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Persistence of Innovation: Stylised Facts and Panel Data Evidence

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Abstract:
This paper investigates whether firms innovate persistently or discontinuously over time using an innovation panel data set on German manufacturing and service firms for the period 1994–2002. It turns out that innovation behaviour is permanent at the firm–level to a very large extent. Using a dynamic random effects discrete choice model and a new estimator recently proposed by Wooldrigde (2005), I further shed some light on the driving forces for this phenomenon. The econometric results show that past innovation experience is an important determinant for manufacturing as well as for service sector firms, and hence confirm the hypothesis of true state dependence. In addition, the results highlight the important role of knowledge provided by skilled employees and unobserved individual heterogeneity in explaining the persistence of innovation.

Key words: Innovation; persistence; state dependence; unobserved heterogeneity; dynamic random effects panel probit model

Jel codes: O31; C23; C25; L20

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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 the innovation behaviour. However, little is known so far about the dynamics in firms' innovation behaviour, and the evidence is mostly based on patents (Geroski et al. 1997, Malerba and Orsenigo 1999 or Cefis 2003). The shortcomings of patents as an indicator of innovative outcome are well–known (e.g., Griliches 1990). 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). Looking instead at innovation indicators as those provided by the Community Innovation Surveys (CIS) data, we can for instance identify a high and quite stable share of innovators at the aggregate or industry level in Germany over the last ten years (Rammer et al. 2005). One interesting question, however, cannot be answered by such macroeconomic numbers: Is it the same group of firms that always set themselves at the cutting edge by introducing new products and processes or is there a steady entry into and exit from innovation activities at the firm level, with the aggregate level remaining more or less stable over time?

This paper analyses the dynamics in firms' innovation behaviour. In particular, it focuses upon the following two research questions: First of all, is innovation persistent at the firm–level? Persistence occurs when a firm which has innovated in one period innovates once again in the subsequent period. Secondly, if persistence is prevalent, what drives this phenomenon? In principle, there are various potential sources for persistent behaviour (see Heckman 1981a,b): Firstly, it might be caused by true state dependence. This means that a causal behavioural effect exists, in the sense that the decision to innovate in one period in itself enhances the probability to innovate in the subsequent period. The theoretical literature delivers several potential explanations for state dependent behaviour: (i) success breeds success (Mansfield 1968), (ii) innovations involve dynamic increasing returns (Nelson and Winter 1982 and Malerba and Orsenigo 1993), and (iii) sunk costs in R&D investments (Sutton 1991). Secondly, firms may possess certain characteristics which make them particularly "innovation-prone", i.e., more likely to innovate. To the extent that these characteristics themselves show persistence over time, they will induce persistence in innovation behaviour. Such attributes can be classified into observable (i.e., known to the econometrician) characteristics, like firm size or financial resources, and unobservable ones. For instance, technological opportunities, managerial abilities or risk attitudes are important for the firms' decision to innovate, but are typically not observed. If these unobserved determinants are correlated over time, but are not appropriately controlled for in estimation, past innovation may appear to affect future innovation merely because it picks up the effect of the persistent unobservable characteristics. In contrast to true state dependence this phenomenon is therefore called spurious state dependence. And thirdly, serial correlation in exogenous shocks to the innovation decision can cause permanent behaviour over time.

The answers to both questions are important from a theoretical as well as a policy point of view. From a theoretical point of view they are interesting because endogenous growth models differ in their underlying assumptions about the innovation frequency of firms. While Romer (1990) assumes that 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 (Cefis 2003). From a policy point of view the distinction between permanent innovation activities due to firm–inherent factors and true state dependence has some important implications. If innovation is state dependent, innovation–stimulating policy measures such as government support programmes are supposed to have a more profound effect because they do not only affect current innovation activities but are also likely to induce a permanent change in favour of innovation. If, on the other hand, individual heterogeneity induces persistent behaviour, support programmes are unlikely to have long–lasting effects and policy should concentrate more on measures which have the potential to improve innovation–relevant firm–specific factors.

The analysis is based on panel data from the German innovation survey covering the period 1994–2002. First, some stylised facts of how permanently firms innovated are presented using transition rates. The sources for persistent behaviour are then analysed and identified by means of a dynamic random effects binary choice model. This panel data approach allows us to control for individual heterogeneity, a potential source of bias which was not taken into account in most of the previous empirical studies.

The paper contributes to the literature in that it is one of the first which investigates firm–level persistence using innovation data and that it is able to exploit data from a unique long panel, which are nonetheless internationally comparable. Furthermore, a new estimation method proposed by Wooldridge (2005) is applied, and the paper is the first to provide empirical evidence on innovation persistence in service firms. Investigating the dynamics in the innovation behaviour of service firms is interesting not only because this sector has experienced a rapid development over the last two decades, but also from a theoretical point of view. Looking at the potential explanations for true state dependence, the third one in particular is strongly related to R&D, which is less important and less common in services. Thus, one hypothesis that will be investigated is that innovation is less permanent in services compared to manufacturing.

The outline of the paper is as follows. Section 2 sketches some theoretical arguments in favour of and against state dependence in innovation behaviour. Section 3 summarises the main empirical results so far. The underlying panel data set is explored in section 4, while section 5 comments on some measurement issues. The following section 6 depicts some stylised facts about persistence effects and section 7 presents the econometric analysis and results. The final section contains some concluding remarks.

2 Theoretical Explanations

Economic theory provides at least three potential explanations of why innovation behaviour might demonstrate state dependence over time.

The first one is the well–known hypothesis of "success breeds success". However, this view is based on different arguments in the literature. Phillips (1971), for instance, argued that successful innovations positively affect the conditions for subsequent innovations via an increasing permanent market power of prosperous innovators.[1] Mansfield (1968) and Stoneman (1983), however, emphasised that a firm's innovation success broadens its technological opportunities which make subsequent innovation success more likely. 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. Another line of reasoning is the existence of financial constraints. 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 innovations (Nelson and Winter 1982). Common to all these various "success breeds success" theories is the notion that a firm can gain some kind of locked–in advantage over other firms due to successful innovations (Simons 1995).

The second hypothesis is based on the idea that knowledge accumulates over time as represented by the changes in an organisations repertories of operating and dynamic routines (Nelson and Winter 1982). Evolutionary theory states that technological capabilities are a decisive factor in explaining innovation. Firms' innovative capabilities

[1] 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 argued that success favours growing barriers to entry that eventually allow a few increasingly successful firms to permanently dominate an industry.

in turn are primarily determined by human capital, i.e., by the knowledge, skills and creativity of their employees. Experience in innovation is associated with dynamic increasing returns in the form of learning–by–doing and learning–to–learn effects which enhance knowledge stocks and, therefore, the probability of future innovations. Since a firm's absorptive capacity – i.e. its ability to recognise the value of new external information as well as to assimilate and apply it to commercial ends – 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 behaviour (see, e.g., Nelson and Winter 1982 and Malerba and Orsenigo 1993).[2]

The hypothesis of sunk costs in R&D investments is a third argument in favour of state dependence (see Sutton 1991 or Manez Castillejo et al. 2004). It is stressed that R&D decisions are subject to a long time horizon, and if a firm decides to take up R&D activities, it has to incur start–up costs in building up an R&D department or hiring and training R&D staff. These fixed outlays, once made, are usually not recoverable and can therefore be considered as sunk costs.[3] With respect to persistence, sunk costs represent a barrier to both entry into and exit from R&D activities. Sunk costs may prevent non–R&D performers from taking up such activities because, unlike established R&D performers, potential entrants have to take these costs into account in determining their prices. Conversely, sunk costs may represent a barrier to exit for established R&D performers because they are not recovered in the case that the firm stops R&D and the firm has to incur them again if it decides to re–enter in future periods.

However, even if firms experience sunk costs or knowledge accumulation due to innovations, there are several theoretical explanations of why they may exit from innovation activities in future periods with the consequence that persistence does not emerge. The first two arguments are related to the demand–pull theory which emphasises that innovations are stimulated by demand (Schmookler 1966). If there is, at least in the firm's perception of consumer demand, no need for further innovations due to its own previous introduction of new products or processes, the firm will at least temporarily cease to innovate. This is particularly true if a firm only offers one or a few products and typical product life cycles are several years. Closely related is the second argument that states that unfavourable market conditions in general (i.e. expected decrease in demand) might prevent firms from carrying on with innovations, especially with respect to the timing

[2] 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). However, learning can also occur as a result of unsuccessful innovations.

[3] In contrast to most other kinds of sunk costs, firms can decide strategically upon the amount of R&D expenditure. Costs incurred in this manner are therefore referred to as endogenous sunk costs (Sutton 1991).

of the market introduction of new products. This is one argument in the literature on innovation and business cycles and will be explored in more detail in section 6. Finally, an incumbent innovator might fear that the introduction of further new products or processes will cannibalise his rents from previous innovations and thus stop innovating (Schumpeter 1942). Patent race models, for instance, predict that an incumbent invests less in R&D than challengers because it would erode current monopoly and profits (Reinganum 1983).

3 What do we know so far?

Though theory emphasises that innovation is an inherently dynamic process between heterogenous firms, empirical evidence on persistence in innovation activities is scarce. We can broadly classify the existing literature into three categories according to how the authors measure innovation: patent–based, R&D–based and innovation–based studies.

Patent–based studies have mainly focused on the question whether innovation persistence exists, irrespective of its origin. Malerba and Orsenigo (1999) examined this question using data of manufacturing firms from six countries (France, Germany, Italy, Japan, USA and the UK) which had requested at least one patent at the European Patent Office between 1978 and 1991. Their results showed that only a small fraction of firms were able to persist in patent activities as time went on. However, these firms became rather large innovators (in terms of patents) over time, resulting in the fact that persistent innovators, although small in absolute numbers, accounted for an important part of all patents. Using the same data and a non–parametric approach based on transition probability matrices, Cefis and Orsenigo (2001) and Cefis (2003) corroborated a low degree of persistence in patenting. Only occasional and great innovators had a high probability of remaining in their state.[4] Moreover, persistence was found to differ across industries, but inter–sectoral differences were by and large consistent across countries suggesting that persistence is technology–specific. The result that patent activities among patenting firms exhibited only a little degree of persistence, was also confirmed by Geroski et al. (1997) who used data of UK manufacturing firms which had at least one patent granted in the US between 1969 and 1988. One explanation of why patent–based studies revealed only a small degree of persistence might be the well–known fact that patents are a rather poor indicator of innovative outcomes, see Griliches (1990). However, 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 innova-

[4] They distinguished four states in each year: occasional (zero patent) small (one), medium (two to five) and great innovators (at least six). Firms with zero patents in a given period are nevertheless referred to as occasional innovators since they had at least one patent in the whole period.

tors firms have to win the patent race continuously (Kamien and Schwartz 1975). This means that patent data measure the persistence of innovative leadership rather than the persistence of innovation (Duguet and Monjon 2004).

In contrast to the other studies, Geroski et al. (1997) also examined potential sources of persistence. To test the hypothesis of dynamic economies of scale, they focused on patent spells, which measured the number of successive years in which a firm produced a patent. In this setting, dynamic economies of scale would imply that the probability of the spell ending at any particular time $t + \Delta t$, given it has lasted until t, decreases with the initial level of patents and with the length of time a firm has already spent in that spell. While the first relationship was confirmed by their data, the second one was rejected. All in all, their results suggested that dynamic economies might have led to more persistent patent spells, but only when the threshold of initial patent activities was high enough to overcome the reversed within–spell effects. And only a few firms ever reached this threshold.

Instead of patents, Manez Castillejo et al. (2004) examined R&D activities of Spanish manufacturing firms between 1990 and 2000. They asserted that past R&D experience had significantly affected the current decision to engage in R&D and interpreted this as an indication for sunk costs in building up R&D. Their results further indicated a rapid depreciation of R&D experience in that there was no significant difference between the re–entry costs of a firm that last performed R&D activities two or three years ago and a firm that had never previously conducted R&D.

But R&D, though important, is not the only way for an enterprise to introduce new products and processes, and using R&D indicators tends to lead to an underestimation of innovation activities in small and medium–sized firms as well as service sector firms. Hence, another strand of literature uses the broader concept implied by innovation data. So far, only a few studies have attempted to estimate the dynamics in the innovation process at the firm–level, and empirical results are inconclusive. König et al. (1994) and Flaig and Stadler (1994) were the first to examine dynamic effects using a panel of manufacturing firms in West Germany in the eighties. Applying a dynamic panel probit model, empirical evidence of state dependence in process innovations was supported by the first study. This result was corroborated for process as well as product innovations by the second authors. Duguet and Monjon (2004) for French firms and Rogers (2004) for Australian firms also reported persistence effects. However, due to data limitations both studies did not carry out a panel data analysis and thus did not control for unobserved individual heterogeneity, which leads to biased estimates if heterogeneity is present.[5] Conversely, Geroski et al. (1997) and Raymond et al. (2005) could not ascertain per-

[5] Both studies applied a cross–sectional probit approach, including a dummy variable for whether the firm was an innovator in the previous period as an explanatory variable.

sistence in the occurrence of innovations for UK and Dutch manufacturing firms. But Raymond et al. pointed out that among continuous innovators the innovation success, measured in terms of sales due to new products, had a positive impact on future success.

Among the other things highlighted, this review makes clear that previous studies focused solely on manufacturing. One aim is therefore to extend this kind of analysis to a comparison between the manufacturing and service sector.

4 Data Set

The research makes use of firm level data from the Mannheim Innovation Panel (MIP) in the German manufacturing and service sector (see Table 1). The MIP is based on innovation surveys carried out by the ZEW. The target population covers all legally independent firms with 5 or more employees and the surveys are drawn as stratified random samples. The survey methodology and definitions of innovation indicators comply with the OSLO-Manual (OECD and Eurostat 1997), thereby yielding internationally comparable data. Every fourth year the survey is the German contribution to the European–wide harmonised Community Innovation Surveys (CIS). While in most other European countries innovation surveys take place every 4 years, they are conducted annually in Germany. In manufacturing, we refer in our analysis to the period 1994–2002. In the service sector the survey started later and hence data are only available for the period 1996–2002. This relatively long period ensures that we can observe firms' innovation behaviour over different phases of the business cycle, and the observation period is also longer than the average product life cycle in industry.

The samples are constructed as panels and about 10,000 firms in manufacturing and 12,000 service firms are questioned each year. Since participation is voluntary, response rates vary between 20 to 25 %,[6] and although the survey is designed as a panel study, we have to assert that the main part of the firms participated only once or twice.[7] Furthermore, for analysing the dynamics in firms' innovation behaviour with econometric methods, only those firms which have answered consecutively can be taken into account. Therefore, in the following we distinguish two panel data sets: Panel U is an unbalanced panel comprising all firms for which at least 4 successive observations are available and Panel B is the balanced sub–sample. The latter is needed for estimation purposes.

[6] 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.

[7] Table 11 in the appendix sheds some light on the individual participation behaviour of the sampled firms.

Table 1: Branches of Industry Covered by the MIP

Industry Sector		Service Sector	
Branches of Industry	NACE	Branches of Industry	NACE
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 (BRS)	
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	$74.5-74.8, 90,$
MPO instruments	33		$92.1-92.2$
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, as published by EUROSTAT (1992), using 2–digit or 3–digit levels. MPO: Medical, precision and optical instruments.

Table 2 summarises the main characteristics of both samples. Given our interest in analysing the persistence of innovation behaviour and the need to estimate a dynamic specification with a lagged endogenous variable, I have chosen to maximise the time dimension of the panel. As a result, in manufacturing as well as in the service sector this choice leads to a marked reduction in the number of observations and the resulting panel data sets might not be representative for the total sample. To check representativeness, Tables 12 and 13 in the appendix compare the distribution of firms by industry, size class, region and innovation status in the total sample of all observations, the unbalanced panel and the balanced sub–sample. It turns out 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 percentage 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: 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

5 Measurement Issues

One problem in studying state dependence 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. Using this indicator for yearly waves would induce an artificial high persistence due to overlapping time periods and double counting.[8] Due to data restrictions, previous studies often suffer from this overlapping of time periods problem in the dependent variable (e.g., Duguet and Monjon 2004 or Raymond et al. 2005). Since information on innovation expenditure is available on a yearly basis, I define an innovator as a firm which exhibits positive innovation expenditure in a given year. This implies that, in contrast to the previously mentioned studies, I analyse the persistence in innovation input rather than in innovation outcome behaviour.[9]

From a theoretical point of view it is not unambiguous whether state dependence in innovation 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. In contrast, the "success breeds success" hypothesis is clearly outcome–oriented. By stressing the accumulative nature of innovation and the importance of learning effects in the innovation process, the evolutionary theory is likewise more outcome–oriented since the process of learning involves successful implementation rather than just dedicating some resources to innovation. Econometric

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

[9] I checked the robustness of my results by applying the output-oriented 3–period innovation indicator and taking only every third survey into account, see section 7.4.

evidence shows that, on average, innovation output is significantly determined by innovation input (e.g., Crépon et al. 1998) implying that input persistence should to a certain degree be converted into output persistence. However, it is possible that more than one period is needed to translate innovation effort into new products or processes. Furthermore, firms can not necessarily control their innovation outcome because serendipity might play an important role in the innovation process (Kamien and Schwartz 1982).

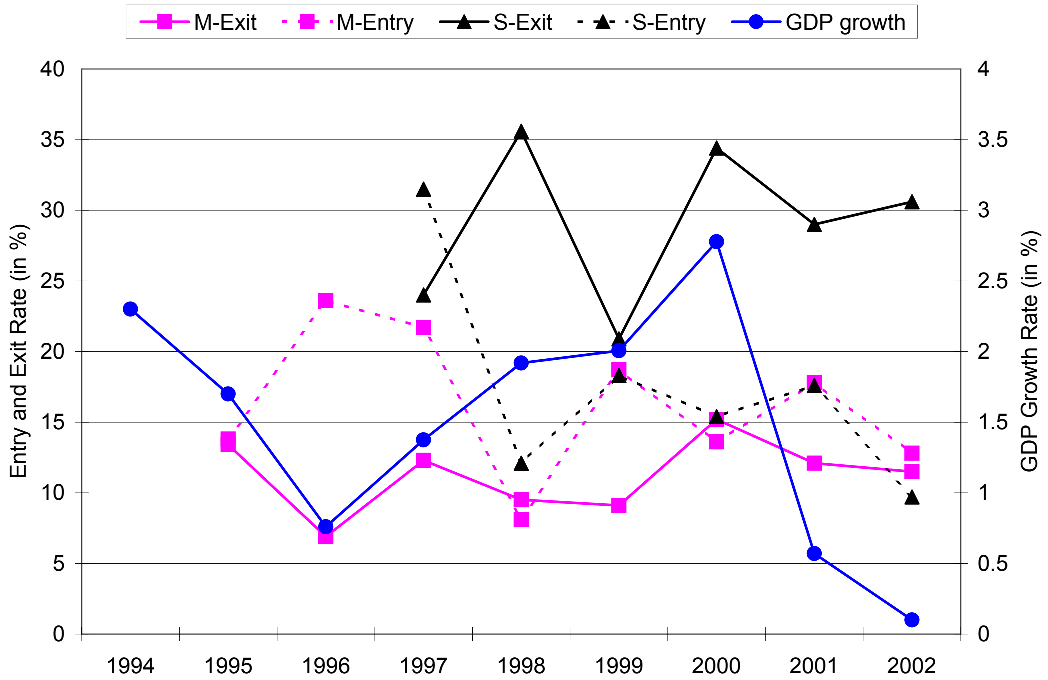
6 Stylised Facts

To answer the first question of "How persistently do firms innovate?", Table 3 reports transition probabilities. First of all, it turns out that there are hardly any differences between the unbalanced panel and the smaller balanced panel which has to be used for estimation purposes. Table 3 indicates that innovation is permanent at the firm-level to a very large extent. Nearly 89% of innovating firms in manufacturing in one period persisted in innovation activities in the subsequent period while 11% stopped their engagement. Similarly, about 84% of non–innovators maintained this status in the following period while 16% entered into innovation activities. That also means that the probability of being innovative in period $t+1$ was about 72 percentage points (hereafter: PP) higher for innovators than for non-innovators in t which can be interpreted as a measure of state dependence. In services, persistence is also observable, though less prevalent than in manufacturing. The state dependence effect amounted to approximately 54 PP. 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 common in most of the service sectors. This result might also occur because, on average, the time needed to develop an innovation is shorter in services and hence covers two calendar years less often. Alternatively, individual or industry heterogeneity, for example in the technological opportunities or in the demand for new innovations, might explain this difference.

Table 3: Transition Probabilities

		Innovation status in $t+1$					
		Unbalanced Panel			Balanced Panel		
	Innovation status in t	Non–Inno	Inno	Total	Non–Inno	Inno	Total
Manufact.	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
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

Figure 1: Innovation Entry and Exit Rates and Business Cycles



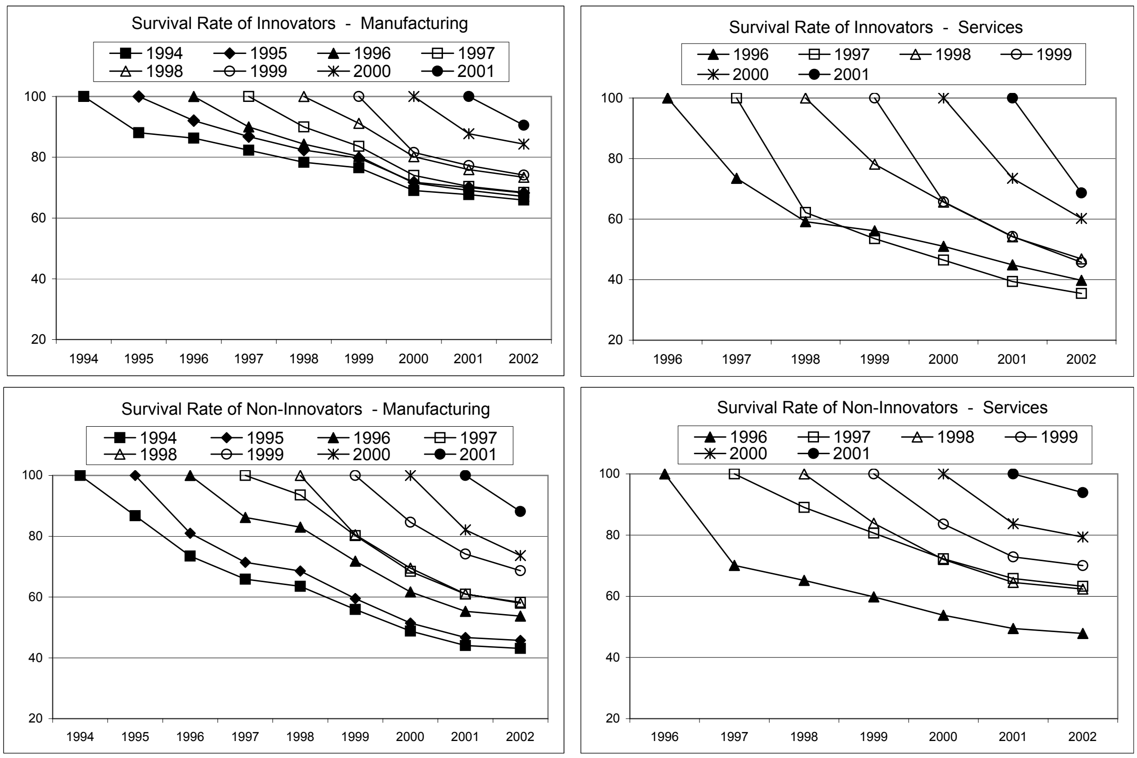
Notes:
The innovation exit rate in any given year t is defined as the share of innovators in year $t-1$ which flow out of innovation activities in year t. Similarly, the innovation entry rate in t is the share of non–innovators in year $t-1$ which start innovation activities in year t. GDP growth denotes the annual percentage change of real GDP (in constant prices of 1995). M and S denote manufacturing and services, respectively. Sample: Unbalanced Panel.
Source: GDP growth rates: Sachverständigenrat (2004). Own calculation.

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 activities and consequently the business cycle, see 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 body of literature, arguments for both pro- as well as counter–cyclical relationships can be found. Pro–cyclical effects are expected to occur because cash–flow as an important source of finance innovations is positively correlated with 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 prosperous market conditions. Aghion and Saint-Paul (1998) showed that firms tend to invest more in productivity growth (i.e. process innovations) 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 came to a near halt in 1996.

Since 1997 economic growth steadily increased again, reaching its peak in 2000. Since 2001 the German economy has again been fighting a significant cyclical slump. Figure 1 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.

Table 14 and Figure 3 in the appendix provide some more information on innovation persistence by size class and industry.

Figure 2: Survival Rates of Innovator and Non–Innovator Cohorts by Years (in %)



Notes: Sample: Balanced Panel.

Looking at the innovative history of firms, Figure 2 depicts the survival rates of different innovator as well as non–innovator "cohorts" by years. The survival rate for instance for the innovator cohort 1994 is the proportion of innovators in year $t = 1994$ that was still innovating in year $t + s$, for $s = 1, 2 \ldots$ In manufacturing, the 3–year

[10] A main cause for this somewhat astonishing development was a severe shortage in high–qualified personnel in 2000, hampering a large number of SMEs in their innovative efforts (Janz et al. 2002).

[11] The standard deviation of exit and entry rates is 2.6 and 5.1 in manufacturing and 5.8 and 7.6 in the service sector.

survival rates were quite similar for different cohorts, amounting to 78% on average (based on cohorts 1994 to 1999). After 5 years, on average 71% of the innovators were still innovating and 66% of initially innovative firms (i.e., cohort 1994) were continuously engaged in innovation throughout the whole period. In services, the survival rates are smaller and exhibit higher variances. On average only 51% of the innovators were still involved in innovation after three years, and the share of incessant innovators (40%) is also much lower (even though the period is shorter). Survival rates of non–innovator cohorts turned out to be lower than for innovators, e.g. 67% on average after three years in both samples. About 43% (manufacturing) and 48% (services) of the initial non–innovators kept out of innovation activities throughout the whole period. Table 4 completes the picture by reporting the number of entries into and exits from innovation. It shows that re–entry into innovation occurs to a non–negligible extent.

Table 4: 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	6.4	8.5	4.5	8.9	9.8	7.2
Total	100	100	100	100	100	100

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

7 Econometric Analysis

7.1 Econometric Model and Estimation Method

A dynamic random effects (RE) probit model is used to distinguish between the sources of the persistence over time and to control for individual heterogeneity.[12] We start on the assumption that 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 $y_{i,t-1}$, on some observable explanatory variables summarised in the k–dimensional row vector x_{it} and on unobservable firm–specific attributes which are assumed to be constant over time and captured by μ_i:

[12] A fixed effects (FE) model would be preferable because it assumes that μ_i is random but leaves its distribution unspecified. However, no general transformation is known how to eliminate μ_i in dynamic FE binary choice models. For the dynamic FE logit model, Honoré and Kyriazidou (2000) proposed a semiparametric estimator, which is, however, extremely data demanding and cannot be used here.

$$y_{it}^* \;=\; \gamma\, y_{i,t-1} + x_{it}\,\beta + \mu_i + \varepsilon_{it} \qquad i = 1, \ldots, N, \qquad t = 1, \ldots, T \tag{1}$$

The effect of other time–varying unobservable determinants is summarised 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 $N(0, 1)$ 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 runs from 1 to 8 in manufacturing and 1 to 6 in services, respectively. If y_{it}^* is larger than zero we observe that firm i engages in innovation, $y_{it} = I\,[y_{it}^* > 0]$, where I denotes the indicator function.

One important problem in parametric dynamic non–linear models refers to the handling of the initial condition y_{i0}. Heckman (1981b) suggested to start on the joint distribution $(y_{i0}, \ldots, y_{iT})|\mu_i, x_i$ and to specify the distributions of $y_{i0}|\mu_i, x_i$ and that of $\mu_i|x_i$ to integrate out the unobserved effect. Alternatively, Wooldridge (2005) proposed to specify the distribution of μ_i conditional on x_i *and* y_{i0} which leads to the joint density of $(y_{i1}, \ldots, y_{iT})|y_{i0}, x_i$. [13] Following the second approach, I assume that that the individual heterogeneity depends on the initial condition and the strict exogenous variables in the following way:

$$\mu_i \;=\; \alpha_0 + \alpha_1\, y_{i0} + \bar{x}_i\, \alpha_2 + a_i, \tag{2}$$

where $\bar{x}_i = T^{-1} \sum_{t=1}^{T} x_{it}$ denotes the time–averages of x_{it}.[14] 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 probability of being an innovator is given by:

$$P\,(y_{it} = 1|y_{i0}, \ldots, y_{i,t-1}, x_i, \bar{x}_i, a_i) = \Phi\,(\gamma\, y_{i,t-1} + x_{it}\,\beta + \alpha_0 + \alpha_1\, y_{i0} + \bar{x}_i\, \alpha_2 + a_i) \tag{3}$$

Integrating out a_i yields a likelihood function that has the same structure as in the standard RE probit 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 that the exogenous variables vary across time. If the structural model contains time–invariant regressors like industry dummies,

[13] This was first suggested by Chamberlain (1980) for a linear AR(1) model without covariates.

[14] Instead of $\bar{x}_i$ the original estimator used $x_i = (x_{i1}, \ldots, x_{iT})$ in equation (2), but time–averages are allowed to reduce the number of explanatory variables (see Wooldridge 2005). Using x_i instead of $\bar{x}_i$ leaves the results nearly unaltered. They are not shown here, but are available upon request.

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 $\bar{x}_i$.

One limitation of the estimator is that it is derived for balanced panels which evidently reduces the number of observations included. But using the sub–sample of balanced data still leads to consistent estimates under certain assumptions. The main advantage of the estimator is that partial effects are identified and can be estimated which is not possible in semiparametric approaches since they don't specify the distribution of individual heterogeneity on which partial effects depend. This allows us not only to determine whether true state dependence exists by referring to 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 assume that μ_i takes its average value (PEA), which can be consistently estimated by $\widehat{E(\mu_i)} = \widehat{\alpha}_0 + \widehat{\alpha}_1\,\bar{y}_0 + \bar{x}\,\widehat{\alpha}_2$, where $\bar{y}_0 = \sum_{i=1}^{N} y_{i0}$, $\bar{x} = \sum_{i=1}^{N} \bar{x}_i$. The second method estimates the average partial effect (APE), averaging across the distribution of the unobserved individual heterogeneity. For the binary lagged dependent variable, for instance, we yield the following two equations:

$$\widehat{PEA} = \Phi\left[\widehat{\gamma} + x_i\,\widehat{\beta} + \widehat{\alpha}_0 + \widehat{\alpha}_1\,\bar{y}_0 + \bar{x}\,\widehat{\alpha}_2\right] - \Phi\left[x_i\,\widehat{\beta} + \widehat{\alpha}_0 + \widehat{\alpha}_1\,\bar{y}_0 + \bar{x}\,\widehat{\alpha}_2\right] \tag{4}$$

$$\begin{aligned}\widehat{APE} \quad &= \quad \frac{1}{N}\frac{1}{T}\sum_{i=1}^{N}\sum_{t=1}^{T}\Phi\left[\widehat{\gamma}_a + x^o\,\widehat{\beta}_a + \widehat{\alpha}_{0a} + \widehat{\alpha}_{1a}\,y_{i0} + \bar{x}_i\,\widehat{\alpha}_{2a}\right] \\ &\quad -\frac{1}{N}\frac{1}{T}\sum_{i=1}^{N}\sum_{t=1}^{T}\Phi\left[x^o\,\widehat{\beta}_a + \widehat{\alpha}_{0a} + \widehat{\alpha}_{1a}\,y_{i0} + \bar{x}_i\,\widehat{\alpha}_{2a}\right].\end{aligned} \tag{5}$$

The subscript a denotes original parameter estimates multiplied by $(1+\widehat{\sigma}_a^2)^{-0.5}$. x^o are fixed values that have to be chosen (sample means averaged across i and t are used).

7.2 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 (Schumpeter 1942). Firm size is measured by the log number of employees (SIZE) and the market structure is captured by the Herschmann–Herfindahl index (HHI); see Table 5 for details. 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, (Nelson 1959), the degree of internationalisation, the availability of financial resources (e.g., Müller 1967, Bond et al. 1999 or Kukuk and Stadler 2001) and technological capabilities. 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). While a positive impact of EXPORT is expected, the hypothesis is that RATING negatively affects the propensity to innovate 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. The data set does not contain a measure for internal financial resources, like profit or cash–flow. On the other side, both enter the index of creditworthiness, and thus RATING also reflects internal financial 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).

One aim of government support programmes is to promote innovation activities. To test whether public funding induces 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). Since all firms which receive financial support are innovators by definition, PUBLIC is an interaction term and measures the additional effect of supported compared to non–supported innovators.

In addition, firm–specific variables reflecting 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. On the one side, enterprises which are part of a conglomerate may have easier access to external capital in a world of capital market imperfections and we would therefore hypothesise a positive relationship. But clearly, GROUP may also capture other effects of the companies' organisational structure on innovative activities. On the other side, some authors have stressed that foreign owned firms are less engaged in innovation activities. One argument in favour of a negative link is that R&D plays a crucial role in the long term strategic planning of a company and managers wish to maintain direct control over such activities, therefore R&D activities usually take place at or in close proximity to the companies' headquarters (see Howell 1984 or Bishop and Wiseman 1999).[15] The observed period is characterised by the

[15] Kleinknecht and Poot (1992) linked this argument into a product life cycle approach. They argue

catching–up process of the Eastern German economy after reunification and the share of innovators had been found higher at the aggregate level in East than in West Germany until the end of the ninetees (see Rammer et al. 2005). Therefore, we expect a higher propensity to innovate for East German firms.[16]

The estimation also controls for ownership structure by distinguishing between public limited companies (PLC), private limited liability companies (LTD) and private partnerships (PRIVPART). One hypothesis 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).

Industry characteristics – alone or in combination with firm–specific features – may also be important for innovation activities. In this context technological opportunities 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. 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 a firm's main product (LCYCLE) and industry dummies.

Table 6 reports the descriptive statistics of the variables used in the estimations. 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, I treated them as time–constant firm–specific variables in the estimation and include them only in equation (2).

that early stages of a cycle are associated with considerable R&D activities which are therefore carried out close to the headquarters, while less R&D activities are necessary in later stages for incremental product or process modifications and can therefore be decentralised.

[16] Note, that the catching–up process in East Germany was patronised by special government support programmes.

Table 5: Variable Definition

Variable	Type	Definition
Alternative endogenous variables		
INNO	0/1	1 if a firm i has positive innovation expenditure in year t. This 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.
INNO_RD	0/1	1 if a firm i has positive expenditure for intra– and extramural R&D in year t.
INNO_NRD	0/1	1 if a firm i has positive innovation expenditure in year t, but no R&D activities.
Explanatory variables varying across individuals and time		
SIZE	c	Number of employees in year $t-1$ (in log).
LCYCLE	c	Length of product life cycle (in years) of firm's i main product in year $t-1$ (in log).
RATING	c	Credit rating index in year $t-1$, ranging between 1 (highest) and 6 (worst creditworthiness).
AGE	c	Age at the beginning of year t (in log).
GROUP	0/1	1 if firm i belongs to a group in year t.
PUBLIC	0/1	1 if firm i received public funding for innovation in year $t-1$.
NOTRAIN	0/1	1 if firm i has no training expenditure in year $t-1$.
TRAINEXP	c	Training expenditure per employee in year $t-1$ if NOTRAIN=0 (in log), otherwise 0.
HIGH	c	Share of employees with a university or college degree in $t-1$.
EXPORT	c	Export intensity in year $t-1$ defined as exports/sales.
Explanatory variables varying across industries and time		
HERFIN	c	Hirschman–Herfindahl Index in year $t-1$, on a 3–digit NACE level, divided by 100. Only available for manufacturing.
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 (*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 industry dummies, respectively, see Table 1.
Time–varying individual–constant explanatory variables		
TIME	0/1	System of time dummies for each year.

Notes: c denotes a continuous variable.

Table 6: Descriptive Statistics[a)]

	Unit	Manufacturing						Services					
		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]	0.555	0.497	0.419	0.268	0	1	0.360	0.480	0.372	0.304	0	1
INNO_RD	[0/1]	0.465	0.499	0.442	0.231	0	1	0.158	0.365	0.308	0.195	0	1
INNO_NRD	[0/1]	0.090	0.287	0.163	0.236	0	1	0.202	0.402	0.254	0.312	0	1
SIZE[b)]	no. empl.	2018.7	14121.3	13566.9	3964.5	1	243638	1782.0	18143.6	18107.3	1512.0	1	271078
LCYCLE[b)]	years	15.4	21.4	21.0	4.3	0.3	200	16.2	22.6	22.0	5.2	1	100
RATING	[Index: 1–6]	2.088	0.600	0.548	0.244	1	6	2.194	0.440	0.407	0.167	1	6
AGE[b)]	years	21.8	23.0	22.5	4.9	0	142	22.3	21.0	20.9	2.4	1	141
GROUP	[0/1]	0.360	0.480	0.409	0.253	0	1	0.223	0.416	0.349	0.227	0	1
PUBLIC	[0/1]	0.243	0.429	0.351	0.246	0	1	0.096	0.295	0.248	0.161	0	1
NOTRAIN	[0/1]	0.176	0.381	0.315	0.215	0	1	0.255	0.436	0.377	0.220	0	1
TRAINEXP[b)]	€	663.2	1135.8	872.0	728.9	0	7702	1223.1	3164.0	2264.1	2213.5	0	25791
HIGH	[0–1]	0.110	0.136	0.117	0.069	0	1	0.200	0.260	0.236	0.110	0	1
EXPORT	[0–1]	0.196	0.246	0.232	0.083	0	1	0.025	0.096	0.084	0.046	0	1
HERFIN	[Index: 0–100]	4.7	6.1	5.6	2.4	0.1	43.2	—	—	—	—	—	—
FOREIGN	[0/1]	0.059	0.236	0.196	0.131	0	1	0.018	0.134	0.118	0.064	0	1
EAST	[0/1]	0.344	0.475	0.469	0.075	0	1	0.420	0.494	0.491	0.054	0	1
PLC	[0/1]	0.078	0.268	0.268	0.000	0	1	0.053	0.225	0.221	0.042	0	1
LTD	[0/1]	0.830	0.376	0.375	0.028	0	1	0.692	0.462	0.457	0.072	0	1
PRIVPART	[0/1]	0.085	0.279	0.278	0.028	0	1	0.220	0.414	0.410	0.063	0	1
Obs				3496						1692			

Notes:
[a)] For the period 1995–2002 (manufacturing) and 1997–2002 (services). In case of lagged explanatory variables, periods used are 1994–2001 and 1996–2001.
[b)] Variable values shown are not log–transformed. For estimation purposes, however, a log–transformation of these variables is used to take the skewness of the distribution into account.

7.3 Econometric Results

Table 7 shows the estimation results of the dynamic RE probit model. Marginal effects are reported, calculated at the average value of the firm–specific effect. One limitation of the estimator is the fact that strict exogeneity of the explanatory variables is assumed.[17] This implies that feedback effects from the innovation variable on future values of the explanatory variables are ruled out, which seems to be contestable for some of the variables usually explaining innovation, e.g. firm size. To assess the impact of including variables, which potentially fail the strict exogeneity assumption, on the estimated state dependence effect, I apply a stepwise procedure. That is, I start estimating an extremely parsimonious specification including only LCYCLE and industry and time dummies as strictly exogenous variables. Then additional explanatory variables are included which might fail this assumption.[18] It emerges from this exercise that the marginal effect of the lagged dependent variable is nearly unaltered. Using a likelihood ratio test, the null hypothesis of no state dependence ($\gamma = 0$) is rejected at the 1 per cent level for each specification and therefore confirming the hypothesis of true state dependence.[19] Hence, the first main result is that even after accounting for individual unobserved heterogeneity, past innovation has a behavioural effect: Conditional on observed and unobserved firm characteristics, an innovator in $t-1$ has a probability of innovating which is approximately 36 PP higher than that of a non–innovator in manufacturing. For service companies the marginal effect amounts to roughly 13 PP. The results further show that the initial condition is also highly significant in both samples. This implies a substantial correlation between firms' initial innovation status and the unobserved heterogeneity.

A third important finding is that in addition to past innovation experience, knowledge provided by skilled employees has a crucial influence on generating innovations over time. In both industries the variables NOTRAIN and TRAIN, and in manufacturing also HIGH, turn out to be significant in the equation explaining individual heterogeneity across firms. That is, firms which do not invest in further training of their employees have a significantly lower propensity to innovate, while for those firms which do invest, an increase in training expenditure per employee of 1 per cent raises the probability of innovating by about 5.5 percentage points in both industries. All in all, these results confirm and highlight the role of innovative capabilities in the dynamics of firms' innovation behaviour.

[17] This assumption is common for this kind of model (see, e.g., Heckman 1981a,b or Honoré and Kyriazidou 2000). Honoré and Lewbel (2002) proposed a semiparametric approach which does not require this 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.

[18] To the best of my knowledge there is no test on exogeneity available for this model. For a static model, Wooldridge (2002) suggested to add the lead of the variable and to test on its significance. Based on this test, PUBLIC is not strictly exogenous on a 1% level and SIZE on a 10% level.

[19] Note that under H_0 a static panel probit RE effects model was estimated.

Table 7: Dynamic RE Probit Estimations

	Manufacturing			Services		
Regression	(1)	(2)	(3)	(4)	(5)	(6)
Structural Equation						
$INNO_{-1}$	0.364***	0.358***	0.333***	0.126***	0.128***	0.103**
	(0.034)	(0.035)	(0.036)	(0.044)	(0.045)	(0.047)
LCYCLE	-0.049	-0.043	-0.053	-0.009	-0.005	-0.039
	(0.044)	(0.031)	(0.044)	(0.109)	(0.109)	(0.112)
SIZE	—	0.111*	0.100*	—	0.011	0.006
		(0.062)	(0.061)		(0.066)	(0.069)
HERFIN	—	0.048	0.055	—	—	—
		(0.057)	(0.056)			
RATING	—	-0.066	-0.068	—	-0.209**	-0.206**
		(0.044)	(0.044)		(0.099)	(0.103)
AGE	—	-0.071*	-0.067*	—	0.050	0.057
		(0.038)	(0.037)		(0.059)	(0.062)
GROUP	—	0.052	0.062	—	0.009	0.010
		(0.050)	(0.050)		(0.063)	(0.066)
NOTRAIN	—	-0.123	-0.116	—	-0.060	-0.068
		(0.162)	(0.160)		(0.155)	(0.161)
TRAINEXP	—	0.014	0.014	—	0.003	0.007
		(0.017)	(0.017)		(0.020)	(0.021)
HIGH	—	-0.100	-0.103	—	-0.027	-0.016
		(0.214)	(0.216)		(0.127)	(0.133)
EXPORT	—	0.459***	0.473***	—	0.109	0.084
		(0.136)	(0.130)		(0.311)	(0.320)
PUBLIC	—	—	0.174***	—	—	0.294***
			(0.045)			(0.102)
Individual Heterogeneity						
$INNO_0$	0.625***	0.460***	0.341***	0.532***	0.370***	0.335***
	(0.042)	(0.045)	(0.047)	(0.059)	(0.065)	(0.064)
M_LCYCLE	0.023	0.030	0.017	-0.047	-0.044	-0.021
	(0.051)	(0.050)	(0.049)	(0.097)	(0.099)	(0.102)
M_SIZE	—	-0.047	-0.056	—	0.022	0.021
		(0.064)	(0.063)		(0.070)	(0.073)
M_HERFIN	—	-0.038	-0.044	—	—	—
		(0.069)	(0.067)			
M_RATING	—	0.026	0.032	—	0.122	0.176
		(0.061)	(0.059)		(0.122)	(0.125)
M_AGE	—	0.116**	0.100**	—	-0.127*	-0.118
		(0.050)	(0.047)		(0.075)	(0.076)
M_GROUP	—	-0.020	-0.026	—	0.070	0.057
		(0.082)	(0.078)		(0.104)	(0.105)
FOREIGN	—	-0.162**	-0.125	—	0.214	0.278
		(0.083)	(0.079)		(0.202)	(0.193)

Table 7 – *continued from previous page*

	Manufacturing			Services		
EAST	—	0.047	-0.051	—	0.022	-0.025
		(0.051)	(0.051)		(0.063)	(0.063)
PLC	—	-0.201**	-0.168*	—	0.211	0.281*
		(0.102)	(0.097)		(0.162)	(0.158)
PRIVPART	—	0.038	0.025	—	-0.049	-0.015
		(0.064)	(0.060)		(0.058)	(0.060)
M_NOTRAIN	—	-0.638***	-0.651***	—	-0.594**	-0.649**
		(0.247)	(0.236)		(0.270)	(0.273)
M_TRAINEXP	—	0.053*	0.054**	—	0.055*	0.056*
		(0.029)	(0.027)		(0.034)	(0.034)
M_HIGH	—	0.646**	0.157	—	0.151	0.010
		(0.316)	(0.312)		(0.205)	(0.209)
M_EXPORT	—	0.347*	0.289	—	0.201	0.006
		(0.198)	(0.194)		(0.428)	(0.460)
M_PUBLIC	—	—	0.370***	—	—	0.528***
			(0.091)			(0.159)
σ_a	0.876	0.709	0.623	0.966	0.850	0.777
	(0.083)	(0.077)	(0.077)	(0.109)	(0.104)	(0.102)
ρ	0.434	0.334	0.280	0.482	0.420	0.376
	(0.047)	(0.049)	(0.050)	(0.056)	(0.060)	(0.062)
ln L	-1132.2	-1077.5	-1047.1	-729.7	-703.9	-680.4
R^2_{MF}	0.193	0.232	0.254	0.120	0.150	0.179
LR_ρ	0.000	0.000	0.000	0.000	0.000	0.000
W_{TIME}	0.013	0.007	0.009	0.000	0.000	0.000
W_{IND}	0.000	0.010	0.030	0.000	0.145	0.138
LR_γ	0.000	0.000	0.000	0.000	0.000	0.000
Corr Pred	83.6	86.1	87.4	76.7	79.1	80.1
Corr Pred 1	84.1	86.4	87.2	63.4	63.6	63.6
Corr Pred 0	83.0	85.7	87.7	84.3	87.9	89.4
Obs	3496	3496	3496	1692	1692	1692

Notes: $***$, $**$ and $*$ indicate significance on a 1%, 5% and 10% level, respectively. M_ denotes the individual time–average of the corresponding variable. Marginal effects are reported, calculated at the average value of the individual–specific error. Columns (2) and (3) report the marginal effect of EXPORT, corrected for the fact that the original regressions also contain the quadratic term. Standard errors were calculated using the delta method. Original coefficient estimates in (2) and (3): EXPORT: 1.604 (0.784) and 1.762 (0.770), EXPORT2: -2.659 (0.906) and -2.710 (0.882). Time and industry dummies are included in the structural and in the heterogeneity equation, respectively. W_{IND} and W_{TIME} test for the null hypothesis that the industry and time dummies are jointly equal to zero. Estimations are based on Gauss–Hermite quadrature approximations using 8 quadrature points. The accuracy of the results have been checked using the STATA command quadchk. Most coefficients change by less than 0.01% and none change by more than 1%, so that the model can be reliably fitted using the quadrature approach.

Fourth, the results provide evidence that unobserved heterogeneity is a key factor for innovation persistence which can be gauged from $\rho = \sigma_a^2/(1+\sigma_a^2)$.[20] Unobserved heterogeneity still explains between 30 and 43% 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 37 to 48%.

In addition to prior innovation experience, skills and unobserved heterogeneity, some observed firm characteristics are also found to be crucial factors in explaining innovation. These results are by and large in line with the literature and with what we expected. Firms that are more financially constrained are less likely to engage in innovation. This effect is highly significant in services and slightly significant in manufacturing. Moreover, firms which receive public funding in the previous period exhibit a higher propensity to innovate in the subsequent period than innovators without financial support in both industries. Firm size, however, is only important in manufacturing, 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 prevalent in services.[21] Firms which are more active on international markets have a higher propensity to innovate in manufacturing. I find, however, an inverse U–shaped relationship for the export intensity with an estimated point of inflexion at 33 % in specification (2). It is also only in manufacturing that ownership matters. That is, public limited companies, in which conflicts of interests between managers and shareholders might arise, have a significantly lower conditional probability of being innovative. However, regarding the second Schumpeterian determinant, I do not find any significant impact of market concentration on innovation. But admittedly, this may be due to the fact that HERFIN is an insufficient proxy of market structure.

The model seems to fit the data quite well. McFadden's pseudo R2 varies between 20 and 25% in manufacturing and based on the preferred specification (2) the model correctly predicts the innovation behaviour for 86% of the observations. Correct predictions in the service sector are likewise high with 79%. However, the model clearly performs worse in predicting the occurrence of innovation for service firms.

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

[21] I also experimented with dummy variables for the export status or export classes, but in no case does export exhibit a significant impact on innovation in services.

Table 8: Importance of State Dependence Effects in Manufacturing and Services

	OSD	PEA[a)]				APE[b)]			
		$\widehat{P(1\|1)}$	$\widehat{P(1\|0)}$	$\widehat{PEA}$		$\widehat{P(1\|1)}$	$\widehat{P(1\|0)}$	$\widehat{APE}$	
				abs.	rel.			abs.	rel.
Manufacturing	74.1	79.3	43.5	35.8	*48.3*	68.9	45.9	23.0	*31.0*
Services	53.7	36.8	24.0	12.8	*23.8*	41.1	32.9	8.2	*15.3*

Notes: OSD: Observed state dependence effect calculated.

a) $\widehat{P(1|1)}$ and $\widehat{P(1|0)}$ denote estimates of the probabilities $P(y_{it} = 1|y_{i,t-1} = 1, x_i, \mu_i)$ and $P(y_{it} = 1|y_{i,t-1} = 0, x_i, \mu_i)$ at the average value of μ_i.

b) $\widehat{P(1|1)}$ and $\widehat{P(1|0)}$ are estimates of the expected probabilities of $P(y_{it} = 1|y^o_{i,t-1} = 1, x^o_i, \mu_i)$ and $P(y_{it} = 1|y^o_{i,t-1} = 0, x^o_i, \mu_i)$ where the expectation is over the distribution of μ_i.

All estimates are based on specifications (2) and (5) in Table 7.

Partial effects at average value 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 8 contrasts the PEA with the estimated average partial effect (APE). It is quite plain that averaging the partial effects across the distribution of the individual heterogeneity reduces the estimates of the state dependence effects. Section 6 has shown that the unconditional propensity to innovate in $t+1$ was 74 PP higher for innovators than for non–innovators in period t in panel B. Controlling for differences in observed and unobserved characteristics, this difference reduces to 36 PP using PEA and 23 PP using APE. This implies that between nearly one third (APE) to one half (PEA) of the innovation persistence in manufacturing can be traced back to true state dependence, while the rest was due to observed and unobserved characteristics. In the service sector state dependence accounts for about 15 (APE) to 24 (PEA) % of the observed persistence.

7.4 Sensitivity Analysis

This section carries out some further analyses to check on the robustness of the results. Table 9 differentiates between R&D–performing and non–R&D–performing innovators to examine whether persistence is mainly driven by R&D activities and whether this can explain the difference found between manufacturing and services. The results suggest that significant state dependence effects exist for both kinds of innovation activities in both samples. But as expected, persistence is much higher for R&D–performing than for non–R&D–performing innovators. Furthermore, the marginal effect of past R&D experience is nearly three times higher in manufacturing with 50 PP than in the service sector with 16 PP. On the other hand, in case of innovators without R&D activities the impact of past innovation experience on the propensity to remain innovative is very much the same in both industries. By and large, the main conclusions drawn in the previous section still hold in the separate estimations.

Table 9: Persistence of Non-R&D– and R&D–Performing Innovators

	Manufacturing		Services	
Dep. Var.	INNO_NRD	INNO_RD	INNO_NRD	INNO_RD
Structural Equation				
INNO_NRD$_{-1}$	0.070***	—	0.093***	—
	(0.022)		(0.034)	
INNO_RD$_{-1}$	—	0.500***	—	0.159**
		(0.037)		(0.077)
ρ	0.258	0.407	0.322	0.337
	(0.049)	(0.061)	(0.060)	(0.111)
R^2_{MF}	0.084	0.320	0.088	0.330
APE: INNO_NRD	0.088	—	0.088	—
APE: INNO_RD	—	0.292	—	0.170

Notes: The regressions include the same set of explanatory variables as in regression (2) in manufacturing and (5) in services, see Table 7. They are not shown here, but are available upon request.

The results so far measured the persistence in innovation input. For manufacturing, the picture can be completed by examining the output persistence for the same set of firms. I use a dummy variable indicating whether the firm has introduced a new product or process within a 3–year period (INOUT) and take only every third survey into account to avoid overlapping, i.e. I used the periods 1994–1996, 1997–1999 and 2000–2002. This strategy leads to a larger reduction of the number of observations. It turns out that the lagged dependent variable is highly significant again and the partial effects are very similar in magnitude, as can be seen from Table 10. That is, the results corroborate true state dependence in innovation output as well. The other main findings asserted for the innovation input are confirmed for the innovation output indicator.

Table 10: Innovation Input and Output Persistence in Manufacturing

Dependent Variable	INNO	INOUT
PEA	35.8	34.2
APE	23.0	21.5
Obs	3496	874

Notes: Estimates are based on the same specification as in column (2) in Table 7.

8 Conclusion

This paper has investigated the persistence of innovation based on data for German manufacturing and service firms during the period 1994–2002. A main finding is that innovation input and output is persistent over time to a very large extent. The econometric analysis reveal that innovation experience is an important driver for this phenomenon: innovating in one period enhances significantly the probability of innovating in the future. Depending on the calculation method of the partial effects, about one third to one half of the difference in the propensity to innovate between previous innovators and non–innovators in manufacturing can be traced back to true state dependence. In the service sector, persistence is generally less prevalent and state dependence effects are less pronounced, yet still highly significant. Furthermore, it turns out that state dependence is much higher for R&D– than for non–R&D–performing innovators (though significant for both) and that this mainly explains the difference between manufacturing and services. The fact that innovation performance exhibits such true state dependence implies, e.g., that innovation–stimulating policy programmes open up potential additional long–lasting effects because they do not only affect the current innovation activities but are likely to induce a permanent change in favour of innovation.

The results further highlight the role of innovative capabilities on the dynamics in firms' innovation behaviour. In addition to past innovation experience, knowledge provided by skilled employees has found to be important in generating innovations over time. Finally, unobserved heterogeneity is important in explaining the persistence of innovation. and leaving out this source of persistence in the empirical analysis can lead to highly misleading results. Some observed firm characteristics like size or export behaviour (determinants which themselves show high persistence) also make some firms also more innovation–prone than others.

In contrast to the results previously found using patents, this analysis has shown that innovation is persistent at the firm–level to a large extent. One interesting question for future research is thus to analyse if the persistence in firms' innovation activities carry over to an asymmetric performance across firms over time. A major issue to be addressed in this line of research will be the direction of causality, that is, does the causality run from innovation to productivity or is the reverse true?

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Appendix: Tables

Table 11: Individual Participation Pattern

	Total			Manufacturing		Services	
No. of	firms		obs	*firms*[b)]	obs	*firms*[a)]	obs
Participation[a)]	#	%	#	#	#	#	#
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)] The number of utilisable observations is higher than that 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.
[b)] Some firms have changed their main business activity which defines their industry assignment 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 12: 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 13: 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		

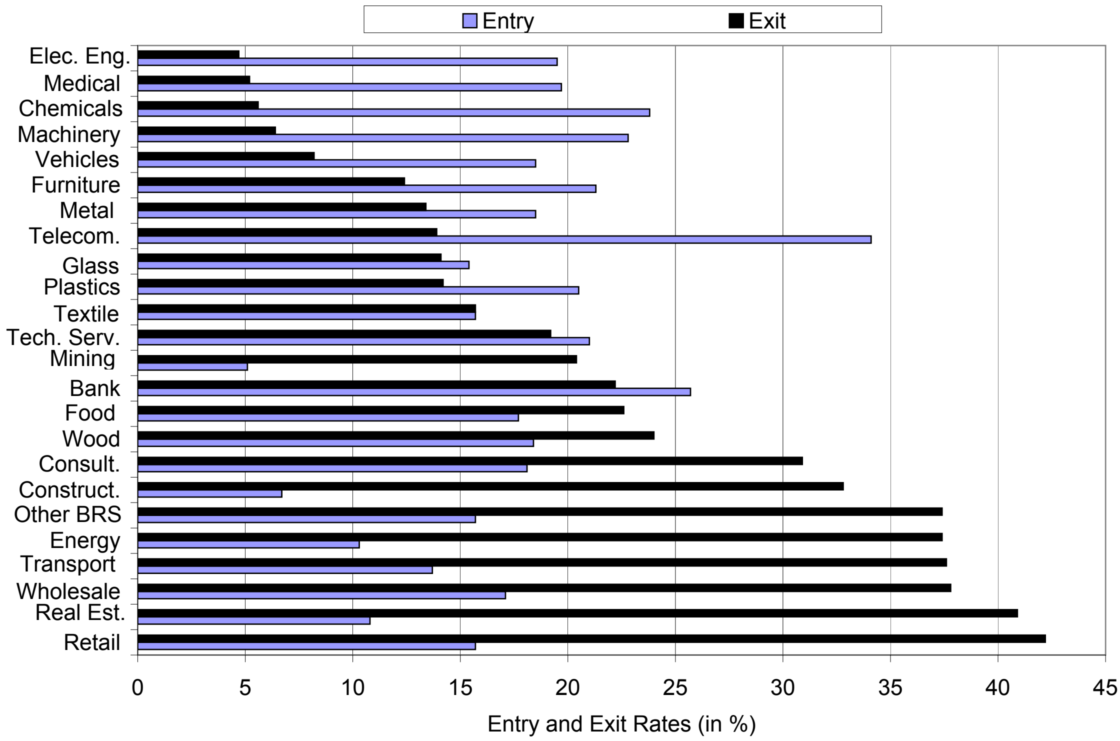
Notes:
[a)] T: Unbalanced panel of all firms within the period 1996–2002. U: Unbalanced panel of firms with at least 4 consecutive observations within 1996–2002. B: Balanced panel of firms within 1996–2002.
[b)] Calculated as share of total number of observations (in %).
Source: Own calculations.

Table 14: Transition Probabilities by Size Class

	Innovation Status		No. of employees					
	Year t	Year $t+1$	< 10	10–19	20–49	50–99	100–499	>=500
Manufact.	Non–Inno	Non–Inno	91.3	87.4	83.9	81.4	78.0	79.0
	Inno	Inno	67.3	79.7	82.4	87.1	89.3	92.8
Services	Non–Inno	Non–Inno	87.1	84.6	85.3	79.6	76.0	77.1
	Inno	Inno	59.5	59.6	69.3	78.6	71.2	87.2

Notes: Sample: Unbalanced Panel.

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



Notes: See Figure 1.