry and Exit Rates into Innovation Activities by Industry



Notes:
Sample: Balanced Panel. Time Period: 1994-2002 in manufacturing, 1996-2002 in the service sector. The connection lines between industries are for ease of presentation, but have no meaning.
Source: Own calculation.

take up such activities rises as well. Nevertheless, the (unconditional) state dependence effect measured as the difference between the probabilities of being innovative in period $t+1$ for innovators and for non–innovators in t is more pronounced in large manufacturing firms (approximately 74 percentage points for firms with more than 500 employees) than in small ones (59 percentage points for firms with less than 10 employees). The same picture emerges in services with a difference of 66 and 48 percentage points.

Figure 3 further demonstrates that innovation activities at the firm level are found to be more persistent in high–technology industries, though also quite high in some low–technology manufacturing and business-related service industries. For instance, the lowest exits can be found in R&D intensive industries like chemicals, vehicles, electrical engineering, medical instruments or machinery while exiting innovation activities is much more likely in the wood/paper, energy/water or construction industry or in most service industries.

Table 7: Innovation History of Firms: Number of entries into and exits from innovation activities

	Manufacturing			Services		
Number of changes	Total	Non–Inno in $t=0$	Inno in $t=0$	Total	Non–Inno in $t=0$	Inno in $t=0$
0	54.9	43.1	65.9	45.0	47.8	39.8
1	11.2	13.7	8.9	13.1	6.5	25.5
2	19.0	24.2	14.2	22.7	28.3	12.2
3	8.5	10.4	6.6	10.3	7.6	15.3
4	4.8	6.6	3.1	6.4	8.2	3.1
5	1.1	1.4	0.9	1.8	0.5	4.1
6	0.5	0.5	0.5	0.7	1.1	0.0
Total	100	100	100	100	100	100

Notes:
[a]) Calculated as share of firms.
Source: Own calculations.

Finally, we look at the innovative history of initially innovating and non-innovating firms. Table 7 indicates that in manufacturing approximately 66 per cent of initially innovative firms were continuously engaged in innovation during the whole period. At the same time about 43 per cent of the initial non–innovators aren't working on innovation at all in manufacturing. This implies that approximately 55 per cent of the firms experienced no change in their innovation state during this period. And concerning those firms which entered into or exited from innovation activities at least once, we find a stronger tendency to return to the initial innovation status. That is, 24.3 per cent changed their innovation behaviour at least once, but returned back to their initial status, while 20.8 per cent remained in the respective new state. This also implies that reentry into innovation occurs to a non–negligible amount. In the service sector the propensity of initial non–innovators not to take up innovation activities at all is similar compared to the manufacturing (48 per cent). However, the share of service firms which were continuously engaged in innovation (39 per cent) is much smaller than in manufacturing (even though the period for services is shorter) and even smaller than the share of incessant non–innovators in services. As in manufacturing we can detect a stronger tendency to return to the initial condition for those firms which switched at least once, that is nearly 30 per cent returned, while 25 per cent of the service firm did not exhibit the same innovation state than at the beginning.

5 Econometric Analysis

5.1 Econometric Model

Though interesting, transition rates only depict the degree of persistence, but don't offer a clue to the causes of this phenomenon since we do not control for observed or unobserved individual characteristics. In the following we therefore investigate whether and to which amount the observed persistence is due to underlying differences in individual characteristics and / or due to a genuine causal effect of past on future innovations using a dynamic random effects probit model. The same model was applied for studying state dependence effects in poverty state (Biewen 2004) or export behaviour (see e.g. Kaiser and Kongstedt 2004). This panel data approach allows us to distinguish between the sources of the time persistence observed in the data and to control for individual heterogeneity, a potential source of bias which was not taken into account in the study of Duguet and Monjon (2002) due to data restrictions.[12]

We start on the assumption that a firm i will invest in innovation in period t if the expected present value of profits accruing to the innovation investment y^*_{it} is positive. The expected profit depends on the previous (realised) innovation experience $y_{i,t-1}$, on some observable firm characteristics X_{it} and on unobservable individual specific characteristics which are assumed to be constant over time and captured by μ_i. The structural model is thus given by:

[12] If individual heterogeneity is present but not controlled for, the coefficients of the observed characteristics are likewise biased if both are correlated, see Carro (2003).

$$y_{it}^{*} = \gamma\, y_{i,t-1} + X_{it}'\,\beta + \mu_i + \varepsilon_{it} \qquad i = 1, \ldots, N, \qquad t = 1, \ldots, T \tag{1}$$

The effect of other time–varying unobervable determinants is summarised in the idiosyncratic error ε_{it}. It is assumed that $\varepsilon_{it}|y_{i0}, \ldots, y_{i,t-1}, X_i$ is *i.i.d.* as $N(0,1)$ and that $\varepsilon_{it} \perp (y_{i0}, X_i, \mu_i)$ where $X_i = (X_{i1}, \ldots, X_{iT})$. N is the number of firms and the index t is running from 1995 in manufacturing and 1997 in services to 2002. If y_{it}^{*} is larger than a constant threshold (without any loss of generality we assume zero) we observe that firm i engages in innovation:

$$y_{it} = \begin{cases} 1 & \text{if} \quad y_{it}^{*} > 0 \\ 0 & \text{if} \quad y_{it}^{*} \leq 0 \end{cases} \tag{2}$$

5.2 Estimation Method

For estimation purposes we have to solve two important theoretical and practical problems: First, the treatment of the unobserved heterogeneity μ_i, and secondly the treatment of the initial value y_{i0}. A random effects model is used when we made some assumptions about the distribution of μ_i given the observables while a fixed effects model assumes that μ_i is random but it leaves its distribution completely unspecified which would be preferable. However, there is no general solution in the literature how to estimate dynamic fixed effects binary choice panel models because no general transformation is known how to elimate unobserved effects, i.e., unlike in linear models a first difference or within transformation does not eliminate μ_i in non–linear models. Honoré and Kyriazidou (2000) proposed a semiparametric estimator for the FE logit model, but their estimator is extremely data demanding and cannot be used here. Carro (2003) suggested a modified maximum likelihood estimator for the dynamic probit model, but the estimator is only consistent when T goes to infinity.[13] Therefore, I decide to apply a random effects model.

Concerning the second problem, there are in general three different ways of handling the initial condition y_{i0} in parametric dynamic non-linear models. The first

[13] Monte Carlo studies though have shown that this estimator performs quite well for 8 or more time periods. The estimator is based on the idea of getting a reparametrization such that the incidental parameters are information orthogonal to the other parameters which reduces the order of the bias of the ML without increasing its asymptotic variance, see Cox and Reid (1987).

one is to assume that y_{i0} is a non–random constant which is usually not a realistic assumption. The second solution is to allow for randomness of y_{i0} and to attempt to find the joint density for y_{i0} and all outcomes y_{it} conditional on strictly exogenous variables x. This approach starts on the joint distribution $(y_{i0}, \ldots, y_{iT})|\mu_i, x$ and it requires to specify the distributions of $y_{i0}|\mu_i, x$ and that of $\mu_i|x$ to integrate out the unobserved effect. However, the joint distribution can only be found in very special cases. Heckman (1981) thus suggested a method to approximate the conditional distribution. Another possibility is to assume that y_{i0} is likewise random, but now to specify the distribution of μ_i conditional on y_{i0} and x which leads to the joint density of $(y_{i1}, \ldots, y_{iT})|y_{i0}, x$. This was first suggested by Chamberlain (1980) for a linear AR(1) model without covariates and Wooldridge (2005) used the same assumption to develop an estimator for dynamic nonlinear random effects models, for instance dynamic random effects probit, logit or tobit models. Following this latter estimation strategy, I further assume for the individual heterogeneity that it depends on the initial condition and the strict exogenous variables:

$$\mu_i \;=\; \alpha_0 + \alpha_1\, y_{i0} + \bar{X}_i'\,\alpha_2 + a_i, \tag{3}$$

where $\bar{X}_i' = T^{-1}\sum_{t=1}^{T} x_{it}$ denotes the time-averages of x_{it}. 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.[14] For the error term a_i we assume:

$$a_i \;\sim\; i.i.d. \quad N(0, \sigma_a^2) \quad \text{and} \quad a_i \perp (y_{i0}, \bar{X}_i) \tag{4}$$

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 the individual heterogeneity in this way, one can show that the probability of being innovator is given by:

$$P\left(y_{it} = 1|y_{i0}, \ldots, y_{i,t-1}, X_i, a_i\right) = F\left(\gamma\, y_{i,t-1} + X_{it}'\,\beta + \alpha_0 + \alpha_1\, y_{i0} + X_i'\,\alpha_2 + a_i\right) \tag{5}$$

Wooldridge (2005) showed that integrating out a_i in equation (5), the likelihood function has the same structure as in the standard RE probit model, except that

[14] Instead of $\bar{X}_i'$ the original estimator used $X_i' = (X_{i1}, \ldots, X_{iT})$ in equation (3), but time-averages are allowed to reduce the number of explanatory variables, see Wooldridge (2005).

the explanatory variables are enriched by the initial condition and the time averages of the strict exogenous variables:

$$Z_{it} = (1, X_{it}, y_{i,t-1}, y_{i0}, \bar{X}_i) \tag{6}$$

Identification of the parameters requires that the exogenous variables vary across time and industry. 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 unless it is assumed a priori that μ_i is partially uncorrelated with the industry dummies. Time dummies which are the same for all i are excluded from $\bar{X}_i$.

The first advantage of the proposed estimator is that it is computationally attractive. The approach further allows selection and panel attrition to depend on the initial condition (innovation state). The third advantage is that partial effects are identified and can be estimated which is not possible in a semiparametric approach since it doesn't specify the distribution of individual heterogeneity on which partial effects depend. This allows us not only to state whether true state dependence exists by supporting on the significance level of the coefficient of the lagged dependent variable, but also on the importance of this phenomenon. One problem in estimating partial effects is the fact that firm heterogeneity is unobservable. Two alternative calculation methods have been proposed to deal with this shortcoming. The first way is to estimate the partial effect as in the standard probit model and assuming that heterogeneity μ_i takes its average value, i.e., $E(\mu_i) = 0$ (PEA). This estimate suffers from the fact that usually the average value only represents a small fraction of firms. Alternatively, one can estimate partial effect after averaging the unobserved heterogeneity across firms (APE), see Wooldridge (2002b) for more details on how to calculate both partial effects.

One limitation of the estimator is that it was derived for balanced panels which reduces the number of included observations evidently. But using the sub–sample of balanced data still leads to consistent ML estimators under certain assumptions. Even more critical is the fact that as in alternative estimation methods for dynamic discrete choice panel models (e.g. Heckman 1981 or Honore and Kyriazidou 2000) the consistency hinges on the strict exogeneity assumption of the regressors and the estimator leads to inconsistent results if the distributional assumptions are not valid. Blindum (2004) and Biewen (2004) both extended the estimator to allow for endogenous dummy variables, but not for a continuous variable that fails strict exogeneity which seems to be more critical in our analysis. Honoré and Lewbel (2002) and Lewbel (2005) recently proposed a semiparametric approach which does not require the strict exogeneity assumption. However, their estimator is based on the existence of one "very exogenous" regressor. But, there seems to be no variable at hand that satisfies this assumption in our case.[15]

5.3 Empirical Model Specification

Theoretical and empirical studies have identified a whole array of innovation determinants, firm size and market structure are the oldest and most prominent ones, see Schumpeter (1942). Firm size is measured by the log number of employees in the previous period (SIZE) and the market structure is captured by the Herschmann–Herfindahl index (HHI) from the previous year measured on a three-digit level, see Table 8 for more detailed variable definitions.

The modern innovation literature stresses that there are additional firm-level determinants other than firm size and market structure. Cohen (1995) distinguished between *firm* and *industry or market* characteristics. Widely–considered firm characteristics explaining innovation activities are product diversification (see Nelson 1959), the degree of internationalisation and the availability of financial resources (see, e.g., Müller 1967, Bond et al. 1999 or Kukuk and Stadler 2001). As the data set does not contain information on product diversification for all years, we cannot take this hypothesis into account. The degree of international competition is measured by the export intensity (EXPORT) and the availability of financial resources is proxied by an index of creditworthiness (RATING). In addition, I include firm specific variables reflecting firm age (AGE), location (EAST), whether the firm is part of a group (GROUP) and whether the group's headquarter is located abroad (FOREIGN). One aim of governmental supporting programmes is to promote innovation activities. To test whether public funding induce a permanent change in favour of innovation, I further include a dummy variable equaling 1 if the enterprise has received any public financial support for innovation activities in the previous period (PUBLIC). The estimation also controls for ownership structure by distinguishing

[15] The key assumption is that of conditional independence. This means that when the values of the other covariates x_{it} are known, additional knowledge of the special regressor does not alter the conditional distribution of $\mu_i + \varepsilon_{it}$. In our case errors and fixed effects capture for instance risk attitudes, management abilities or technological opportunities. The assumption will hold if there exists explanatory variables that are assigned to firms independently of these unobserved attributes. However, there seems to be no variable at hand that satisfies this assumption.

between public limited companies (PLC), private limited liability companies (LTD) and private partnerships (PRIVPART). One hypothesis in the principal agency theory is that managers prefer to carry out less risky investment and innovation projects than owners because managers are closely related to the company and they will be threatened with the loss of job if the investment fails while owners can spread their risk by diversification strategies, see Jensen and Meckling (1976). Dosi (1997) stated that the engagement in innovation activities may also depend positively on firms' technological capabilities. We operationalise this construct by means of three variables: the share of employees with a university or college degree (HIGH), a dummy variable whether a firm has invested in training its employees in the previous period (TRAIN) and the amount of training expenditure (TRAINEXP).

As mentioned above, market or industry characteristics – alone or in combination with firm–specific features – may be important for innovation activities. In this context technological opportunities are expected to play are a significant role. The concept of technological opportunities can be summarized by the fact that the prevailing technological circumstances in some industries are more favourable towards innovation than in other industries. Nelson (1988) showed in a theoretical model that improved technological opportunities increase the incentive to invest in R&D. Technological opportunities are measured by the product life cycle of firm's i main product (LCYCLE) and industry dummies.

Table 9 reports the descriptive statistics of the variables used in estimation. It turned out that for almost all variables the variation across firms (between variation) is much higher compared to that within a firm over time. The variables FOREIGN, EAST, PLC, LTD and PRIVPART can vary across i and t. However, due to the fact, that hardly any within variation showed up, we treated them as time-constant individual specific variables in the estimation.

Table 8: Variable Definition

Variable	Type[a)]	Definition
Variables varying across individuals and time		
INNO	0/1	1 for a firm i with positive innovation expenditure in year t. Innovation expenditure include expenditure for intramural and extramural R&D, acquisition of external knowledge, machines and equipment, training, market introduction, design and other preparations for product and/or process innovations.
SIZE	c	Number of employees of firm i in year $t-1$, in logarithm.
LCYCLE	c	Product life cycle (in years) of firm's i main product, in logarithm.
RATING	c	Credit rating index for firm i in year $t-1$, ranging between 100 (highest creditworthiness) and 600 (worst creditworthiness), in logarithm.
AGE	c	Age of firm i at the beginning of year t, in logarithm.
GROUP	0/1	1 if firm i belongs to a group in year t.
TRAIN	0/1	1 if a firm has positive training expenditure in year $t-1$.
TRAINEXP	c	Training expenditure per employee (in logarithm) of firm i in year $t-1$ if TRAIN=1, 0 else.
EXPORT	c	Export intensity of firm i in year $t-1$ defined as exports/sales.
EXPORT2	c	Squared export intensity.
HIGH	c	Percentage of employees with a university or college degree in firm i in year $t-1$.
PUBLIC	0/1	1 if firm i received public funding for innovation projects in year $t-1$ Share of employees with a university or college degree in firm i in year $t-1$.
Variables varying across industries and time		
HHI	c	Hirschman–Herfindahl Index in year $t-1$, on the 3-digit industry NACE level, divided by 100 to get appropriately scaled coefficients. Only available for manufacturing.
Time-constant individual-specific variables		

Continued on next page.

Table 8 – *continued from previous page*

Variable	Type[a)]	Definition
FOREIGN	0/1	1 if firm i is a subsidiary of a foreign company in year t.
EAST	0/1	1 if firm i is located in Eastern Germany.
PLC	0/1	1 if firm i is a public limited company (*AG*).
LTD	0/1	1 if firm i is a private limited liability company (*GmbH, GmbH & Co. KG*).
PRIVPART	0/1	1 if firm i is a private partnership (*Personengesellschaft, OHG, KG*).
IND	0/1	System of 15 and 9 dummies grouping industries and services respectively, see Table 14.
Time-varying individual-constant variables		
TIME	0/1	System of time dummies for each year.

Notes:

a) c: continuous variable.

Table 9: Descriptive Statistics

		Manufacturing						Services					
	Unit	Mean	Std.dev. Overall	Std.dev. Between	Std.dev. Within	Min	Max	Mean	Std.dev. Overall	Std.dev. Between	Std.dev. Within	Min	Max
INNO	%					0	1	0.358	0.480	0.363	0.314	0	1
SIZE[a)]		1985.3	13973.0	13372.8	4096.1	1	243638	1753.3	17809.3	17760.1	1646.5	1	271078
LCYCLE	years	15.1	15.9	14.3	6.8	0.3	100.0	16.3	22.5	22.0	5.1	1	100.0
RATING	index [100–600]	210.1	62.6	55.5	29.1	100	600	220.3	45.6	41.2	19.6	100	600
AGE[a)]	years	21.5	23.0	22.4	5.2	0	142	21.8	21.0	20.9	2.6	1	141
GROUP	%	0.356	0.479	0.407	0.252	0	1	0.214	0.410	0.340	0.231	0	1
TRAIN	%	0.176	0.381	0.315	0.215	0	1	0.253	0.435	0.373	0.225	0	1
TRAINEXP[a)]		670.3	1140.7	855.1	756.0	0	77019.0	1236.0	3219.0	2271.8	2284.0	0	25791
EXPORT	%	0.199	0.248	0.233	0.085	0	1	0.025	0.096	0.084	0.047	0	1
HIGH	%	0.107	0.133	0.113	0.071	0	1	0.198	0.260	0.235	0.111	0	1
PUBLIC	%	0.243	0.429	0.347	0.253	0	1	0.095	0.293	0.240	0.169	0	1
HHI	index [0–100]	4.7	6.1	5.3	3.0	0.1	43.2	—	—	—	—	—	—
FOREIGN	%	0.057	0.231	0.189	0.133	0	1	0.018	0.132	0.116	0.064	0	1
EAST	%	0.343	0.475	0.469	0.074	0	1	0.421	0.494	0.491	0.058	0	1
PLC	%	0.078	0.268	0.268	0.000	0	1	0.053	0.223	0.220	0.047	0	1
LTD	%	0.830	0.376	0.375	0.031	0	1	0.692	0.462	0.457	0.072	0	1
PRIVPART	%	0.085	0.280	0.278	0.031	0	1	0.220	0.415	0.410	0.063	0	1
Obs				3933						1974			

Notes:
[a)] Variables are not log-transformed. For estimation purposes, however, a log-transformation of these variables is used.
Source: Own calculations.

5.4 Econometric Results

Table 10 reports the estimation results of the dynamic RE probit model including just the Schumpeter determinants, product life cycle and industry and time dummies as exogenous variables and compares the results with the static pooled model and static RE model. Note, that marginal effects are reported and in the dynamic RE model they are calculated at the average value of the individual–specific error. Furthermore, in case of the static pooled model, the standard errors have been adjusted to account for the fact that observations are not necessarily independent within firms. It turns out that including the lagged dependent variable is an important piece in the model specification. That is, even after accounting for individual unobserved heterogeneity, the variable comes out highly significant in both manufacturing and services, confirming therefore the hypotheses of true state dependence. The results further shows that some of the variables which are significant in the static estimation loose this property in the dynamic specification, for instance firm size is no longer significant in services. One interpretation of this results is that firm size which is likewise highly time–persistent just takes on the impact of the lagged dependent variable in the static case.

As mentioned above, one problem of the dynamic RE panel probit model is the fact that strict exogeneity of the exogenous variables is assumed. This implies that there are no feedback effects from the innovation variable on future values of the explanatory variables which seems to be contestable for some of the variables usually explaining innovation behaviour, e.g. firm size, market structure or export behaviour. To assess the impact on state dependence of including variables which potentially fail the strict exogeneity assumption I further check on the robustness of the results by applying a stepwise procedure. That is, I start estimating an extremely parsimonious specification (1) including only LCYCLE and industry and time dummies as exogenous variables. Specification (2) than adds the Schumpeter determinants (which underlies the comparison) and (3) incorporates some firm characteristics from which I suppose that strict exogeneity seems to be statisfied.[16] Specification (4) and (5) further includes some presumably not strictly exogenous variables. The estimation results are summarised in Tables 11 and 12 for manufacturing and services, respectively.

It comes out from this exercise that the marginal effect of the lagged dependent variable is nearly unaltered in the different estimations. That is, even after ac-

[16] I used the procedure proposed by Wooldridge (2002a) and added the lead of the corresponding variables and tested on the significance of this coefficient.

counting for individual unobserved heterogeneity, past innovation has a behavioural effect: Conditional on observed and unobserved firm characteristics, an innovator in $t-1$ has got a probability to innovate which is approximately 35 percentage points higher than that of a non–innovator in manufacturing. For service companies the marginal effect ranges between 10.5 and 13 percentage points. The results further show that the initial condition is also highly significant. This implies a substantial correlation between the unobserved heterogeneity and the initial value.

The importance of the unobserved heterogeneity in explaining the total variance can be gauged from $\rho = \sigma_a^2/(1+\sigma_a^2)$.[17] Table 10 already showed that introducing the lagged dependent variable leads to a distinct reduction of the importance of the unobserved heterogeneity. But, still unobserved heterogeneity explains between 30 and 43 per cent of the variation in the dependent variable in manufacturing depending on the specification of μ_i. In the service sector this effect is in a similar range with 48 to 37 per cent.

Besides prior innovation experience and unobserved heterogeneity, some observed firm characteristics have also found to be important factors in explaining innovation. Firms being more financially contrained, are less likely to engage in innovation. This effect is highly significant in services and just passes significance in manufacturing. Moreover, firms getting public funding in a prior period exhibit a higher propensity to innovate in the subsequent period in both industries. In contrast, firm size is only important in manufacturing, but not in the service sector. This is likewise the case for the degree of internationalisation, a result which is maybe not that surprising because exporting is less prevailing in services. Firms which are more active on international markets have a higher propensity to innovate in manufacturing. However, we find an inverse U–shaped relationship for the export intensity with an estimated point of inflextion of 32 per cent in specification (5). Ownership only matters in manufacturing as well. That is, public limited companies in which conflicts of interests between managers and shareholders might arise, have a significant lower conditional probability of being innovative. In addition, the estimates show that a substantial correlation between the innovative capabilities and the unobserved heterogeneity exists in both industries. However, regarding the second Schumpeterian determinant, we do not find any significant impact of market concentration on innovation. But admittedly, this may be due to the fact that HHI is a bad proxy of market structure.

[17] Note that $\varepsilon_{it}|y_{i0},\ldots,y_{i,t-1},X_i \sim N(0,1)$ and $\mu_i|y_{i0},\bar{X}_i \sim N(0,\sigma_a^2)$.

Table 10: Comparison: Marginal Effects in Static Pooled, Static Random Effects and Dynamic Random Effects Probit Model

	Manufacturing			Services		
	Pooled Probit	Static RE Probit	Dynamic RE Probit	Pooled Probit	Static RE Probit	Dynamic RE Probit
INNO_{-1}	—	—	0.357***	—	—	0.128***
			(0.035)			(0.044)
LCYCLE	-0.063**	-0.081***	-0.036	0.060	0.038	0.079
	(0.068)	(0.080)	(0.031)	(0.057)	(0.060)	(0.092)
SIZE	0.140***	0.208***	0.127**	0.087***	0.134***	0.020
	(0.014)	(0.013)	(0.062)	(0.014)	(0.021)	(0.064)
HERFIN	0.014	0.034	0.049	—	—	—
	(0.041)	(0.036)	(0.056)			
INNO_0	—	—	0.538***	—	—	0.452***
			(0.045)			(0.063)
M_LCYCLE	—	—	0.010	—	—	-0.063
			(0.050)			(0.084)
M_SIZE	—	—	-0.035	—	—	0.041
			(0.063)			(0.066)
M_HERFIN	—	—	-0.040	—	—	—
			(0.070)			
σ_μ	—	1.806	0.805	—	1.367	0.923
		(0.118)	(0.082)		(0.120)	(0.107)
ρ	—	0.765	0.393	—	0.651	0.460
		(0.023)	(0.049)		(0.040)	(0.058)
LR_ρ	—	0.000	0.000	0.000	0.000	0.000
W_{TIME}	0.002	0.006	0.010	0.000	0.000	0.000
W_{IND}	0.000	0.000	0.000	0.000	0.000	0.000
ln L	-1824.4	-1258.5	-1108.1	-933.4	-760.2	-722.5
ln L_{Cons}	-2402.1	-1403.1	-1403.1	-1105.5	-828.9	-828.9
R^2_{McFad}	0.241	0.103	0.210	0.156	0.083	0.128
R^2_{VZ}	0.472	—	—	0.307	—	—
Obs Prob	55.5	55.5	55.5	36.0	36.0	36.0
Pred Prob	57.8	72.0	64.6	34.8	26.4	
Corr Pred	71.8	69.6	85.4	72.0	72.5	77.0
Corr Pred 1	77.9	80.9	86.0	42.0	43.7	59.8
Corr Pred 0	64.1	55.6	84.8	88.9	88.7	86.7
Obs	3496	3496	3496	1692	1692	1692

Notes:
$***$, $**$ and $*$ indicate significance on a 1%, 5% and 10% level, respectively. Standard errors in pooled probit model adjusted for clustering on firms. A constant (significant at the 1% level in each regression) as well as time and industry dummies are included in each regression, but not reported.

Table 11: Robustness of Econometric Results in Manufacturing

Regression	(1)	(2)	(3)	(4)	(5)
Structural Equation					
$INNO_{-1}$	0.364***	0.357***	0.358***	0.357***	0.331***
	(0.034)	(0.035)	(0.035)	(0.035)	(0.036)
LCYCLE	-0.037	-0.036	-0.040	-0.043	-0.043
	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)
SIZE	—	0.127**	0.121*	0.109*	0.100
		(0.062)	(0.062)	(0.063)	(0.061)
HERFIN	—	0.049	0.051	0.048	0.054
		(0.056)	(0.056)	(0.057)	(0.060)
RATING	—	—	-0.059	-0.066	-0.068
			(0.044)	(0.044)	(0.044)
AGE	—	—	-0.074*	-0.070*	-0.067*
			(0.038)	(0.038)	(0.037)
GROUP	—	—	0.053	0.055	0.065
			(0.050)	(0.050)	(0.050)
TRAIN	—	—	—	0.126	0.120
				(0.162)	(0.160)
TRAINEXP	—	—	—	0.014	0.015
				(0.017)	(0.017)
EXPORT	—	—	—	0.587**	0.637**
				(0.292)	(0.284)
EXPORT2	—	—	—	-0.010***	-0.010***
				(0.003)	(0.003)
HIGH	—	—	—	-0.090	-0.092
				(0.213)	(0.216)
PUBLIC	—	—	—	—	0.176***
					(0.045)
TIME	yes	yes	yes	yes	yes
Individual Heterogeneity					
$INNO_0$	0.627***	0.538***	0.541***	0.461***	0.342***
	(0.042)	(0.045)	(0.045)	(0.045)	(0.047)
M_LCYCLE	0.019	0.010	0.016	0.019	0.004
	(0.052)	(0.050)	(0.050)	(0.049)	(0.046)
M_SIZE	—	-0.035	-0.034	-0.045	-0.055
		(0.063)	(0.064)	(0.067)	(0.063)
M_HERFIN	—	-0.040	-0.041	-0.039	-0.045
		(0.070)	(0.071)	(0.069)	(0.067)
M_RATING	—	—	0.029	0.026	0.031
			(0.062)	(0.061)	(0.059)
M_AGE	—	—	0.117**	0.114**	0.097**
			(0.051)	(0.050)	(0.047)
M_GROUP	—	—	0.019	-0.026	-0.033

Continued on next page.

Table 11 – *continued from previous page*

Regression	(1)	(2)	(3)	(4)	(5)
			(0.085)	(0.082)	(0.079)
FOREIGN	—	—	-0.130	-0.163**	-0.127
			(0.084)	(0.083)	(0.080)
EAST	—	—	0.017	-0.047	-0.051
			(0.051)	(0.051)	(0.051)
PLC	—	—	-0.209*	-0.201**	-0.167*
			(0.110)	(0.103)	(0.100)
PRIVPART	—	—	0.024	0.037	0.023
			(0.069)	(0.064)	(0.061)
M_TRAIN	—	—	—	0.646***	0.664***
				(0.248)	(0.236)
M_TRAINEXP	—	—	—	0.054*	0.055**
				(0.029)	(0.027)
M_EXPORT	—	—	—	0.351*	0.299
				(0.198)	(0.194)
M_HIGH	—	—	—	0.653**	0.161
				(0.316)	(0.312)
M_PUBLIC	—	—	—	—	0.367***
					(0.091)
IND	yes	yes	yes	yes	yes
σ_μ	0.877	0.805	0.795	0.713	0.630
	(0.083)	(0.082)	(0.082)	(0.077)	(0.078)
ρ	0.435	0.393	0.387	0.337	0.284
	(0.046)	(0.049)	(0.049)	(0.049)	(0.050)
LR_ρ	0.000	0.000	0.000	0.000	0.000
W_{TIME}	0.012	0.010	0.006	0.006	0.008
W_{IND}	0.000	0.000	0.000	0.012	0.036
ln L	-1132.6	-1108.1	-1100.8	-1078.2	-1047.8
ln L_{Cons}	-1403.1	-1403.1	-1403.1	-1403.1	-1403.1
R^2_{McFad}	0.193	0.210	0.216	0.232	0.253
Obs Prob	55.5	55.5	55.5	55.5	55.5
Pred Prob	63.7	64.6	64.7	64.7	65.8
Corr Pred	83.6	85.4	85.6	86.1	87.4
Corr Pred 1	84.2	86.0	84.6	85.4	87.5
Corr Pred 0	82.9	84.8	86.3	86.7	87.2
Obs	3496	3496	3496	3496	3496

Notes:

Table 12: Robustness of Econometric Results in the Service Sector

Regression	(1)	(2)	(3)	(4)	(5)
Structural Equation					
$INNO_{-1}$	0.129***	0.128***	0.130***	0.130***	0.105**
	(0.044)	(0.044)	(0.045)	(0.035)	(0.047)
LCYCLE	0.070	0.079	0.060	0.052	0.034
	(0.091)	(0.092)	(0.092)	(0.093)	(0.095)
SIZE	—	0.020	0.017	0.013	0.008
		(0.064)	(0.064)	(0.066)	(0.069)
RATING	—	—	-0.208**	-0.208**	-0.206**
			(0.099)	(0.099)	(0.103)
AGE	—	—	0.052	0.049	0.055
			(0.038)	(0.059)	(0.061)
GROUP	—	—	0.006	0.010	0.011
			(0.063)	(0.062)	(0.065)
TRAIN	—	—	—	0.058	0.068
				(0.154)	(0.161)
TRAINEXP	—	—	—	0.003	0.008
				(0.020)	(0.021)
EXPORT	—	—	—	0.417	0.289
				(0.622)	(0.639)
EXPORT2	—	—	—	-0.004	-0.002
				(0.008)	(0.008)
HIGH	—	—	—	-0.025	-0.013
				(0.127)	(0.133)
PUBLIC	—	—	—	—	0.294***
					(0.102)
TIME	yes	yes	yes	yes	yes
Individual Heterogeneity					
$INNO_0$	0.527***	0.452***	0.429***	0.360***	0.326***
	(0.059)	(0.063)	(0.063)	(0.064)	(0.064)
M_LCYCLE	-0.074	-0.064	-0.070	-0.067	-0.055
	(0.083)	(0.084)	(0.084)	(0.085)	(0.087)
M_SIZE	—	0.041	0.022	0.022	0.022
		(0.066)	(0.068)	(0.070)	(0.073)
M_RATING	—	—	0.083	0.121	0.175
			(0.123)	(0.123)	(0.125)
M_AGE	—	—	-0.147**	-0.126*	-0.116
			(0.075)	(0.074)	(0.075)
M_GROUP	—	—	0.068	0.067	0.055
			(0.106)	(0.104)	(0.106)
FOREIGN	—	—	0.266	0.207	0.271
			(0.202)	(0.201)	(0.194)
EAST	—	—	0.044	0.034	-0.013

Continued on next page.

Table 12 – *continued from previous page*

Regression	(1)	(2)	(3)	(4)	(5)
			(0.062)	(0.063)	(0.062)
PLC	—	—	0.209	0.199	0.268*
			(0.166)	(0.161)	(0.158)
PRIVPART	—	—	-0.063	-0.048	-0.015
			(0.059)	(0.058)	(0.060)
M_TRAIN	—	—	—	0.611**	0.666**
				(0.269)	(0.273)
M_TRAINEXP	—	—	—	0.057*	0.059*
				(0.034)	(0.034)
M_EXPORT	—	—	—	0.225	0.027
				(0.475)	(0.476)
M_HIGH	—	—	—	0.148	0.011
				(0.206)	(0.210)
M_PUBLIC	—	—	—	—	0.516***
					(0.159)
IND	yes	yes	yes	yes	yes
σ_μ	0.961	0.923	0.884	0.841	0.773
	(0.108)	(0.107)	(0.105)	(0.104)	(0.102)
ρ	0.480	0.460	0.439	0.414	0.374
	(0.056)	(0.058)	(0.059)	(0.060)	(0.062)
LR_ρ	0.000	0.000	0.000	0.000	0.000
W_{TIME}	0.000	0.000	0.000	0.000	0.000
W_{IND}	0.000	0.000	0.000	0.142	0.135
ln L	-729.9	-722.5	-712.3	-703.6	-680.6
ln L_{Cons}	-828.9	-828.9	-828.9	-828.9	-828.9
R^2_{McFad}	0.119	0.128	0.141	0.151	0.178
Obs Prob	36.0	36.0	36.0	36.0	36.0
Pred Prob	28.2	28.6	28.9	28.5	30.6
Corr Pred	77.1	77.0	78.6	78.9	80.1
Corr Pred 1	63.4	59.8	61.9	63.6	63.2
Corr Pred 0	84.9	86.7	87.9	87.5	89.7
Obs	1692	1692	1692	1692	1692

Notes:

All in all, our model seems to fit the data quite well. The McFadden's pseudo R2 varies between 20 and 25 per cent in manufacturing and based on specification (5) the model correctly predicts the innovation behaviour for 87 per cent of the observations. This number is much higher than in the static model. Correct predictions in the service sector are likewise high with 80 per cent. However, the model clearly performs worse in predicting the occurance of innovation.

As mentioned above, partial effects at average value (PEA) suffer from the fact that usually the average value only represents a small fraction of firms. To amplify what has been said so far on the importance of state dependence effects, Table 13 contrast the PEA with the estimated average partial effect (APE). It is quite plain that averaging the unobserved heterogeneity across firms reduces the estimates of the state dependence effects. Section **??** showed that for the balanced panel the propensity to innovate in period $t+1$ was approximately 74 percentage points higher for innovators than for non-innovators in t. Controlling for differences in observed and unobserved characteristics, this differences reduces to 33.1 per cent using PEA and 18.5 per cent using APE. This implies that depending on the calculation method between 45 (PEA) and 25 (APE) per cent of the innovation persistence in manufacturing was due to state dependence, while the rest was due to persistence in observed and unobserved characteristics. In the service sector state dependence accounts for 20 (PEA) to 11.5 (APE) per cent of the observed persistence.

Table 13: State Dependence in Manufacturing

	OTR	PEA				APE			
		$P(1\|1)$	$P(1\|0)$	PEA		$P(1\|1)$	$P(1\|0)$	APE	
				abs.	rel.			abs.	rel.
Manufacturing	74.1	46.0	79.1	33.1	*44.7*	65.4	46.9	18.5	*25.0*
Services	53.7	27.6	38.1	10.5	*19.8*	39.8	33.7	6.1	*11.5*

Notes:
OTR denotes the observed transition rate.

6 Conclusion

In this paper I provide empirical evidence on the innovation decision by German manufacturing and service firms during the period 1994–2002. Using the estimator recently proposed by Wooldridge (2005) for dynamic binary choice panel data models, I have analysed whether innovation behaviour shows up persistence at the firm level and whether state dependence drives this phenomenon.

Our first main finding is that innovation behaviour is permanent at the firm level to a very large extent. Year-to-year transition rates indicate that nearly nine out of ten innovating firms in manufacturing in one period persisted in innovation activities in the subsequent and about 84 per cent of non–innovators maintained this state in the following period. But innovation is not a one and for all phenomenon, looking for instance at the innovative history of firms we find, that in manufacturing about 45 per cent and in services 55 per cent of the firms experienced at least one change in their innovation behaviour. And persistence varies slightly across time but no clear link to economic activity emerges. In general, persistence is less pronounced in the service sector and exhibits a higher variance across time. Less surprisingly, persistence turns out to be higher in larger firms and in high–technology industries, but is although relatively high in small firms.

Our econometric results confirm the hypothesis of true state dependence. Partial effects were calculated highlighting the importance of this phenomenon. Depending on the calculation method xx to xx per cent of the difference in the propensity to innovate between previously innovators and non-innovators can be traced back to true state dependence. Although persistence is less prevalent in the service sector, there is no significant difference in the importance of state dependence effects. The results further emphasise the important role of unobserved heterogeneity in explaining the persistence of innovation. Leaving out this source of persistence in the empirical analysis can lead to highly misleading results. Some observed firm characteristics like firm size or export behaviour (determinants which themselves show high persistence) makes some firms also more innovation–prone than others.

Obviously, one topic on the agenda of future research is to test for dynamic completeness, that is, to extend the Wooldridge estimator to allow for higher lag structures of the lagged endogenous variable. Here we assume that dynamics are correctly specified by a first order process.

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Appendix C

Table 14: Branches of Industry Covered by the MIP

Industry Sector		Service Sector	
Branches of Industry	NACE[a)]	Branches of Industry	NACE[a)]
Mining	$10-14$	Distributive services	
Manufacturing		Wholesale	51
Food	$15-16$	Retail/repairing	$50, 52$
Textile	$17-19$	Transport/storage/post	$60-63, 64.1$
Wood/paper/printing	$20-22$	Real estate/renting	$70-71$
Chemicals	$23-24$	Business related services	
Plastic/rubber	25	Banks/insurances	$65-67$
Glass/ceramics	26	Computer/telecomm.	$72, 64.2$
Metals	$27-28$	Technical services	$73, 74.2-74.3$
Machinery	29	Consultancies	$74.1, 74.4$
Electrical engineering	$30-32$	Other BRS[b)]	$74.5-74.8, 90,$
MPO[c)] instruments	33		$92.1-92.2$
Vehicles	$34-35$		
Furniture/recycling	$36-37$		
Energy/water	$40-41$		
Construction	45		

Notes:
[a)] The industry definition is based on the classification system NACE Rev.1 (Nomenclature generale des activites economique dans la Communautes europeennes) as published by Eurostat (1992), using 2-digit or 3-digit levels.
[b)] Business related services.
[c)] Medical, precision and optical instruments.

Table 15: Individual Participation Pattern

	Total			Manufacturing		Services	
Participation	firms		obs	*firms*[a)]	obs	*firms*[a)]	obs
	#	%	#	#	#	#	#
1	5949	43.3	5949	*2803*	2803	*3146*	3146
2	2499	18.2	4998	*1223*	2446	*1276*	2552
3	1769	12.9	5307	*876*	2629	*893*	2678
4	1109	8.1	4436	*575*	2298	*535*	2138
5	803	5.8	4015	*464*	2320	*339*	1695
6	590	4.3	3540	*323*	1936	*267*	1604
7	560	4.1	3920	*337*	2360	*223*	1560
8	253	1.8	2024	*253*	2024	–	–
9	220	1.6	1980	*220*	1980	–	–
Total	13752	100	36169	*7074*	20796	*6678*	15373

Notes:
[a]) Some firms have changed their main activity which defines their industry belonging and have switched between manufacturing and services during the considered period. The number of firms is the average number of firms, calculated as the number of observations divided by the number of participation.
Source: ZEW, own calculations.

Table 16: Transition Rates by Year, Unbalanced Panel

Innovation Status		Years							
Year t	Year $t+1$	94–95	95–96	96–97	97–98	98–99	99–00	00–01	01–02
Manufacturing[a)]									
Non–Inno	Non–Inno	86.2	76.4	78.3	91.9	81.3	86.4	82.2	87.2
	Inno	13.8	23.6	21.7	8.1	18.7	13.6	17.8	12.8
Inno	Non–Inno	13.4	6.9	12.3	9.5	9.1	15.2	12.1	11.5
	Inno	86.6	93.1	87.7	90.5	90.9	84.8	87.9	88.5
Services[a)]									
Non–Inno	Non–Inno	–	–	68.5	87.9	81.7	84.6	82.4	90.3
	Inno	–	–	31.5	12.1	18.3	15.4	17.6	9.7
Inno	Non–Inno	–	–	24.0	35.6	20.9	34.4	29.0	30.6
	Inno	–	–	76.0	64.4	79.1	65.6	71.0	69.7

Notes:
[a)] Sample: Unbalanced Panel.
Source: Own calculations.

Table 17: Transition Rates by Industry

Sector	Non–Inno in t & Non–Inno in $t+1$	Inno in t & Inno in $t+1$	Share of Innovators
Mining	95.6	80.0	21.2
Food	73.6	81.0	55.3
Textile	86.9	77.1	35.4
Wood/paper	84.0	68.4	34.9
Chemicals	86.9	95.5	68.0
Plastics/rubber	82.1	81.5	51.2
Glass/ceramics	84.0	84.6	50.0
Metal	84.2	86.9	51.0
Machinery	79.1	91.8	69.1
Electrical engineer.	81.4	94.7	77.1
Medical instruments	89.6	96.9	81.5
Vehicles	80.8	98.3	82.6
Furniture/recyling	86.7	88.9	54.7
Energy/water	91.0	70.7	20.6
Construction	93.3	52.9	16.1
Wholesale	84.6	53.2	24.5
Retail	92.3	71.4	26.0
Transport/storage	85.3	62.9	28.8
Bank/insurance	81.5	76.4	46.7
Telecommunication	36.7	85.2	75.9
Technical services	76.7	80.6	53.3
Consultancies	74.7	63.2	39.6
Other BRS	86.1	63.1	30.6
Real estate/renting	89.9	50.0	18.2

Notes:
[a]) Sample: Balanced Panel.
Source: Own calculations.