Persistence of Innovation in Taiwan's Manufacturing Firms

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This study examines the persistence of innovation and the determinants of innovations in Taiwan's manufacturing sector, using a panel dataset of manufacturing firms over the period 1990–2003. This study employs a new estimation method for the dynamic random effect probit model to account for firm heterogeneity and also to handle the problem of initial conditions. The empirical results find a strong effect of state dependence after controlling for firm heterogeneity and the initial condition, supporting the hypothesis of true persistent innovation. This finding is also supported for subgroups of scientific and non-scientific industries, implying that the causal effect from past innovation to current innovation exists across industries. Less surprisingly, the phenomenon of innovation persistence is stronger in scientific industries relative to non-scientific industries. We also highlight some important factors that affect continuity in the performance of innovations.

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1 Introduction

Innovation is widely recognized as the major driving force of economic growth as well as industrial evolution and this argument applies also to

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Taiwan (Yang, 2006). Since the mid-1980s, the industrial structure transformed gradually from labor-intensive into technology-intensive in Taiwan, and meanwhile, the government had undertaken several measures to actively support industrial R&D, aiming to improve firms' technological capabilities. As a result, Taiwan has graduated from imitation to innovation within the past couple of decades, by building its indigenous technological capability and raising the level of technology, particularly for the electronics industry. This achievement can also be verified by the output of innovation. Taiwanese patent applications have grown extremely fast both domestically and in the U.S.. A study of "influential patenting" by the technology consulting firm CHI, Inc., placed Taiwan 4th in the world in terms of the quantity of its U.S. patents since year 2000. Using patents granted in the U.S., Trajtenberg (2001) provides an international comparative analysis and shows that Taiwan ranks high in terms of patents per capita, compared to the G7 and the other "Asian Tigers".

Given this record of development, it is indisputable that Taiwanese firms have been very successful in narrowing the technological gap between them and their counterparts in the leading countries. However, one essential and important question that what are the sources of innovations in Taiwan is less investigated. Are innovations contributed by a continuous renewal of innovating firms or by firms' persistent innovation? That is, whether innovative activities are subject to "creative destruction" or "creative accumulation". This longstanding debating on Schumpeter's hypotheses have aspired many theoretical models on interpreting the potential sources of innovation, while there remains little systematic evidence on the issue of innovation persistence at the firm level. Taiwan's outstanding performance on innovations provides as a good study case to investigate this issue. Due to the availability of data, this study focuses on examining whether the behavior of persistent innovation exists in Taiwanese manufacturing firms.

The question alternatively is whether the persistence in innovation behavior, if any, should be strongly related to the technological environment where a firm locates. The concept of "technological opportunity" has been coined to capture the vitality of the underlying sciences and technologies as the sources of technical progress that firms draw upon during innovation (Palmberg, 2004). Generally speaking, the sources of technological opportunity include advances in scientific understanding and technique, technical advancement originating in other industries, and feedback resulting from an industry's own technical advances. Indeed, technological opportunity is

a key determinant of technical changes and it deeply influences firms' innovation behaviors. In industries with high technological opportunity, the pace of technological change is very rapid. The technological environment faced by these firms is relatively fertile, and there are more potential new technologies available to apply for patents. Moreover, technological progress usually exhibits the cumulative feature in fertile technology fields, i.e., most innovations originate from previous innovations. According to this view, an environment with high technological opportunity may cause persistence in innovation. Alternatively, the appearance of innovation is relatively rare in the environment of low technological opportunity, implying that the likelihood of successful innovations is not high. Under the circumstance of low technological opportunity, it is hard to judge whether a firm performs innovative activity persistently with a prior expectation.

The aim of this paper is to examine whether firms' innovative behavior is persistent and to analyze the determinants of firms' innovation by providing several distinct novelties. First, this study employs a new estimator of the dynamic panel data model with unobserved heterogeneity proposed by Wooldridge (2005) to control for individual heterogeneity and initial condition, two potential sources of bias which were not taken into account in most previous studies. Observed persistence may be attributed to persistence on observable firm characteristics, serial correlation of errors, true dependence or permanent unobserved heterogeneity. If these permanent unobserved heterogeneity and serial correlation of errors are not well controlled, the state dependence coefficient obtained in dynamic models will be seriously biased. Given that we are interested in isolating the effects of true state dependence in firms' innovative behavior, this study therefore employs a new estimator proposed by Wooldridge (2005) to empirically discuss this issue. Second, this study additionally separates firms into high and low technological opportunity groups and then analyzes if there is innovative persistence in both groups. This consideration allows us to clarify the potential importance of technological environment on firms' innovation dynamics and provides implications for science and technology policies. Third, this study also investigates the dynamics in firms' innovation behavior by focusing on a newly industrialized country, Taiwan, which has experienced an excellent performance on innovations in past decades. Although several studies have assessed the persistence of innovation at the firm level using panel data, most of these studies focus on manufacturing firms in developed economies, such as the U.S., France, UK, and Germany. Investigating the dynamics in the

innovative activity for Taiwanese firms is interesting not only because Taiwan has experienced a successful technology development over the last two decades, but also from a research policy point of view.

The rest of this paper is organized as follows. Section 2 starts with a brief review of the theoretical literature about innovation persistence and then summarize the findings of the empirical studies on the persistence of innovation. In section 3, we sketch the innovative activities of Taiwan since the late 1980s and onward. Moreover, the panel data set underlying this study is explored. Section 4 presents the econometric model, estimation technique, and the empirical specification. Section 5 contains the estimating results for the persistence of innovation. This study further investigates whether there is difference in dynamics in the innovation behaviors of firms between low and high technological opportunity industries. Section 6 draws some concluding remarks and discusses the policy implications.

2 Theoretical Literature and Previous Empirical Studies

2.1 Theoretical arguments

Are innovations contributed by a continuous renewal of innovating firms or by firms' persistent innovation? The endogenous growth theories have opposite standpoints on the assumption of innovation sources. Despite Aghion and Howitt (1992) take on the view that technological change can be attributed to the process of creative destruction, most models argue that there exists a strong persistence of innovators. Indeed, both creative destruction and creative accumulation are not mutually exclusive. Most of the innovators would be involved in a creative destruction process, while there would remain an innovative core.

Why most theoretical arguments suggest that firms' innovation behaviors would be persistent -that is, the persistent behavior might be caused by true state dependence, meaning that the innovation state in one period influences the innovation behavior of a subsequent period. The most prominent streams of theoretical arguments on explaining the persistence of innovations at the firm level include mainly: (i) the hypothesis that "success-breeds-success", (ii) the hypothesis of dynamic increasing return in innovation, and (iii) organizational capabilities and sunk costs in R&D.[1]

[1]The summary of theoretical arguments is mainly referring to Duguet and Monjon (2004). Their paper contains a comprehensive review of theoretical models.

The first is the well known hypothesis of "success-breeds-success". This concept was firstly proposed by Mansfield (1968). He argues that a firm's innovation success broadens its technological field which increases the success probability of subsequent innovations. However, an alternative and well-known explanation of success-breeds-success originated from the existence of financial constraints on R&D investment. Internal financing is widely recognized as the main financing source of R&D activity owing to the presence of asymmetric information or a principal-agent problem (Himmelberg and Petersen, 1994). Once the past innovations reach commercial success, the innovating firm can appropriate profits that it then provides sufficient internal funding for the firm to invest in current innovative activity, resulting in a "success-breeds-success" process (Nelson and Winter, 1982).

The hypothesis of dynamic increasing returns in innovation is originated from the cumulative feature of the learning process on innovative activity (Cohen and Levinthal, 1989; Malerba and Orsenigo, 1993), implying that technological capability serves as a predominate influence on explaining innovation. This line of literature assumes that technological capability does not depreciate rapidly over time, and therefore knowledge that has been used to produce past innovations can be applied to develop subsequent innovations. Benefiting from the accumulation on technological capability, experience in innovation is usually associated with dynamic increasing returns in the form of learning-by-doing, learning-to-learn, or scope economies, which enhance the success probability of future innovations. Therefore, this cumulative nature of knowledge should produce persistence at the firm level and induce state dependence in innovation behaviors.

The last stream of literature relies on the hypothesis of sunk costs of R&D. Sutton (1991) classifies R&D investment as one of key endogenous sunk costs of market structure. That is, engaging in R&D incurs some unrecoverable sunk costs, such as start-up costs in establishing an R&D department, the purchase of specific assets, and the hiring and training of R&D staff. Under the assumption of a linear model of innovation that stresses a simple linear relationship between the R&D expenditure of a firm and its innovations such that the persistence of innovation coincides with that of R&D expenditure. With respect to persistence, the sunk cost a firm spends may spread over a long-term horizon. When a firm can support the sunk cost of R&D it can make inventions that lead to product or process innovations (Cohen and Klepper, 1996).

2.2 Previous empirical studies

Although the theoretical literature emphasize that innovation is an inherently dynamic process, firm-level empirical studies on the persistence of innovation is quite limited. Three types of studies are identified according to how the studies measure innovation. They are patent-based, R&D-based, and innovation-based. In this section, we summarize only the findings of the patent-based empirical studies that are relevant to our study which uses patents as a measure of innovations.[2]

Geroski et al. (1997) first carry out a firm-level study concerning this issue. They use data of UK manufacturing firms which applied for U.S. patents between 1969 and 1988, and define the degree of innovation persistence of a firm as the number of consecutive years during which it has a recorded patent, and then examine potential sources of persistence. Overall, their empirical results suggest that dynamic scale economies might have led to a more persistent patent spell, while only very few firms are persistently innovative.

Applying the same approach of duration dependence Weibull model in Geroski et al. (1997), Cabagnols and Bas (1999) employ a dataset of France manufacturing firms to test the hypothesis of dynamic economies of scale and report similar results. Moreover, Cabagnols (2006) uses the same data as Geroski et al. (1997) to examine more precisely the impact of technological accumulation (measured by past patents) on firms' ability to persist in innovation. He finds that the impact of past patents on current innovations is significantly positive, lending evidence of persistence in innovations.

The descriptive statistics study by Malerba and Orsenigo (1999) also examine the issue of persistence by using data of manufacturing firms from six countries (France, Germany, Italy, Japan, the U.S. and the U.K.) which have requested at least one patent at the European Patent Office (EPO) over the period 1978–1991. This study shows that there are substantial entry-into and exit-from patenting activities, implying that the population of innovators changes remarkably over time. The high entry and exit rates are associated with a large fraction of enterprises (usually small firms) that in-

[2] For R&D-based and innovation-based studies on the persistence of innovations, please see Raymond et al. (2006) for a comprehensive survey. Peters (2009) employs the firm level data from the Mannheim Innovation Panel (MIP) in the German manufacturing and service sector, which contributes to the European wide harmonized CIS. The results also confirm the hypothesis of innovation persistence.

novate only once and then cease to innovate further. Additionally, there would still remain a stable group of large, consistent innovators that continue to be persistent innovators over time. The results of this study are confirmed by Cefis and Orsenigo (2001) who extend this kind of analysis to a firm-level cross-country comparison. They find that "great-innovators" have a high probability of staying in their innovative state while persistence is much lower in the intermediate classes for which a strong tendency towards the non-innovator state is ascertained. Recently, Jang et al. (2007) apply the same approach of Markov chain as that in Cefis and Orsenigo (2001). They find that on average, the persistency of Japanese firms in sustaining their innovative activities is stronger than US firms, while South Korean firms are more tenacious than their Taiwanese counterparts. Consequently, there would result a strong persistence of innovation in a core of firms.

Cefis (2003) uses a UK sub-sample of the dataset of Malerba and Orsenigo (1999) to investigate this issue. The author applies the Markov chains approach based on transition probability matrices to examine the probability of remaining in the same state of patenting. The empirical results show that the probability to remain in the polar state (with zero and at least 6 patents) is very high, but the other probabilities are low, leading to low persistence in general. Duflos (2006) uses a non-linear GMM estimator for exponential models to evaluate the impact of past innovative activity on firms' innovation propensities. This study shows that innovative activity at the firm level depends strongly on the technological importance of past innovations. However, this study only includes the US pharmaceutical industry. The author also suggests that large firms may persist in using patents strategically to retain sales.

Drawn from the review, the existing studies overall conclude that firms' innovation persistence is rather weak, and that innovation is persistent in a small number of firms. Divergent points of view on this issue emerge, in part, because the various studies use different definitions of persistence in innovation, indicators of persistence, and econometric techniques. The ambiguities and uncertainties remain in both theoretical and empirical literature, suggesting the need for future empirical work.

The core objective of this study is to use a different measure of innovation persistence based on patent data and to employ a new estimator of the dynamic random effect (RE) probit model proposed by Wooldridge (2005) to empirically discuss this issue. Our longitudinal and comprehensive firm-level data allows this study to control for firm heterogeneity and initial con-

dition in the dynamics of innovation. Moreover, the case study of Taiwan provides an excellent example of how a developing country can catch up on the development of technology and science.

3 Taiwan's Innovative Activity and Dataset

3.1 Taiwan's innovative activity, 1986–2003

Before turning into the micro data, econometric model and specification, this section reviews recent trends of innovative activities in aggregate data. Taiwan's postwar economic miracle is a well-known story among economists. The nation adopted the industry development model of OEM (original equipment manufacturer), for firms to make products under contracts for multinational corporations, which then market the resulting product under their own brand names. Taiwanese firms have learned and adopted foreign technologies to improve technological capabilities, which have been gradually associated with low-tech, imitative behaviors, for a long time. This means that these firms do not have to shoulder the burden of high R&D expenses.

We cannot infer from this that there is no active R&D or innovations taking place in Taiwan. Indeed, the government ever since the early1980s has undertaken several measures to actively support industrial R&D. There were a surge of innovative activities by both private and public sectors in the past two decades, resulting in an excellent performance on innovation outputs. This island has therefore graduated from imitation to innovation by building its indigenous technological capability and raising the level of technology.

Table 1 displays Taiwan's innovative activity since the mid-1980s. The second and third columns show trends in aggregate R&D spending and the ratio of R&D spending to GNP, respectively. The amount of R&D expenditure has increased more than eight times - from NT$28.702 billion in 1986 to NT$240.820 billion in 2003. The increasing trend on R&D expenditure reveals that a great effort for scientific and technological development has devoted in Taiwan. Accordingly, the ratio of R&D spending to GNP went from 0.98% in 1986 to 2.45% in 2003. Although it is still a little lower than that of developed countries, the increasing trend indicates that R&D activity is increasingly emphasized in this island.

Concerning the innovative outputs, columns 4 and 5 show the Taiwan

Table 1: Taiwan's Innovative Activity, 1986–2003

	R&D (NT$ million)	R&D/GNP (%)	Patent Applications by Residents	Taiwan's US Patents Granted, excluding New Design (rank)
1986	28,702	0.98	18,372	208 (15)
1987	36,780	1.11	18,227	343 (13)
1988	43,839	1.21	17,152	457 (11)
1989	54,789	1.36	17,917	591 (11)
1990	71,548	1.62	19,964	732 (11)
1991	81,765	1.66	22,940	906 (10)
1992	94,828	1.74	26,118	1,001 (9)
1993	103,617	1.74	28,246	1,189 (8)
1994	114,682	1.78	29,307	1,443 (7)
1995	125,031	1.79	28,900	1,620 (7)
1996	137,955	1.83	31,185	1,897 (7)
1997	156,321	1.91	33,657	2,057 (7)
1998	176,455	1.96	34,243	3,100 (7)
1999	190,520	2.03	32,643	3,693 (5)
2000	197,631	2.06	36,369	4,667 (4)
2001	204,974	2.17	40,210	5,371 (4)
2002	224,428	2.31	35,926	5,431 (4)
2003	240,820	2.45	39,663	5,298 (4)

Data source: Indicators of Science and Technology, Taiwan, various issues. U.S. Patent and Trademark Office (USPTO).

patents applied for by residents and U.S. patents granted to Taiwan inventors, respectively. The number of domestic patent applications increased steadily from 18,372 in 1986 to 39,663 in 2003. Despite the patent number per billion NT dollars seems to decline, it is perhaps caused by the fact that the average cost of R&D projects has increased over time and/or the average patent quality has improved. Turning to the U.S. patents, in which it is usually the case that patents are sought first and foremost (where the standards for patentability are more stringent and the largest export-targeted country), the right column of Table 1 shows that the number of successful Taiwan patent applications increased sharply. The growth in the annual number of patents is very impressive, starting from 208 in 1986 to 5298

in 2003 (i.e. they grew by a surprisingly factor of 25). In terms of patent counts, Taiwan's U.S. patents ranks 4th in the world since the year 2000, following U.S., Japan, and Germany.

Up to now, Taiwanese firms have been successful in closing the technological gap between them and their counterparts in developed countries, especially in the electronics industry. Are innovations contributed by firms' persistent innovation? The Taiwan evidence can serve as an interesting example for the longstanding debate.

3.2 Dataset

In order to examine whether there is persistence in innovation and to explore the factors determining firms' innovations, this study begins by exploring the innovation patterns of firms. The research makes use of firm level data from all manufacturing firms of 1990 listed on the Taiwan Stock Exchange (TSE). Given the need of estimating a dynamic specification with lagged endogenous variables, we build up a panel as long as possible. Hence, we collected the panel data based on firms in year 1990, and extended the data to 2003. The observations for 1990 are used as regressors, representing the initial condition, and the rest observations from 1991 to 2003 enter the regression. We exclude firms which have experienced a substantial increase in turnover due to mergers during the analysis period. Some firms with incomplete data for all relevant variables were also eliminated. After the cleaning procedure, the total number of firms remaining for the empirical analysis is a 14-year panel of 279 firms, containing 3,576 observations.[3] Arising from the conditions for Initial Public Offering (IPO), most of the firms listed on TSE belong to the classification of large enterprises and hence the dataset is suitable for testing the hypothesis of persistent innovation.[4] To investigate the potential influence of technological opportunity on firms' innovation dynamics, this study further separates the sample into two sub-groups: high and low technological opportunity. According to the classification of Yang and Chen (2001) for the TSE firms, the high technological opportunity group includes firms whose TSE codes are classified as Petrochemistry

[3] If the conditional mean of innovation decision in non-selected sample is the same as selected sample, so that selection is ignorable in the conditional mean sense, then the selected sample is consistent More details please see Wooldridge (2002, section 17.2.2).

[4] According to the Taiwan's official classifications on firm size, a firm that has more than two hundred employees is classified as a large enterprise.

(13), Machinery and Equipment (15), Electrical and Cable (16), Transport Equipment (22), and Electronics Industries (23). This study classifies scientific industries as within the high technological opportunity group, while non-scientific industries represent the low technological opportunity group.

One problem in studying state dependence in innovation is: What is a preferable measure for innovation? As mentioned in the previous section, there are three types of innovation measures used in previous studies: patent, R&D, and major innovation (e.g. CIS data in Germany and SPUR data in U.K.). In Taiwan, there are two types of available information on measuring innovation: R&D spending and patents. The majority of the existing empirical literature on innovative persistence uses patents as an indicator of innovation,[5] while the econometric techniques employed are quite different owing to the specification of empirical models. The intrinsic variability on patent quality prevents the patent count from serving as a perfect indicator of innovation.[6] This study therefore uses "whether a firm has patents" as a measure of innovations. In order to examine whether there is true state dependence in innovations, in contrast to the previously mentioned studies, we define an innovator as a firm which exhibits a positive patent count in a given year. This implies that we analyze the persistence in innovation output rather than in innovation input behavior. The patent count data drawn from the Taiwan Intellectual Property Office (TIPO) database were matched to our sample firms for the 1990–2003 period. One point worth noting is that the TIPO dataset is the unique innovation count data and has been used by economic researchers in Taiwan.

Before turning into the empirical estimation, we first use our sample to observe whether innovation behavior is persistent. Table 2 shows the transition probabilities on patents for the whole sample, scientific industries, and non-scientific industries, respectively. The figures in Table 2 are calculated by the conditional probability. We define the innovation persistence as the same innovation status which exhibits "Inno" in year t and year $t+1$. Therefore, it can be clearly found that innovation behavior seems to be persistent for the entire sample firms to a large extent. In the period 1990–2003, nearly 79% of innovating firms in one period kept on innovating in the following period. Within the scientific industries, nearly 84% of innovating

[5] Manez-Castillejo et al. (2006) used R&D as the indicator.

[6] How past patents affect current patent applications is widely used to test the "standing-on-the shoulder effect" vs. "fishing-out effect", rather than the "persistence effect" in the empirical literature of innovation economics.

Table 2: Transition Probabilities of Patents, 1990–2003

Innovation Status		Patents		
$Year_t$	$Year_{t+1}$	ALL	Scientific	Non-Scientific
Non-Inno[a]	Non-Inno	89.52	77.78	94.23
	Inno	10.48	22.22	5.77
Inno[b]	Non-Inno	21.28	16.24	36.64
	Inno	78.82[c]	83.76	63.36

Notes: a. Non-Inno represents non-innovator. We define the non-innovator as the observations which don't exhibit a positive patent count.

b. Inno represents innovator. We define the innovator as the observations which exhibit a positive patent count.

c. The transition probabilities of patents are calculated by the share of the innovators in year $t + 1$ conditional on the innovators in year t.

firms in one period persisted in innovating in the following period, showing that the innovation behavior to be highly persistent. Concerned with the non-scientific industries, the persistence effect seems to be prevalent and exhibits a similar extent as that of all sample firms. Despite that innovating firms exhibit a significantly lower (63%) probability to maintain this same status as compared to their counterparts in scientific industries, 84% of non-innovating firms remained as non-innovators. This result implies that innovations might be less important in the non-scientific industries.

The distribution of the number of granted patents among industries and the frequency of innovation are listed in Tables 3 and 4, respectively. As shown in Table 3, the average number of granted patents of scientific industry (12.991) is obviously higher than that of non-scientific industry (0.631). It shows that the scientific industries have a better innovation performance than their non-scientific counterparts in terms of granted patents. Looking further into individual industry, the electronics industry ranks the first in acquiring patents among scientific industries, which accounts for 83% of the total number of patents. As for firms' innovation frequency, Table 4 shows that there are 43% firms having no innovations during 1991–2003, while 8.67% of firms kept on innovating annually during this period. More-

Table 3: The distribution of the number of granted patent, by industry

Scientific industries	Granted patent	Obs	Mean	S.D.
(13) Petrochemistry	152	209	0.727	(1.951)
(15) Machinery and Equipment	668	218	3.064	(5.322)
(16) Electrical and Cable	452	157	2.879	(6.232)
(22) Transport Equipment	251	59	4.254	(8.531)
(23) Electronics	15,960	668	23.892	(93.227)
Subtotal	17,483	1,383	12.991	(65.744)
Non-Scientific industries	Granted patent	Obs	Mean	S.D.
(11) Cement industry	5	104	0.048	(0.256)
(12) Foods	87	298	0.292	(1.385)
(14) Textiles	44	583	0.075	(0.358)
(17) Chemicals	79	228	0.346	(1.172)
(18) Glass-ceramic	214	91	2.352	(6.475)
(19) Paper & Pulp	67	85	0.788	(1.684)
(20) Steel	182	303	0.601	(2.583)
(21) Rubber	449	104	4.317	(9.770)
(99) Others	576	190	3.032	(5.728)
Subtotal	1,703	1,914	0.637	(3.236)
Total	19,186	3,297	5.819	(43.076)

over, there are 20.9% of firms having innovations at least eight years during 1991–2003. Looking further into the electronics industry, there is only 8.83% having no innovations any year. In contrast, 19.46% of electronics firms continue to having innovation. Regarding to firms which have innovations at least eight years, it accounts for a little higher than half, 50.6%. Drawn from the simple statistics, it implies that the electronics industries greatly contribute to the sources of innovative persistence for Taiwan's Manufacturing.

In order to compare the experiences in advanced countries, this study also adopts the definition in Manez-Castillejo et al. (2006) and Peters (2009)

Table 4: The Frequency of Innovation, 1991–2003

Frequency	Full Sample	%	Electronics	%
0	1,422	43.13	59	8.83
1	242	7.34	40	5.90
2	196	5.94	33	4.94
3	138	4.19	20	2.99
4	165	5.00	33	4.90
5	124	3.76	46	6.89
6	117	3.55	26	3.89
7	204	6.19	73	10.93
8	65	1.97	39	5.84
9	52	1.58	13	1.95
10	65	1.97	52	7.78
11	91	2.76	26	3.89
12	130	3.94	78	11.68
13	286	8.67	130	19.46
Total	3,297	100.00	668	100.00

that defines an innovator as a firm which exhibits positive R&D expenditures in a given year and then displays the corresponding transition probabilities on engaging in R&D in Table 5. Table 5 clearly shows that the innovative behavior is highly persistent among innovating firms. The probabilities to remain in the status of innovators are nearly 85% for the entire sample, 94% for scientific firms, and 76% for non-scientific firms. This rate of state dependence is somewhat higher than that of Spain (Manez-Castillejo et al., 2006) and Germany (Peters, 2009) during a similar period.[7] However, one important point worth noting is that the pattern of state transition for non-innovating firms is quite different. In the 1990–2003 period, non-innovating firms had a much higher propensity at 44% to enter into innovative activity. For non-scientific industries, the transition rate approaches as high as 68% that is significantly higher than the 17% in Germany (Peters, 2009). The possible interpretations are twofold: one would be the encouraging fact that Taiwan's non-scientific firms have devoted more efforts

[7] The data period for Spain and Germany is 1990–2000 and 1994–2002, respectively.

Table 5: Transition Probabilities of R&D, 1990–2003

Innovation Status		R&D Engagement		
$Year_t$	$Year_{t+1}$	ALL	Scientific	Non-scientific
Non-Inno[a]	Non-Inno	56.40	32.06	66.06
	Inno	43.60	67.94	33.94
Inno[b]	Non-Inno	15.62	6.10	24.10
	Inno	84.38[c]	93.90	75.90

Notes: a. Non-Inno represents non-innovator. We define the non-innovator as the observations which don't exhibit positive R&D expenditures.

b. Inno represents innovator. We define the innovator as the observations which exhibit positive R&D expenditures.

c. The transition probabilities of R&D are calculated by the share of the innovators in year $t + 1$ conditional on the innovators in year t.

to R&D activity since 1990. Alternatively, this result could arise from the highly upward bias in reporting R&D expenditures by firms, because the R&D outlays can be used to get the benefit of tax reduction, special low-interest loan, R&D funding, and so on. If the later explanation is true, then using the R&D-based indicator to discuss the issue of persistent innovation will result in biased estimations.

According to the literature on examining the innovation-business cycle nexus, innovation behavior can exhibit a pro-cyclical as well as a counter-cyclical relationship due to the effects of cash flow or opportunity cost. Himmelberg and Petersen (1994) found a significant relationship between firm R&D expenditures and internal finance using a panel of small high-tech firms, suggesting that cash flow influences R&D expenditures and that these expenditures are procyclical. Alternatively, Bean (1990) and Saint-Paul (1993) argued that firms reorganize the importance of R&D on stimulating TFP growth during recessions and negative demand shocks. The interpretation is that the opportunity cost of inventive activity in terms of forgone profits by investing capital in technological improvements is lower during recession, i.e. countercyclical. During the 1990–2003 period, Taiwan's economy underwent different business cycles and 1997 was character-

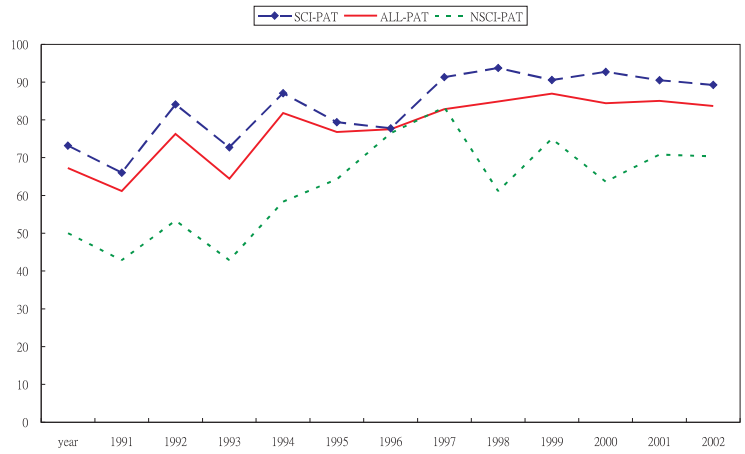


Figure 1: Transition Probabilities, by Year

ized as a turning point year. Before the 1997 Asian financial crisis, Taiwan's economic yearly growth remained at an average growth rate of 6.68%. Following 1998, there were various macroeconomic shocks that impeded Taiwan from keeping a high rate of economic growth resulting in an average of 3.41% over the 1998–2003 period.[8] Figure 1 demonstrates the transition probabilities by years and shows that, despite different business cycles, the propensity to remain innovative seemed to exhibit a pro-cyclical pattern for the entire sample and that the propensity steadily increased before 1998, followed by a slightly downward trend. Moreover, the impact of macroeconomic shocks on innovation persistence seems to be larger for non-scientific industries rather than scientific industries.

The preliminary descriptive analyses in summary show that the innovation behavior was quite permanent in Taiwan manufacturing firms over the 1990–2003 period. In addition, the industry which a firm belong to might affect firms' dynamics in innovations.

[8]These macroeconomic shocks include the 921 earthquake in 1999, Taiwan's first time of political power turnover in 2000, and the 911 attack on the U.S. in 2001, and so on.

4 Econometric Model and Empirical Specification

To model the dynamic process of a firm's innovation behavior, the dynamic unobserved effects model is employed in this study. It assumes that firm i devotes efforts on innovation in period$t$ if the expected present profit of the innovation y_{it}^* is positive. We then specify the dynamic of a firm's innovation behavior depends on the previous innovation behavior $y_{i,t-1}$, a vector of firm-specific characteristics z_{it}, and on unobserved firm-specific attributes c_i that are assumed to vary between firms and constant over time. Therefore, the structural model is specified as follows:

$$y_{it}^* = \rho y_{i,t-1} + z_{it}\beta + c_i + \varepsilon_{it}, \tag{1}$$

where ε_{it} is the error term, capturing the effect of other time-varying influences. It is assumed that $\varepsilon_{it}|y_{i0}, y_{i1}, \cdots, y_{i,t-1}, z_{it}$ is independently and identically distributed as $N(0, 1)$ and that $\varepsilon_{it} \perp (y_{i0}, z_i, c_i)$ where $z_i = (z_{i1}, z_{i2}, \cdots, z_{it})$.[9] If y_{it}^* is positive, then we can observe that a firm will engage in innovation behavior where I represents the indicator function:

$$y_{it} = I\left[y_{it}^* > 0\right]. \tag{2}$$

Assuming that the time sequence of innovation behaviors starts at $t = 0$-that is, y_{i0} is the initial value, and then the successful probability of innovation behavior in time t is given by:

$$P\left(y_{it} = 1|y_{i,t-1}, \cdots, y_{i0}, z_i, c_i\right) = \Phi\left(z_{it}\beta + \rho y_{i,t-1} + c_i\right). \tag{3}$$

Controlling for the unobserved firm heterogeneity c_i, a firm's innovation behavior can be regarded as independent with previous behavior if $\rho = 0$. Alternatively, if there exists state dependence, then the null hypothesis $\rho = 0$ is rejected and we can argue that a firm' innovation behavior is persistent.

The joint probability density function of equation (3) given ($y_{i0} = y_0, z_i = z, c_i = c$) can be written as:

$$f\left(y_1, y_2, \cdots, y_T|y_0, z, c; \beta\right) = \prod_{t=1}^{T} f\left(y_t|y_{t-1}, \cdots, y_1, y_0, z_t, c; \beta\right)$$

[9] To consistently estimate ρ, the distribution assumption of ε is crucial. For instance, if ε is AR(1) instead of i.i.d., ρ may incorrectly pick up the persistence of the shocks.

$$= \prod_{t=1}^{T} \Phi\left(z_t\beta + \rho y_{t-1} + c\right)^{y_t} \left[1 - \Phi\left(z_t\beta + \rho y_{t-1} + c\right)\right]^{1-y_t}. \quad (4)$$

There are two econometric problems that should be dealt with in the above model: the unobserved individual effect and the initial condition for the dynamic model. To deal with the first problem of unobservable individual effect in a panel data model, both random effect (RE) and fixed effect (FE) models that treats the individual effect as a random variable and fixed parameter respectively are standard estimation method. The FE model is less limitation on the assumption for the distribution of c_i, making it preferable in practice. Because there is no general solution in the literature regarding how to estimate a dynamic FE binary choice panel data model and there is a time-invariant explanatory variable in the empirical equation,[10] this study therefore applies the RE model.

Concerning the second problem, this study employs the new estimator proposed by Wooldridge (2005) to deal with the initial condition y_{i0}. The logic on handling the initial condition to assume y_{i0} is likewise random and specifies the distribution of c_i conditional on y_{i0} and z_i, which leads to the joint density of $(y_{i1}, y_{i2}, \cdots, y_{it})|y_{0i}, z_i$. Under this assumption, Wooldridge (2005) develops an estimator for dynamic non-linear RE models, including dynamic RE probit, logit and tobit models. He assumes that the individual heterogeneity depends on the initial condition and the strict exogenous variables in the following way:[11]

$$c_i = \alpha_0 + \alpha_1 y_{i0} + \bar{z}_i\gamma + a_i, \quad (5)$$

where $\bar{z}_i = (1/t)\sum z_{it}$ denotes the time-average of z_{it}.[12] Moreover, the error term a_i is assumed to be i.i.d. as $N(0, \sigma_a^2)$ and that $a_i \perp (y_{i0}, \bar{z}_i)$. Thus,

[10] Honore and Kyriazidou (2000) propose a semiparametric estimator for the FE logit, but their method cannot be used here due to the existence of a time-invariant variable in this study.

[11] Specifying a distribution of heterogeneity conditional on the initial condition not only can choose the auxiliary distribution to be flexible, but also can straightforward estimation by using standard software (Wooldridge, 2005).

[12] Including the time-average variables to control for some observed heterogeneity is intuitive. While we can not correctly identify the causal effects of these variables on the dependent variable, we can include them in the model for unobserved heterogeneity (Wooldridge, 2005).

$\varepsilon_i|y_0, \bar{z}_i$ follows a $N(\alpha_0 + \alpha_1 y_{i0} + \bar{z}\gamma, \sigma_a^2)$ distribution. Given the assumptions on the distribution of the unobservable firm heterogeneity, Wooldridge (2005) shows that the probability of having innovation behavior is as follows:

$$\begin{aligned} P\left(y_{it} = 1|y_{i0}, \cdots, y_{i,t-1}, z_i, \bar{z}_i, c_i\right) \\ = \Phi\left(\rho y_{i,t-1} + z_{it}\beta + \alpha_0 + \alpha_1 y_{i0} + \bar{z}_i\gamma + a_i\right). \end{aligned} \tag{6}$$

By integrating out a_i in equation (6), it yields a likelihood function that has the same structure as in the standard RE probit model except that the regressors include lagged dependent variable, the initial condition, and the time-averages of the strict exogenous variables.

This parametric approach allows this study to identify whether true state dependence exists by referring to the significance level of the estimated coefficient for the lagged dependent variable.[13]

Based on the econometric model discussed above, the empirical model is specified to test if there is a causal effect existing whereby past innovation behavior itself enhances the probability of current innovation behavior defined as

$$\begin{aligned} \text{INNO}_{it} = {} & \beta_0 + \rho\text{INNO}_{i,t-1} + \beta_1\text{SCI}_{it} + \beta_2 \ln \text{RD}_{it} + \beta_3 \ln \text{SIZE}_{it} \\ & + \beta_4 \ln \text{AGE}_{it} + \beta_5 \ln \text{KL}_{it} + \beta_6 \ln \text{ADV}_{it} + \beta_7\text{PROFIT}_{it} \\ & + \beta_8\text{INNO}_{i0} + \beta_9\text{ARD}_i + \beta_{10}\text{ASIZE}_i + \beta_{11}\text{AAGE}_i \\ & + \beta_{12}\text{AKL}_i + \beta_{13}\text{AADV}_i + \beta_{14}\text{APROFIT}_i + \varepsilon_{it}, \end{aligned} \tag{7}$$

where INNO_{it} is a binary variable that equals 1 if firm i devotes to innovation behavior in year t. This study uses an output index of innovations, patent, as a proxy for innovation. If a firm has successful patent applications in year t, then INNO_{it} equals 1.

As for the explanatory variables, theoretical and empirical studies have identified numbers of determinants - mainly firm-specific and industry-specific characteristics. Because the main hypothesis this study would like to examine is whether there is persistence in firms' innovation, the firm's one-year lagged dependent variable INNO_{it-1} is included as the measure of

[13]The same concept also can apply to dynamic unobserved effects poisson model. However, as is well known, the poisson model has the restriction that the mean and variance are equal.

state dependency. Importantly, it is of great concern on whether the coefficient for this variable is used to indicate if past innovation is significantly related to current innovation. A positive relationship can be used to verify the persistence of a firm's innovation, whereas a negative impact perhaps represents the extinction of innovative opportunity (Crepon and Duguet, 1997). The second question of concern is whether the dynamics inc innovation vary between high and low technology opportunity groups and therefore the industry-specific dummy variable SCI, which equals unity for scientific industries, is included to preliminarily test the effect of technological opportunity on innovations.

Research and Development (R&D) spending, in logarithm (ln RD), is the most important variable in the patent production function. The literature focusing on the R&D-patent relationship has addressed the question of whether one could measure the lag structure of R&D expending, while largely concluding that the lag structure is very poorly identified (Hausman et al., 1984) They suggest that using the contemporaneous level of R&D spending in the empirical specification can obtain similar elasticity as that including the lag structure of R&D. This strategy of using only the ontemporaneous level of R&D spending in the patent equation is then widely adopted in existing literature, such as Hall and Ziedonis (2001), Sakakibara and Branstetter (2001), Zachariadis (2003), and Arora et al. (2008).[14]

The size of the firm (SIZE) is measured as the number of employees. Large firms usually have noteworthy advantages in supporting R&D. They also enjoy economies of scale in generating patents due to the operating cost of maintaining a legal department to deal with intellectual property issues. However, Audretsch and Acs (1991) argued that small firms tend to outweigh large firms in innovation performance in a more technology-intensive environment. Term AGE is a firm's age and it is adopted to capture the learning-by-doing effect on innovation. The term KL denotes the firm's capital intensity, measured as the ratio of physical capital to employees. This variable is considered to test the 'strategic response' hypothesis proposed in Hall and Ziedonis (2001); that is, whether firms with large sunk costs respond strategically to an environment with more emphasis on innovations by expanding their own portfolios of patents with which to trade.

Advertising expenditure (ADV) is an important strategy conducted by

[14]Even though the R&D expenditure is included in the form of lag one period, we experienced similar results.

firms to respond to the competition in markets and therefore this variable is employed to measure the toughness in market competition. Moreover, the financing of innovation is widely studied in previous literature,[15] a firm's profitability (PROFIT) is also included to measure the availability of internal financial resources and it is expected to have a positive impact on firms' innovations. Except for a firm's profitability, other explanatory variables enter the empirical specification in the form of logarithm.

Term INNO_{i0} denotes the status of a firm's innovation in the initial period. The time-average of explanatory variables are included based on the suggestion of Wooldridge (2005) on dealing with the problem of unobservable firm heterogeneity, while their estimated coefficients cannot be interpreted with economic meanings. The variable definitions and the descriptive statistics of the variables used in the estimations are summarized in Table 6.

5 Empirical Results

5.1 Persistence of innovations and its determinants

Table 7 shows a series of estimates.[16] Column (1) is specified as the basic model that does not deal with the problem of initial conditions in the dynamic probit model with unobserved heterogeneity. The first main result is that the coefficient for a one-year lag innovation is positive and significant at the 1% statistical level after controlling for other potential influences, tending to support the hypothesis of true state dependence - that is, Taiwan's large enterprises seemed to show a permanent innovation behavior over the past decade. The result further shows that technological opportunity is an important influence on firms' innovations, suggests that innovation is higher for scientific firms than non-scientific ones.[17]

Applying the remedy proposed by Wooldridge (2005) to correct the unobserved heterogeneity and initial condition problem, the estimates of dyn-

[15] For the importance of financing on firms' R&D, please see Hall (2002) for a comprehensive survey.

[16] To save the space, the estimates for the time-average of explanatory variables are not shown in Table 5. One additional reason is that the estimated coefficients do not contain meaningful economic implications.

[17] We have also analyzed the state dependence for patent counts and R&D data, separately. Empirical results still support the hypothesis of true state dependence. The results are available on request.

Table 6: Variable Definitions and Basic Statistics

Variables	Definition	ALL	Scientific	Non-Scientific
		Mean (S.D.)	Mean (S.D.)	Mean (S.D.)
INNO	Dummy Variable. $PAT = 1$ if a firm has successful patent applications in year t.	0.299 (0.458)	0.537 (0.499)	0.127 (0.334)
SCI	Technological Opportunity Dummy: SCI = 1 if a firm belongs to scientific industries that include Machinery and Equipment, Chemical Manufacturing, Basic Metal, Transport Equipment, and Electronics Industries.	0.419 (0.494)		
RD	R&D Expenditures (NT$ million)	139.412 (587.024)	290.962 (878.524)	30.254 (93.070)
SIZE	Firm Size: the number of employees	1,157.28 (1,713.28)	1,459.563 (2,069.963)	938.860 (1,359.492)
AGE	Firm Age: surveyed year minus the starting year.	27.275 (10.701)	24.033 (10.935)	29.587 (9.905)
KL	Capital Intensity: The ratio of fixed capital to employee (NT$ million)	4.433 (6.644)	3.046 (3.858)	5.436 (7.932)
ADV	Advertising Expenditure (NT$ million)	36.660 (143.105)	49.159 (141.297)	27.653 (143.759)
PROFIT	Profitability: the firm's post-tax profitability. (%)	3.533 (19.221)	4.871 (18.316)	2.559 (19.802)

Table 7: The Estimates for Dynamic Random Effect Probit Model

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
INNO_1	0.863***	0.692***	0.812***	0.779***	0.763***	0.720***	0.696***	0.691***
	(0.095)	(0.093)	(0.086)	(0.087)	(0.087)	(0.091)	(0.092)	(0.092)
SCI	1.173***	0.597***	1.289***	0.787***	0.789***	0.720***	0.609***	0.599***
	(0.164)	(0.158)	(0.155)	(0.147)	(0.145)	(0.162)	(0.165)	(0.159)
lnRD	0.104***	0.048***		0.071***	0.064***	0.049***	0.048***	0.047**
	(0.014)	(0.018)		(0.017)	(0.018)	(0.018)	(0.018)	(0.018)
lnSIZE	0.327***	0.155			0.174**	0.106	0.145	0.139
	(0.066)	(0.097)			(0.088)	(0.092)	(0.093)	(0.094)
lnAGE	0.138	0.643**				0.989***	0.645***	0.673***
	(0.138)	(0.249)				(0.202)	(0.241)	(0.245)
lnKL	0.044	0.220**					0.221**	0.222**
	(0.061)	(0.088)					(0.087)	(0.088)
lnADV	0.022*	0.009						0.009
	(0.012)	(0.015)						(0.015)
PROFIT	−0.004*	−0.002						
	(0.002)	(0.002)						
$INNO_0$		1.143***	1.752***	1.277***	1.107***	1.201***	1.195***	1.142***
		(0.175)	(0.223)	(0.181)	(0.171)	(0.186)	(0.180)	(0.175)
CONS	−5.661***	−2.192**	−2.141***	−3.057***	−5.139***	−4.402***	−1.884*	−2.236**
	(0.676)	(0.993)	(0.130)	(0.198)	(0.542)	(0.734)	(1.025)	(0.987)
σ_a		0.806	0.961	0.802	0.767	0.821	0.811	0.803
		(0.091)	(0.097)	(0.077)	(0.077)	(0.080)	(0.085)	(0.090)
γ		0.394	0.480	0.391	0.370	0.403	0.397	0.392
Log-likelihood	−984.463	−932.224	−1,059.147	−1,007.690	−995.691	−944.928	−936.467	−932.569
Obs	3,297	3,297	3,297	3,297	3,297	3,297	3,297	3,297

Note: Figures in parentheses are standard deviations. ***, ** and * denote coefficient significant at 1%, 5% and 10% statistical level, respectively.

amic RE probit model are displayed in column (2). Despite the estimated impact of $\text{INNO}_{i,t-1}$ on innovations decreases slightly, this coefficient is still positive and significant at the 1% statistical level, giving evidence for the persistence of innovation at the firm level. Moreover, the estimated magnitude for the coefficient of SCI is reduced substantially to one-half as large as that in column (1) after controlling firm heterogeneity and initial condition, implying that the behavior of persistent innovations might lies within firms rather than between industries. One point worth noting is that the results provide evidence that both the initial condition and unobserved heterogeneity are key factors for innovation persistence. The estimated coefficient for initial condition, 1.143, implies that if a firm has successful patent applications in the initial year, then it has, on average, 86% higher probability to achieve innovations than its non-innovation counterparts in the current year, after controlling for other variables. The importance of the unobserved heterogeneity in explaining the total variance can be gauged from. Column (2) of Table 7 reveals that unobserved heterogeneity explains about 40% of the variation in the dependent variable. Thus, if the firm heterogeneity and initial condition are not taken into account, then the estimates would suffer estimation bias.[18]

With respect to observed characteristics, the results show that some of the variables change their impacts significantly relative to that in column (1). The estimated coefficient of R&D expenditure is 0.048 and is significant at the 1% statistical level. Due to the specification of the empirical model, it cannot be interpreted as the elasticity of R&D with respect to patents and therefore it cannot be used to compare with previous studies on patent-R&D nexus.

The estimated coefficient of SIZE is positive and nearly statistically significant at the 10% level, tending to support Schumpeter's hypothesis that large firms (usually having market power) are inclined to have the wherewithal to exploit innovations. The positive and significant coefficients for firm age show that a firm with a longer life has a higher propensity toward innovation, arising from the learning-by-doing effect on innovation. The results also show that capital intensity serves as a crucial factor of innova-

[18] We have also analyzed the state dependence for two-year lag and three-year lag, separately. Empirical results find that the longer the interval time span, the weaker the innovation's persistent effect. The results still support the hypothesis of true persistent innovation. Similarly, the persistent effect is found to be stronger in scientific industries. Besides, the initial condition of innovation is significant in all specifications.

tion propensity, supporting the 'strategic response' hypothesis proposed in Hall and Ziedonis (2001) that given the circumstance of more emphasis on innovations, firms with large sunk costs tend to respond strategically by expanding their own portfolios of patents, while the impacts of advertisement and profits are not significant.

One problem with the dynamic RE probit model is that it assumes that explanatory variables must be strictly exogenous, implying that there is no feedback effect caused from innovation to further the value of explanatory variables. To assess the impact of including variables that perhaps fail the strict exogeneity assumption on the estimate for state dependent variable, this study applies the stepwise procedure to check the robustness of the hypothesis of persistent innovation. Serial estimates are shown in columns (3) through (8) of Table 7.

The estimates for explanatory variables are overall quite similar to that in column (2). The coefficient for lagged innovation variable is positive and significantly related to current innovation conditional on observed and unobserved characteristics. This finding supports the view of the persistence of innovation behavior. The impact of past innovation on current innovation behavior decreases as more explanatory variables are included. In addition, past innovation behavior, technological opportunity, R&D expenditure, firm size, age, and capital intensity again have a crucial influence on innovation behavior.

5.2 The effect of technological opportunity on innovation persistence

In this section, one further sensitivity analysis is carried out to check the robustness of the results. This study differentiates between high and low technological opportunities groups (scientific industries and non-scientific industries) and implements similar econometric techniques used in obtaining Table 7 to examine whether innovation persistence is mainly related to different technological environments. The estimates are reported in Tables 8 and 9.

The results suggest that significant state dependence effects exist in both samples. However as expected, persistence effects are much higher for scientific industries than for non-scientific industries and that the estimated magnitude for the past innovation coefficient is nearly twice as high in scientific industries as in the non-scientific industries. This result is economically intuitive: within the scientific industries, the creation of new technologies

Table 8: The Estimates for Dynamic Random Effect Probit Model — Scientific Industries

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
INNO_1	0.838***	0.714***	0.874***	0.832***	0.791***	0.737***	0.734***
	(0.124)	(0.121)	(0.111)	(0.111)	(0.119)	(0.119)	(0.120)
lnRD	0.110***	0.056**	0.095***	0.074***	0.060**	0.055**	0.056**
	(0.021)	(0.026)	(0.024)	(0.024)	(0.026)	(0.026)	(0.026)
lnSIZE	0.375***	0.355***		0.304***	0.224**	0.260**	0.273**
	(0.090)	(0.118)		(0.103)	(0.109)	(0.111)	(0.112)
lnAGE	−0.023	0.256			0.925***	0.470	0.412
	(0.157)	(0.314)			(0.251)	(0.298)	(0.305)
lnKL	0.107	0.320***				0.298***	0.307***
	(0.084)	(0.111)				(0.109)	(0.110)
lnADV	0.002	−0.022					−0.018
	(0.016)	(0.020)					(0.020)
PROFIT	−0.010***	−0.009***					
	(0.003)	(0.003)					
$INNO_0$		1.124***	1.016***	0.963***	1.086***	1.099***	1.096***
		(0.227)	(0.215)	(0.205)	(0.241)	(0.230)	(0.222)
CONS	−4.638***	0.166	−2.095***	−4.114***	−3.045***	0.286	0.022
	(0.834)	(1.324)	(0.301)	(0.867)	(1.185)	(1.232)	(1.274)
σ_a		0.847	0.786	0.803	0.883	0.855	0.815
		(0.130)	(0.099)	(0.112)	(0.139)	(0.137)	(0.120)
γ		0.417	0.382	0.392	0.438	0.422	0.399
Log-likelihood	−557.904	−525.893	−589.142	−581.236	−543.384	−533.470	−530.459
Obs	1,383	1,383	1,383	1,383	1,383	1,383	1,383

Note: Figures in parentheses are standard deviations. ***, ** and * denote coefficient significant at 1%, 5% and 10% statistical level, respectively.

Table 9: The Estimates for Dynamic Random Effect Probit Model — Non-Scientific Industries

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
INNO_1	0.748***	0.471***	0.591***	0.559***	0.559***	0.554***	0.529***
	(0.152)	(0.154)	(0.145)	(0.146)	(0.150)	(0.150)	(0.151)
lnRD	0.091***	0.027	0.042*	0.051**	0.040	0.040	0.037
	(0.020)	(0.026)	(0.025)	(0.025)	(0.026)	(0.026)	(0.026)
lnSIZE	0.337***	−0.582***		−0.398**	−0.323*	−0.343*	−0.389**
	(0.010)	(0.223)		(0.179)	(0.182)	(0.193)	(0.196)
lnAGE	0.511**	1.310***			0.847**	0.914**	1.047**
	(0.250)	(0.454)			(0.367)	(0.427)	(0.439)
lnKL	0.019	−0.014				−0.050	−0.059
	(0.098)	(0.156)				(0.150)	(0.153)
lnADV	0.049**	0.047**					0.048**
	(0.019)	(0.023)					(0.023)
PROFIT	0.007	0.012**					
	(0.005)	(0.005)					
$INNO_0$		1.529***	1.890***	1.513***	1.557***	1.563***	1.477***
		(0.331)	(0.308)	(0.296)	(0.309)	(0.311)	(0.321)
CONS	−6.847***	−4.191***	−3.174***	−5.254***	−4.667***	−3.867**	−4.109***
	(1.237)	(1.584)	(0.257)	(0.748)	(1.130)	(1.571)	(1.555)
σ_a		0.783	0.777	0.742	0.754	0.756	0.758
		(0.132)	(0.115)	(0.119)	(0.122)	(0.122)	(0.128)
γ		0.380	0.377	0.355	0.362	0.363	0.365
Log-likelihood	−417.640	−386.491	−412.832	−405.176	−394.125	−393.820	−390.593
Obs	1,914	1,914	1,914	1,914	1,914	1,914	1,914

Note: Figures in parentheses are standard deviations. ***, ** and * denote coefficient significant at 1%, 5% and 10% statistical level, respectively.

might exhibit the accumulation feature toward the circumstance of rapid technological change - that is, new inventions usually arise from past innovations or refer to past technological knowledge, implying that there should be a strong persistent effect. Despite successful innovations which are relatively lower within non-scientific industries, the innovating-firms seem to engage in innovative behavior persistently within this group.

The main conclusions drawn in the previous subsection still hold overall in the separate estimations, while there are several important points worth noting. First, the size effect of innovation exhibits an opposite impact between scientific and non-scientific industries. Large firms tend to have a higher propensity to invent innovations while small firms tend to be more innovative within non-scientific industries. That is, under the competitive circumstances of industry, large size firms for scientific industries seem to be inclined to have more innovation However, to non-scientific industry, which mostly are firms of traditional industry, the more possibilities for them to focus on production rather than innovation activities. Second, the coefficient of capital intensity turns out to be insignificant, while the impact of advertising tends to be significantly positive in non-scientific industries. This result indicates that advertising investment seems to more important rather than the 'strategic response' strategy for non-scientific industries. Third, the firm's profitability has a positive impact on innovation behavior for non-scientific firms as expected, suggesting a pro-cyclical pattern on innovative activity. On the other hand, the coefficient for profitability is significantly negative for scientific firms, implying that scientific firms might engage in innovative activity more aggressively when they encounter the threat of survival competition. Finally, drawn from the estimated γ in Tables 8 and 9, unobserved heterogeneity explains the variation in the dependent variable in the scientific industries that is larger than in the non-scientific industries.

6 Conclusions and Policy Implications

This paper investigates the persistence of innovation behavior of firms based on a panel data of Taiwan's manufacturing firms during the period 1990–2003 when Taiwan's innovations increased substantially. Moreover, it analyzes whether there is a difference in innovation dynamics between high and low technological opportunity industries. Previous studies have focused on firms' innovation persistence by analyzing the number of innovation outputs (patents and/or major innovations). This study examines persistence of

innovations by using a binary variable whereby a firm has successful patent applications and then employs a new estimator of the dynamic RE probit model proposed by Wooldridge (2005) to proceed with our study.

The econometric results confirm the hypothesis of true state dependence after controlling for initial conditions and unobserved firm heterogeneity. The technological environment is perhaps a crucial influence on innovation output, while the behavior of innovation persistence exists for firms of both high and low technological opportunity groups. Less surprisingly, persistence turns out to be higher in scientific industries and is relatively high in non-scientific industries. However, the study has obtained that unobserved heterogeneity is important, indicating that innovation persistence is, to some degree, linked to individual unobserved heterogeneity. This study also finds that R&D expenditure, firm size, firm age, capital intensity, advertisement, and profitability affect the continuity in the performance of innovations and some of these explanatory variables exhibit an opposite impact between scientific and non-scientific industries. These findings make a contribution to the understanding of the determinants of firms' persistence in innovative behavior.

This study's analysis also finds important policy implications. Taiwan's government has used several measures, such as tax incentives, financial assistance, R&D grants, and other measures to promote innovative activities since the 1980s. If a favorable industrial environment, where innovations can originate in new and small firms commencing operations outside the circular flow of existing production activities, is created it would stimulate further technological progress. From the perspective of technology development, Taiwan's successful experience in closing the technological gap with developed countries can provide an example of technological development for other developing countries.

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台灣製造業廠商創新持續性

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本研究的目的在於利用台灣證券交易所掛牌上市的製造業公司在 1990 至 2003 年的追蹤資料, 以動態觀點來實證檢驗廠商創新持續性及廠商創新活動的決定因素。利用 dynamic random effect probit model, 控制個別廠商無法觀察之異質性及解決初始條件問題後, 實證結果證實台灣製造業廠商存在創新持續的現象。再者, 進一步將樣本區分成高技術機會群與低技術機會群兩群, 分別檢驗不同技術機會環境下的廠商創新行爲是否持續。結果顯示, 不論是否爲科學性產業的創新行爲皆存在創新持續的現象。而此效果尤以科學性產業較爲明顯。本文亦強調影響廠商創新績效的重要因素, 此皆爲有助於瞭解廠商創新活動的決定因素。

關鍵詞: 創新, 持續性, 狀態相依, dynamic probit model
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