Innovative Factors Affecting the Diffusion of the New Nanotechnology Paradigm, 1983–2013

Alenka Guzmán, Flor Brown, and Edgar Acatitla

By examining innovative factors that could influence the diffusion of the new nanotechnology paradigm (NNP) across countries, we identify several innovative variables that relate positively to high nanotechnology diffusion across countries. In accordance with the Poisson count regression model based on the proposed nanotechnology patent data of the United States Patent and Trademark Office, we find that the lag time of nanotechnology knowledge diffusion, the size of research teams, the invention scope of each nanotechnology patent, and technological cooperation seem to affect the NNP, with the first variable having a massive effect. Our objective is to use patent microdata to contribute to empirical research on nanotechnology diffusion.

Keywords: Nanotechnologies, Diffusion, Innovative factors, United States Patent and Trademark Office patents

JEL Classification: O33, O34

I. Introduction

Several researchers have recognized the promising new nanotechnology paradigm (NNP) in various fields, including communications (Akyildiz *et al.* 2008); health (Chakravarthy *et al.* 2018); cosmetics (Kaur and

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Agrawal *2007*); food and agriculture (Prasad *et al.* 2017; He *et al.* 2019); energy resources, such as oil and gas (Afolabi and Yusuf 2019); new materials for various uses (Aono *et al.* 2012); and the recent COVID-19 vaccine (Shin *et al.* 2020, among others). The findings in the nanosciences particularly focus on studying, designing, creating, and improving materials and systems at the nanoscale (Kroto 2013; Lyshevski 2001). Although nanotechnologies first emerged in the 1990s, their diffusion has grown exponentially over the last few years. Diffusion analysis is the key to understanding how the knowledge of this new paradigm is spread and used to solve technological problems, thereby contributing to social and economic welfare.

The transition from the individual to the organizational pattern diffusion of the information and communication technology (ict) paradigm has been studied previously (Fischman 1992) by examining ict household and business use (Pilat *et al.* 2004). Nevertheless, the nature of the NNP becomes increasingly complex as the interaction between different scientific and technological fields multiplies.[1]

The aim of this research is to ascertain which factors that are associated with nanotechnology innovation affect nnp diffusion across countries. Nanotechnology diffusion is regarded as a knowledge transfer process among fields, institutions, and countries, with citation networks identified through the United States Patent and Trademark Office (USPTO) patent data (Li *et al.* 2009). Encouraging government and business investment to enable commercial science and technology development and vice versa is considered to be the role of the knowledge-diffusion networks of patent inventors (Jian *et al.* 2014). The influence on the knowledge diffusion and recombination of individual researchers in social networks has been studied by means of scientific publication data and university citation data from China and the United States (Liu *et al.* 2015). Prolific inventors from different institutions and their influence on knowledge diffusion, along with their cultural and institutional differences, have become a topic of research (Liu *et al.* 2011). Another approach to nanotechnology diffusion is the analysis of the differences in interaction, knowledge diffusion intensity, and diffusion speed between nanoscience and nanotechnology (Guang

[1] Nanotechnologies increase the convergence of different scientific and technological fields and tend to be highly concerned with society (Rocco *et al*, 2013).

2010).

Given that only a few studies have focused on analyzing and measuring NNP diffusion by considering additional variables that address the nature of innovative activity in nanotechnologies, our research aims to contribute to the filed by proposing a methodology for measuring diffusion across countries and identifying the innovative factors associated with this phenomenon on the basis of knowledge and innovation economy approaches.

Thus, we pose the following question: Which elements of the innovation process influence NNP diffusion? Our research hypothesis states that by considering forward patent citation as a NNP diffusion proxy variable,[2] high nanotechnology diffusion across countries is positively related to the following variables: the invention scope of each nanotechnology patent, the previous stock of knowledge, the great extension toward technological fields, technological collaboration, the size of the inventor team, the international mobility of inventors, the flows of scientific knowledge, the innovation efforts of government nanotech, innovation firms, and the lag time of nanotechnology diffusion.

The second section presents the theoretical and empirical background of the subject of this research. The third provides an analysis of the innovative nature of USPTO patents in nanotechnology classes. In the fourth section, the empirical model that is proposed to test the research hypothesis is specified and developed. Finally, the last section presents the conclusions.

II. Theoretical Background

Diffusion has been defined as the way and speed with which new developments are passed through a social system (Rogers 2003). In this process, new ideas are communicated by their creators to others interested in the innovation field. Diffusion causes the social system to change somehow in terms of structure and function. The results of new developments or inventions being passed on and then either adopted or rejected produce the social change (Ibid).

[2] If patent P_2 cites patent P, this suggests that there are knowledge flows from patent P_1 to patent P_2 (Hall *et al.* 2005).

The full adoption and diffusion of technological innovation prompts a positive economic effect as spread dynamics occur. Adoption has been defined as implementing a new technology by a company and diffusion as spreading that technology throughout an economy (Hanel and Niosi 2007).

The concept of diffusion has been addressed from different theoretical angles. The first theories of diffusion, which were proposed in the 1920s, were utilized as epidemic models in different scientific fields. In economics, adoption and diffusion have mainly been analyzed by using the equilibrium and evolutionary approaches, yet some convergence has occurred between the two approaches in empirical studies (Ibid).

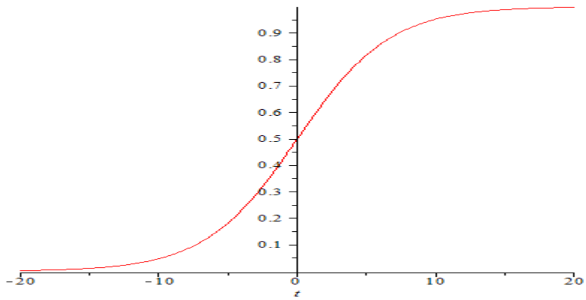
We allude to technological diffusion when we consider the products and methods that are used in manufacturing (Gomulka 1990) or the process of how innovations spread to micro- and macroenvironments (Vence 1995; Lai 2017). At the micro level, the focus has been on the estimation of technological innovation adoption and dissemination effects on a firm's productivity level and profit amount. The analysis of the macro level, on the other hand, is directed toward effects on the economic growth and welfare of the population. Useful feedback for innovators can be produced when a large number of users adopt a new technology (Jaffe 2015).

Therefore, the standard—or epidemic—and evolutionary approaches have provided different elements for explaining technological diffusion (Hall 2005). In the standard or epidemic approach (Griliches 1957; Mansfield 1961; Davies 1979; Comin and Mesteri 2014), disease contagion models are typically used to study technological innovation diffusion. Within such a context, diffusion is understood as the dissemination of technological innovations throughout the market via imitation.

In the case of the standard approach, the simplest mathematical model is the logistics equation as follows:

$$\frac{dx}{dt} = \beta x(1 - x), \tag{1}$$

where x is the market share, β stands for the technological innovation diffusion speed, $1 - x$ is the market share that innovation can potentially take, and t represents time. The analytic solution is expressed as



Source: prepared by the authors with Matlab software

FIGURE 1
MARKET SHARE OF THE EVOLUTION OF TECHNOLOGICAL INNOVATION DIFFUSION
VALUES: $\beta = 0.30$ AND $t = -20$ TO 20.

$$x(t) = \frac{1}{[1 - \varepsilon^{(-\beta(t-t_0))}]}, \tag{2}$$

where t_o is initial condition value, ε is the potential innovation adoption market share, and t is the time.

The dynamics of the speed of technological innovation diffusion across time is shown in the following figure by an asymmetric "*S*" shape.

Griliches (1960) proposed the following research problem: What factors explain the difference between areas by considering the origin (beginning date), slope, and limit (relative speed) as the three parameters in the diffusion process? Mansfield (1961) poses the question of how quickly follower firms adopt innovations that are introduced by innovator firms in four industries. His findings confirmed his hypothesis in that the imitation rate is high for highly profitable innovations and for firms with relatively low investments. Davies (1979) disengaged from the supposition that all firms have the same likelihood of adopting innovation within a certain time. He proposed that the professional development of managers and the existence of financial institutions with sophisticated infrastructure are factors that affect innovation adoption speed.

In the evolutionary approach, technological diffusion is analyzed in the context of economic change. Dosi (1982) addressed technological paradigm diffusion. In contrast to the diffusion index used in the standard approach, evolutionary theory recognizes that the displacement of old technology by innovations is not immediate but gradual. The technological diffusion process, as a dynamic social phenomenon, is not linear and thus could be explained by the technology demand scope, the technology push approach, and the interaction of the two (Ibid).

In contrast to the neoclassical equilibrium approach, the adoption and diffusion process for technological novelties occurs in an environment of uncertainty and limited information. Nevertheless, whoever decides to adopt these technological novelties is exposed to externalities in a growing learning context that favors diffusion and incremental innovation (Hall 2005; Antonelli 2017). Even if the firm that introduces an innovation becomes the innovation's monopolistic owner, the mere fact of mainly considering large firms as follower adopters overestimates the diffusion rate. Although learning becomes the key in the new technology adoption process, not all potential follower firms can assume adoption costs under uncertain conditions (Hanel and Niosi 2007).

Clearly, knowledge diffusion does not occur perfectly between firms or countries (Rogers 2003). Technology diffusion across countries is a long-term process, and adoption lag time depends on per capita income (World Economic and Social 2018).

The emergence period of a technological paradigm is known as the technological trajectory (Ibid). The National Innovation System (nis) framework fosters innovation and diffusion by considering the role of private and public institutions (Nelson and Winter 1982) and the different social actors involved in the nis. The intensity of invention and the innovation and diffusion of new technological paradigms are also tied to the differing degrees of nis development, including i) how nis relationship channels (Bertalanffy 1968) are characterized; ii) how well they are coordinated, as in the case of links among universities, institutions, and firms; and iii) capabilities for using new technologies internally and to further new industries, with an effect on economic, institutional, and cultural scopes, known as the techno–economic paradigm (Freeman and Pérez 1988; Pérez 2010).

A. Empirical Studies through Patent Analysis

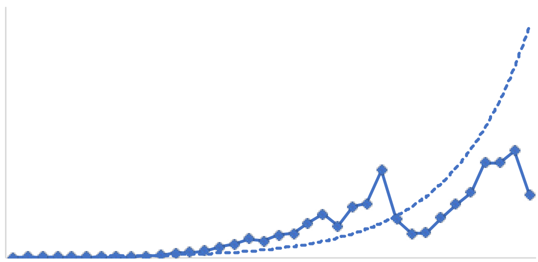
Schmookler (1962) conducted a pioneering study on the technological diffusion path by using patents. By following the contribution and potentiality of patent data, we find other empirical research that analyzed diffusion (MacGarvie 2005; Hall 2005) and technological knowledge flows or spillovers (Griliches 1984; Criscuolo 2001; Jaffe and Trajtenberg 1999; Henderson *et al.* 2005; Jaffe and Trajtenberg 2002; Jaffe and De Rassenfosse 2017). Changes in the nature of patent citations have been analyzed recently (Kuhn *et al.* 2020), and some of the findings should be considered for further research. In the case of nanotechnology, we find how to capture patent data to analyze a firm's activity, knowledge flows, and patent citation (Igami and Ozaki 2007), among other topics.

We propose a methodology that includes patent data in the field of nanotechnology to contribute to the empirical studies on paradigm diffusion.

III. Innovative Nature of Patents in the Nanotechnology Field, 1983–2013

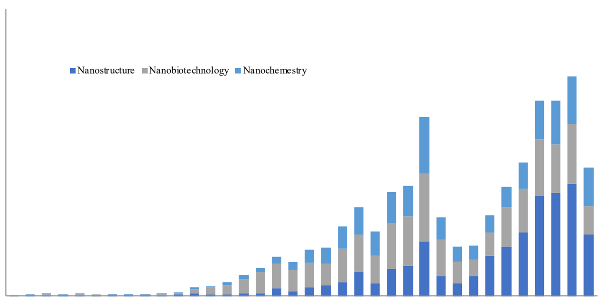
In the 1980s, nanotechnology inventive activity was marginal and slow growing perhaps due to the early stage of nanoscience development and diffusion. Moreover, agents remained uncertain and did not invest heavily in r&d efforts. Newly patented nanotechnology knowledge did not grow exponentially until the 1990s, revealing the emergence of a nnp; the average growth rate (AGR) in the period of 1990–2003 was 25.09% from 85 patents to 1561 patents. The increase rate for the next 10 years (2003–2013) reduced to 5.67%. The AGR for the 18 414 nanotechnology patents granted by the uspto during 1975–2013 was 20.29% (see Figure 2).[3] This significant performance reflects the expansion of nanotechnologies as a radical change in technological problem-solving. Institutions have gradually increased research efforts, and even some uncertain firms have joined the creative nanotechnology path. The implementation of policies that promote nanotechnology research facilitates an adequate environment for the development of new products and manufacturing processes in this new paradigm. Therefore, the evolution of nanopatents suggests the accelerated diffusion of the nnp over the last decade.

[3] The USPTO granted the first nanotechnology patent in 1975; three additional patents were granted after 3 years, and the number of patented novelties continued to increase yearly.



Source: USPTO patents in nanotechnology class 977

Figure 2
Nanotechnology patents granted by USPTO to residents and non-residents



Source: USPTO patents in nanotechnology class 977

Figure 3
Nanotechnology patents Granted by USPTO to residents and non-residents by technological fields, 1975-2013

An important feature of nnp diffusion is extension to various technological sectors (Igami and Okazaki 2007). We identify that 42% of the 18 414 patents pertain to nanostructure, a third to nanobiotechnology, and one quarter to the nanochemical class. This distribution reflects a strengthening of nanostructure participation by 4% and a reduction in nanobiotechnology by the same percentage, whereas nanochemical participation remains stable.

The research focuses on a sample of 376 uspto-granted patents[4] from

[4] The first study that utilized this sample was conducted by Acatitla (2016). In

1982 to 2013 chosen through simple random sampling from 18 414 USPTO patents, nanotechnology class 977 (see Appendix Table 1), which encompasses all patents in the technical field of nanotechnologies from 1975 to 2013.[5] Industrialized and emerging countries are included in this sample. Our USPTO sample shows that resident nanotechnology patents account for 63% of the total patents. Far behind are Japan (10%), South Korea (7%), Germany (4%), Taiwan (3%), and China (2%), among others.

A. Assignee Patent

A total of 30.85% of the nanotechnology patents sample has been assigned to institutes and universities and 69.15% to firms (see Table 1).

Table 1
Nanotechnology patents by assignee and category, 1983-2013

Nanotechnology classes	*Institute & University Patents*	*Firm patents*
Biotechnology	1	13
Computer & communication	2	15
Electrical and electronic	32	88
Mechanical	4	11
Drugs and medicines	14	43
Chemical	56	79
Others	7	11
Total	116	260

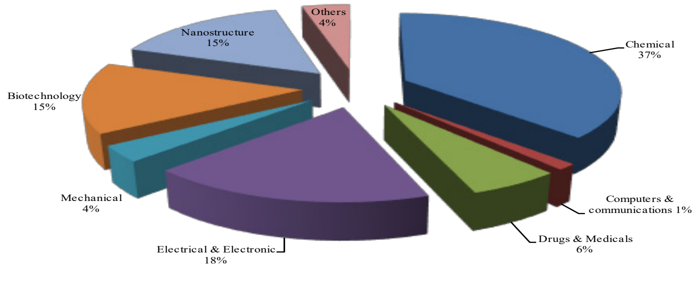
Source: sample of 376 USPTO patents in nanotechnology classes CCL/977/700-863

B. Sectoral Scope

In consideration of Jaffe and Trajtenberg's (2002) classification system, the scope of technological classes might expand. In the sample of 376 patents, the nanochemical class has the highest relative

this case, the model and outcomes differ.

[5] Given the difficulty of having all the information for the 18 467 patents, we decided to work with a random sample, for which we calculated the sample size with a confidence level of 95.5% and 5% margin of error.



Source: USPTO patents in nanotechnology class 977

Figure 4

Distribution of USPTO patents granted in nanotechnology, 1983-2013 by Trajtenberg technological classification

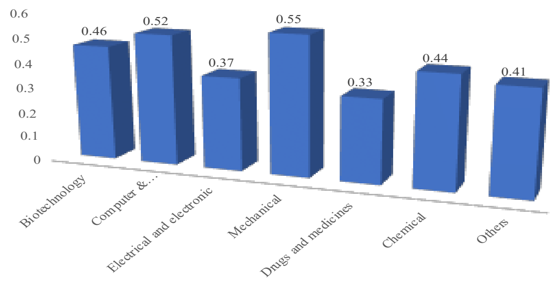
importance (37.2%). Nanotechnologies are also contributing to other new technological paradigms, such as ICTs (electrical & electronic, 18.3%; computer and communication, 1.3%; and other biotechnology, 15.2%) (see Figure 4).

The generality technological index (*GTI*) (Jaffe and Trajtenberg 2002) is another way to confirm the spread of nanotechnologies to various technological fields.

$$GTI = 1 - \sum_{i}^{nj} S_{ij}^2, \tag{3}$$

where S_{ij}^2 expresses the percentage of forward citation made on patent i belonging to class j among group n_i of patent classes. When the *GTI* is equal to or near 1, patent i has a broad effect on other technological sectors. Conversely, when the *GTI* approaches 0, patent i does not broadly affect other technological sectors.

In accordance with our *GTI* estimation based on a sample of 376 patents and in consideration of the three main sectors, we discover that on average, the *GTI* does not approach 1 but instead has a moderate effect on other sectors: biotechnology (0.46), nanostructure (0.39), and nanochemistry (0.33). Nevertheless, patents with *GTIs* close to 1 have a high effect on inventive activity in other technological fields. Such



Source: Own elaboration based on sample of 376 USPTO patents in nanotechnology classes CCL/977/700-863

FIGURE 5
AVERAGE GTI ACROSS SECTORS USPTO NANOTECHNOLOGY PATENTS, 1983-2013

is the case of patent 6203983 in the nanochemical field, which has a *GTI* of 0.71 but has a diversified influence on electric and electronics, drugs and medicines, and computer and communication. An example of concentrated effect is patent 6383286, which is assigned to the nanostructure sector with a *GTI* near 0 and an electrical and electronic concentration (see Figure 5).

When looking at countries and the average GTI for the technological sectors of nanotechnology patents, the highest for South Korea is in computer and communication (0.72), showing its important spread to other technological fields. Although the United States and Germany

TABLE 2
GENERALITY TECHNOLOGICAL INDEX BY COUNTRIES AND TECHNOLOGICAL

Technological sectors	*United States*	*Japan*	*South Korea*	*Germany*
Biotechnology	0.5	0.4	0	0
Computer & Communication	0.44	0.5	**0.72**	0
Electrical and electronic	0.42	0.28	0.33	0.49
Mechanical	**0.55**	0	0	0
Drugs and medicines	0.35	1	0.32	0.27
Chemical	0.43	**0.36**	0.43	**0.54**
Others	0.45	0.32	0	0.41

Source: Own elaboration based on sample of 376 USPTO patents in technological classes 977/700-863 have similar indexes, that of the former is in the mechanical field, whereas that of the latter is in the chemical field (see Table 2).

C. Diffusion of Inventive Nanotechnology Activity across Countries

Patent citation studies provide empirical support to understanding the diffusion pattern of new technologies. Knowledge flow studies have used backward and forward citations as proxy variables. Not all patents cited, though, are made by inventors but rather by IP offices. They remain a proxy indicator of how the patent could be a source for new knowledge that becomes patented or a proxy value of the patent cited (OECD 2013).

D. Backward Patent Citation

Although patent citation analysis has certain limitations and given that the inclusion of a citation in a patent application does not necessarily assure that the inventor possesses knowledge about the technology included in the cited patent (Thompson 2006), we use the number of *BwPatCit* as a proxy variable of the stock of previous knowledge. Such an approach allows us to identify how the new knowledge codified in the patent is spread among other agents specialized in the technological topic.

For *BwPCit*, we find that for the 376 patents in the USPTO sample, 6551 are *BwPCit*. Each patent has on average 17.4 patents cited, suggesting that every nanotechnology patent depends on a wide knowledge source.

We observe that the largest efforts in nanotechnology innovation are made by a handful of industrialized and certain emerging Asian countries. Nearly four fifths of *BwPCit* are from the United States with a per-patent average of 21.8, which is higher than the total average. Japan follows with 10% of *BwPCit* and a low per-patent average of 7.3%. The other countries are far from the United States and only contribute marginally to the entire *BwPCit*. The average *BwPCit* per patent is 11 for Taiwan, 7.4 for Germany, and 0.6 for South Korea.

E. Forward Patent Citation

The forward patent citation variable, *FwPCit*, is considered to be the economic value of patents (Hall *et al.* 2005) and also as an indicator of technological knowledge diffusion (Gay *et al.* 2005). Accounting for the fact that a patent represents a novel and successful contribution over and above the previous state of knowledge represented by citations, then the principle of a citation of patent X to patent Y means that X represents a portion of previously available knowledge upon which Y is constructed (Jaffe and Trajtenberg 2002; Gay and Le Bàs 2005).

In the same sample, we find that nanotechnology patents have received 4628 *FwPCit* with a per-patent average of 12.3. Concentrated in industrialized countries, the United States accounts for two thirds, and Japan accounts for 10%. At the low end are Taiwan, Germany, and Korea, which have a similar share of approximately 4% of total *FwPCit* participation.

The industrialized countries with more nanotechnology patents than other countries feature different specializations and different NNP diffusion patterns: a high degree of specialization indicates great diffusion in certain technological fields. For the United States, 43.6% of the *FwPCit* received by American patents pertains to the nanostructure field (1350 *FwPCit* of 94 patents in nanostructures), which is the country's main nanosector and represents 29.1% of the whole patent sample. As for Japan, 72% of *FwPCit* is made in the nanobiotechnology field or 8.1% of the entire *FwPCit* sample. The per-patent average of the 332 *FwPCit* in biotechnology is 15.8, which is higher than the average for nanostructure (6.6) and nanochemistry (11.5). This result points to the strength, importance, and diffusion of nanobiotechnology in Japan. The importance and diffusion of the nanochemical (46%) and nanostructure (36.6%) sectors are great in Germany, although the average *FwPCit* per patent of this country is higher in nanobiotechnology than in nanochemical and nanostructure. We thus identify three main sectors.

For other East Asian countries, nearly three fifths of the *FwPCit* of South Korean patents are concentrated in nanobiotechnology or 4.1 of the sample's total *FwPCit*. Given its high *FwPCit* per patent, the nanochemical sector informs us just how important and how diffused its inventions are. As shown in Table 3, the strong sector in Taiwan is nanochemistry with 35.6% of the total *FwPCit*. The average per-patent *FwPCit* reflects the importance of innovation and diffusion.

Table 3
Nanotechnology patent values by country and technological fields 1983-2013 Average *FwPCit* per patent

Country	*Main nanotechnology fields*	*Average FwPCit per patent*
United States	Nanostructure	14.3
Japan	Nano-biotechnology	15.8
South Korea	Nano-chemical and nano-biotechnology	11 and 10.8
Germany	Nano-biotechnology, nano-chemical and nanostructure	15, 11.2 and 10.5
Taiwan	Nano-chemical	35.6

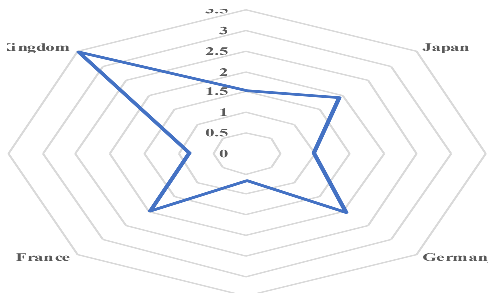
Source: sample of 376 USPTO patents in technological classes CCL/977/700-863

F. Backward Patent Citation Lag Time

How long ago (number of years) a patent was cited is considered as a proxy indicator of backward citation lag time (*lagBwPCit)* (Gay *et al.* 2005). In this research, this indicator reflects the speed of NNP diffusion lag time. This statistical problem is avoided because this is not the average lag time commonly used in diffusion studies and could affect the per-patent citation rate. Most lag time studies use the application year. In this study, we use the application year for the patent that cites and the patent cited.

Our estimations show that the *lagBwPCit* for the entire patent sample in the nanotechnology field is 1.53 years. Nevertheless, differences exist across sectors and countries. The average *lagBwPCit* for the United States is close to the overall average, but the lag time for nanostructures is low. In the case of Japan, the *lagBwPCit* is high with a short period of time for nanostructures. The average for Germany is 2 years, but the average *lagBwPCit* for nanostructures and biotechnology is the same as in all the countries. By contrast, diffusion speed is higher in Asian countries than in other countries. Notably, South Korea and Taiwan have low average *lagBwPCit* that, compared with that for other sectors, is lower for biotechnology in Korea and for nanostructure in Taiwan (see: Figure 6 and Table 4).[6]

[6] If we were to take other developing countries into account, would the average



Source: Own elaboration based on sample of 376 USPTO patents in nanotechnology classes CCL/977/700-863

Figure 6

Average GTI across sectors USPTO nanotechnology patents, 1983-2013

Table 4

Nanotechnology diffusion lag time across countries and across sectors

Country	*Average diffusion lag time (years)*	*Technological sector*	*Average diffusion lag time (years)*
United States	1.5	Nanostructure	1.38
Japan	1.94	Nanostructure	1.6
South Korea	0.92	Nano-biotechnology	0.6
Germany	2	Nanostructure and Nano-biotechnology	1.5
Taiwan	0.6	Nanostructure	0.5

Source: Own estimations on sample of 376 USPTO patents in technological classes CCL/977/700-863

Different nanotechnology diffusion patterns are found across historically industrialized countries and those recently industrialized. A taxonomy grounded in eight of the countries with the highest number of USPTO-granted nanotechnology patents is thus proposed. On the basis of patent citations, differentiations can be made on i) the capacity for

lag time be higher?

spreading new technological knowledge, which is measured by forward patent citations recorded by the nanopatents from each country, and ii) the speed of new nanotechnology knowledge diffusion estimated on the basis of lag time citations.

These diffusion patterns may be explained by the dynamics and degree of development of each country's NIS, which are partially reflected in the nature of innovative nanotechnology activity. In Japan, South Korea, Germany, and China, firms make major contributions to nanotechnology patents. By contrast, as also occurs in China, government efforts lead to patents in France. The United States stands out for scientific knowledge flows in patent citations, shedding light on the connections between science and technology; it also stands out for the great accumulation of knowledge estimated by the average number of *BwPat Cit*. In turn, China stands out for technological collaboration, which is estimated on the basis of copatents, and in international mobility, in other words, the participation of foreign inventors in research teams. For research team size, all the countries, other than the United Kingdom, in the group have a high level. The IGT is a variable that provides an idea of how nanotechnology knowledge extends to other technological fields. As a new paradigm, it has great extension potential especially when considering cognitive convergence between several scientific and technological fields that deal with nanotechnology. Seven countries in Table 5 are still at a midlevel, although Taiwan is at a high level (0.53) and the United Kingdom is at a low level.

With respect to the diffusion capacity of their newly patented nanotechnology knowledge, the United States, Japan, South Korea, Germany, and Taiwan are at the high end; France and China are at the midlevel; and the United Kingdom is at the low level.

TABLE 5
NANOTECHNOLOGY DIFFUSION PATTERNS

High Diffusion/High speed	*High Diffusion/Medium speed*
Taiwan	Unites States, Japan and Germany
Medium Diffusion/High speed	*Medium Diffusion/Medium speed*
China	France
Slow Diffusion/High speed	*Slow Diffusion/Slow speed*
South Korea	United Kingdom

Source: based on table 6, Taxonomy of patterns diffusion of NNP

TABLE 6

TAXONOMY OF NNP DIFFUSION PATTERNS IN INDUSTRIALIZED AND EMERGING COUNTRIES, 1983 -2013

Variable/Country	*United States*	*Japan*	*South Korea*	*Germany*	*Taiwan*	*France*	*China*	*United Kingdom*
Difnan (new nanotechnology diffusion) *FwPatcit*	13.2	11.8	4.7	11.4	15.7	6.1	9.4	5.2
	High	High	Low	High	High	Medium	Medium	Low
LagBwPatCit (Diffusion lag time in nanotechnology patent citation)	1.53	1.94	1	2.06	0.66	2	0.85	3.5
	Medium	Medium	High	Medium	High	Medium	High	Low
ClNano (invention scope of each nanotechnology patent)	21.7	22.1	17.9	21.2	14.8	18.8	17	13.7
	High	High	High	High	Medium	High	High	Medium
MobIn (International inventor mobility)	0.11	0.02	0.04	0.2	0.08	0.125	0.42	0.25
	Low	Low	Low	Medium	Low	Low	High	High
FirmInv (Firms's nano innovations -patents whose firms are holders-)	0.66	0.92	0.96	0.73	0.41	0.42	1	0.75
	Medium	High	High	High	Medium	Medium	High	High
Goveff (Government innovative effort in nanotechnology. -patents asignee of universities and research institutes-)	0.31	0.1	0.12	0.26	0.58	0.75	1	0.25
	Low	Low	Low	Low	Medium	High	High	Low
IGT (Generality Technological Index -number of technological fields recognized in a patent)	0.42	0.37	0.41	0.43	0.53	0.44	0.36	0
	Medium	Medium	Medium	Medium	Medium	Medium	Medium	Low
A (Technological knowledge stock -*BwPatCit*-)	21.7	7.2	9.7	7.4	11	5	18.1	7.2
	High	Low	Medium	Medium	Medium	Low	High	Low
PatBibSc (Scientific knowledge flows -number of scientific articles cited per patent)	18.7	4.7	5.9	1.9	4.08	2.3	3.8	8
	High	Low	Low	Low	Low	Low	Low	Medium
CoopTec (Technological cooperation -co-patent assignee)	0.04	0.02	0.04	0.06	0.08	0.25	1	0
	Low	Low	Low	Low	Low	Low	High	Low
SizeRt (Size of team research -number of inventors -)	3.13	3.05	3.28	3.53	2.83	3	3	2
	High	High	High	High	High	High	High	Medium

Source: Own elaboration, based on USPTO patents nanotechnology classes 977/700-863

The diffusion speed of new nanotechnology knowledge is highly relevant, with South Korea, Taiwan, and China identified as the countries that cite the most recent patents more quickly and thus have higher speed than other countries.[7] By contrast, the United States, Japan, Germany, and France take a little longer in citing previous patents than other countries. Lastly, given that the citation lag time for the United Kingdom is higher than for other countries, its speed is slower.

We thus identify six diffusion patterns (see: Table 6)[8]:

IV. Innovation Factors Affecting the Empirical Study on Nanotechnology Diffusion

We propose a Poisson regression count model to test the research hypothesis at the micro nanotechnology patent level. The model includes the following countries: United States (63.3%), Japan (10.4%), South Korea (7.5%), Germany (4%), Taiwan (3.2%), Canada (2.7%), France (2.1%), China (1.9%), United Kingdom (1.1%) Israel (0.8%), and Australia (0.5%). Other countries with marginal participation are Belgium, Denmark, India, Ireland, Italy, Mexico, Norway, Netherlands, Singapore, Sweden and Russia. Each of these countries account for 0.27%, that is, each has a single patent.

A. Data Sources

The size of the sample of 376 uspto-granted patents is estimated as

$$\frac{Npq}{i^2(N-1)+z^2pq} \tag{4}$$

where

[7] Strengthening the patent system noticeably benefited innovation in South Korea, stimulating R&D efforts. In this context, the country became gradually situated at the forefront of technological knowledge in different fields. See: Oh and Park, 2013. This situation helps us understand the diffusion speed of nanotechnology knowledge. For the case of rapid patenting expansion in China, see Thomas, 2013.

[8] For classification, the highest value for the average number of citations and the average citation lag time is taken for each of the countries and divided by 3. Therefore, each subgroup represents a classification type: high, mid, or low.

N is the size of the population considered (18 467 patents); ***Z*** is the value related to the Gauss distribution $Z_{\alpha = 0.05} = 1.96$; and ***P*** is the expected prevalence of the parameter to be evaluated.

If unknown, we assume $\boldsymbol{p} = 0.5$; $\boldsymbol{q}$ is taken as $q = 1 - p$; and i represents the expected error which in this case is 5%, therefore, $i = 0.05$. Now, through estimation, we have $n = 17687.6868/47.0004$. Therefore, $n = 376.33$, which we round up to $n = 376$ patents.

B. NNP Diffusion Model

The Poisson probability distribution function (PDF) could be characterized as

$$f(y, \mu) = \frac{e^{-\mu}(\mu)^{y}}{y\,!}, \tag{5}$$

where y is the variable containing the observed model counts, and μ is the predicted or fitted mean of the distribution of counts.

The likelihood form of the PDF is

$$L(\mu, y) = \prod_{i=1}^{n} \exp\{y_i \log(\mu) - \mu_i - \log(y_i\,!)\}. \tag{6}$$

Applying logarithms to the previous equation yields

$$L(\mu, y) = \sum_{i=1}^{n} \{y_i - \log(\mu) - \mu_i - \log(y_i\,!)\}. \tag{7}$$

The linear predictor must be transformed into the log (μ) form to calculate the predicted mean.

$$\ln(\mu) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots \beta_n X_n. \tag{8}$$

The fitted value μ may then be determined by taking the exponentiation by both

sides of the equation.

$$\mu = \exp(xb), \tag{9}$$

Table 7

Independent variables of nanotechnology innovation nature

	Proxy variable	It is expected that the higher:
ClNano	Invention scope of each nanotechnology patent. We use the number of claims as the proxy variable.	... number of claims, the higher the spread of new knowledge (Tong and Frame; 1994, Lanjouw *et al.* 2004).
	Stock of previous knowledge. We use the number of backward patent citations (BwPCit) as a proxy variable.	.... number of *BwPCit*, the higher the probability that a patent will be cited by a successive patent (Duguet *et al.* 2005, Gay *et al.* 2005).
GTI	Generality Technological Index indicates the number of technological fields where an invention is recognized. In other words, the extension of the patents towards other technological fields (Trajtenberg & Jaffe, 2002).	... to 1 GTI, if the the wide range of technological fields, and therefore more diffusion (Jaffe and Trajtenberg 2002).
CoopTec	Technological cooperation. The co-patent assignee is used as a proxy variable, which is expressed as a dummy variable.	... cooperation among firms, institutions & individuals, the higher the knowledge diffusion of NNP. (Zingg and Fischer 2019; Ozcan and Islam 2017).
SizeRT	Size of research teams. It refers to the number of inventors involved in the generation of the patent.	... or larger the team, the higher the number of ideas that can be generated and cited (Nagaoka and Naotoshi 2014; Breitzman and Thomas 2015).
MobIn	International inventor's mobility. This is a dummy variable where 0 means that there is only a presence of inventors of the same nationality of the patent while 1 indicates the presence of foreign inventors.	... mobility of inventors favors the spillover of codified and tacit knowledge (Nagaoka and Naotoshi 2014).
Pat-BibSC	Scientific knowledge flows. We use the number of scientific articles cited per patent as a proxy variable for academic knowledge used by patents to build the new invention.	... BibSc contribute to the higher FwPCit (Kim *et al.* 2014; Youtie *et al.* 2016).
GovEff	Government's innovative effort in nanotechnology. We use the number of patent assignee of universities and research institutes as a proxy variable. A patent is the result of R&D effort.	... government innovation efforts, the higher patents and NNP diffusion (Wooley and Rottner 2008; Kwon *et al.* 2014)
FirmsINV	Firms' nano innovations. We used patents whose firms are the holders.	... firms patents granted a greater probability to scale at the industrial level and eventually commercialized, so higher the diffusion (Woolley *et al.* 2008.
lagBwPCit	Diffusion lag time of nanotechnology patents. The proxy variable used is the backward patent citation lag time. It refers at how much years takes for a patent to cite a previous patent.	... longer time to cite a previous patents, their diffusion happens lower. On the contrary, speed citation occurs faster (Comin and Mestieri 2014; Kwon *et al.* 2014).

where the dependent variable is *DifNani* = NNP diffusion. In successive patents, *FwPCit* is used as a proxy variable for the diffusion of the nanotechnology paradigm. Group X_i is composed of the variables presented in Table 7:

C. Statistical Evidence

Of the 376 patents sampled, 45% was granted in 1998–2008, and the percentage decreased in 2008–2013 (41%). The number of *FwPCit* for successive patents as a proxy variable of nnp diffusion is higher in the two early periods because few patents for citation exist and probability decreases as the number of patents increases. The average number of claims is high and similar across all subperiods. Between 1983 and 2008, the nanotechnology patent diffusion lag time (*LagFwPCit*) exceeds 2 years, but from 2008 to 2013, the time taken to make *FwPCit* diminishes to 6 months. In terms of *BwPCit*, we see that recent patents cite, on average, a large number of previous patents. This situation suggests dynamic knowledge flow. As we have seen earlier, *GTI* shows that the scope of diffusion to other technological sectors is moderate. The size of the research team remains small in comparison with research teams with more than five inventors. Inventor mobility and technological cooperation are linked to a certain extent. Nevertheless, both are still weak. By contrast, patents have a significant average number of citations in scientific articles, especially when the nnp probability is high (1993–1998). In other words, over the period when nanotechnology patents were still scarce, existing nanoscience literature had to be used as a source of knowledge. Government efforts remain low, and firms are only slightly more active in generating nnp patents (see: Table 8).

Patents in the United States, Japan, South Korea, Germany, and Taiwan have 5732 *BwPCit*, which amount to 87% of the total. This result indicates major knowledge flows as a source of invention activity. The main industrialized countries account for 82% of the 4628 *FwPCi*t comprising the 376 patents. We assume that diffusion basically occurs in industrialized countries.

The diffusion lag time for nnp has an average of 1.53 years, which is 4 years lower than that estimated by Gay *et al.* 2005. We assume dynamic nnp diffusion.

Table 8

Average patent variables that are determinants of diffusion of the New Nanotechnology Technological Paradigm

BwPCit	*GTI*	*SizeRt*	*MobIn*	*CoopTec*	*Pat-BibSC*	*GovEff*	*FirmsInnv*
7.9	0.5	3.1	0.1	0	3.8	0.1	0.8
22	0.4	3.2	0.2	0.081	27.5	0.2	0.8
13.4	0.4	3.1	0.1	0.058	11.2	0.3	0.7
20.8	0.4	3.2	0.1	0.083	16.8	0.4	0.6

Source: sample of 376 USPTO patents in nanotechnology classes CCL/977/700-863

In view of the previous results, we formulate the following equation:

Difnan = f(Cl, A, lagFwPcit, SizeRT, MobIn, Cooptec, GovEff, FirmUnv, PatBibSc). (10)

Upon estimating the Poisson model, we find that the equidispersion criterion is not satisfied. Given that the Pearson dispersion statistic is 35.09[9], the model is overdispersed and standard errors are biased, suggesting that the predictors are significant when they should not be (Appendix Table 2).

We estimated a negative binomial model and a generalized Poisson model (Appendix Table 3) to address overdispersion. In consideration of the AIC and BIC criteria and mean predictions for both models, we decided to use the generalized Poisson model (see Appendix Table 4). This model is a mixture of Poisson distributions[10].

D. Empirical Outcomes

The estimation shows that out of 10 independent variables of the innovative nature of nanotechnology considered in our model, only four

[9] If a Poisson model is equidispersed, then the Pearson dispersion statistic has a value of 1.0. Values greater than 1.0 are termed overdispersed, and those less than 1.0 are underdispersed. Extradispersed data refer to data that are not equidispersed; i.e., data that are either under- or overdispersed

[10] The generalized Poisson probability function (Hilbe 2014) is

$$f(y;\theta,\delta)=\frac{\theta_i(\theta_i+\delta y_i)^{y_{i-1}e^{-\theta_i-\delta y_i}}}{y_i\,!},\ y_i=0.1.2\cdots$$

affect the diffusion of this new paradigm, whereas six do not.

The four independent variables with an effect on *DifNan* are *LagFwPCit*, research team size (*SizeRT*), the invention scope of each nanotechnology patent (*ClNano*), and technological collaboration (*CoopTec*).

The dependent variable of marginal effects associated with the variation in the independent variable estimation enables identifying those with a great influence on nanotechnology diffusion and their magnitude.

The most important factor that affects *DifNan* is *LagFwPCit*. As observed in Table 9, nanotechnology diffusion increases by 270% for each additional year of lag time over which the *BwPatCit* is made. The diffusion of new patented nanotechnology knowledge understandably increases over time. The countries that spend highly on R&D in this new paradigm are likely to have low lag times in diffusing major inventions in the field. That is the case in Asian countries, such as China and South Korea, that have created capabilities for absorbing frontier knowledge for use in local innovations (Kwon *et al.* 2014).[11] Comin and Mestieri (2014) pointed out that technology diffusion occurs over the long term and suggested that diffusion lag time is associated with economic differences. However, innovation adoption time depends on the proportion of firms, the profitability of relative innovation adoption, and the amount of investment required (Mansfield 1961).

Concerning *SizeRT*, the involvement of one additional inventor in a research team increases *DifNan* to over 50.7%. This elasticity measure suggests that team size allows for efficient interaction among the researchers who contribute to diffusion as they develop new ideas (invention). High inventor number is known to be associated with increased presented externalities and diffusion. This result emphasizes the importance of inventor teams, which often combine the academic and industrial sectors (Crescenzi *et al.* 2017). Breitzman and Thomas (2015) showed that in the initial 5 years of patents, significantly more citations are made on those with teams of eight or more coinventors than on others. Nagaoka and Naotoshi (2014) found a significant relationship between large inventor size and international copatents;

[11] Kwon *et al.* 2014 identified that not only South Korea and Taiwan, but also China, have reached patent quality and a relative technological frontier although inventors in China have not yet diminished the frontier-related citation lag.

this relationship is indicative of large and highly complex R&D as a result of joint international ventures. Furthermore, Bianco and Venezia (2019) pointed out that large inventor team size is associated with highly diverse knowledge, often leading to superior outcomes.

Another factor that increases *DifNani* is the invention scope of each nanotechnology patent. By considering the claims that state the unique aspects of an invention, specify them, and how the entire invention is built, as the number of claims increases, the innovation broadens and its potential increases (Lanjouw *et al.* 2004). Therefore, an invention with a large scope tends to be diffused. In this case, one additional claim increases *DifNani* by 16.3%.

Even if *CoopTec* influences *DifNan*, contrary to what is expected, when a coassignee patent increases by 1, the number of forward patents decreases by (−) 447%. This situation means that during the period studied, the link of different actors in innovation remains weak. This result coincides with the findings of Zingg and Fischer (2019) for private–public collaboration in nanotechnology. The absolute number of such patent filing is still low.[12]

The six independent variables that do not influence the dependent variable are the stock of previous knowledge ($\dot{A}$), international inventor's mobility (*MobInv*), firms' nanoinnovations (*FirmsInv*), governments' innovative efforts in nanotechnology (*Goveff*), scientific knowledge flows (*Pat-BibSC*), and *GTI*.

Regarding the lack of effect of $\dot{A}$ on the dependent variable, *BwPatCit* provides information on the patent's technological background, which also reflects accumulated knowledge. If a patent has many citations, then the invention has numerous antecedents (Jaffe *et al.* 2017). In contrast to the findings for the correlation between *BwPatCit* and *FwPCit*, patents may go back in time to cite related patents and inventions, but patents for relatively new inventions understandably have few backward citations given that little related history precedes them (Ibid.). That is the case of nanotechnology wherein patents in this study have an average of 12.3 *BwPatCit*.

For *Pat-BibSC*, although new scientific discoveries may contribute significantly to patent quality, this situation tends to be more the case

[12] The shared property of a patent between firms and institutes/universities presumes a previous collaborative agreement in which R&D efforts are also shared (Henderson *et al.* 2005; Messeni 2009).

for patents from the academic rather than the corporate world. The broad expanse of public science, however, does not necessarily result in high-quality inventions. (Wang and Zexia 2019). We can expect that knowledge flow between science and technology to be gradually strengthened in this new paradigm.

We expected that *MobInv* could favor the spillover of codified and tacit knowledge, but the presence of foreign inventors has not sufficiently increased to influence *DifNan* favorably. A study on international collaboration in the invention process found that invention team size seems to grow significantly with international co-ownership (Nagaoka and Naotoshi 2014). In contrast to some empirical studies[13], this study found that up until the period studied, this variable has not been significant. Nowadays, the networks of nanotechnology researchers have increased.

For *Goveff*, although government efforts are key factors for nanotechnology diffusion, they have not been sufficient to promote the diffusion of this new paradigm.[14] However, this variable of the model considers only public institution patents, and we excluded nanotechnology r&d expenditure or human capital in these disciplines. Consequently, fully evaluating government efforts in the new technological paradigm expansion by using the *Goveff* variable is impossible.

The same situation occurs with the innovation of firms and could be explained by uncertainty and the limited information on the technological adoption and diffusion process (Hall *et al.* 2005). Furthermore, not all firms are capable of following an innovation adoption path with learning (Hanel and Niosi 2007) or a creative path (Antonelli 2017) as a key element. It may also be associated with weak knowledge flows between firms and the scientific sector. Table 9 shows the marginal effects of independent variables.

[13] Bianco and Venezia (2019) found that patent scope expands with outside inventors and that technological and market values benefit from highly experienced inventors. However, inventors with previous patents come up with unique product designs that are highly valuable from a scientific standpoint and have a great array of applications.

[14] The United States experience has especially influenced several industrialized countries to open agencies or institutions concerned with the regulation and ethics of new nanotechnology knowledge. Nevertheless, these agencies do not necessarily focus on innovation research and patenting.

Table 9
Marginal effects of indepent variables affecting the Nanotechnology diffusion

	dy/dx	Std. Err.	z	P>z
$\dot{A}$	0.16	0.02	7.11	0.00
ClNano				
	-0.01	0.02	-0.53	0.59
GTI	0.40	1.63	0.24	0.81
CoopTec	-4.48	2.83	-1.58	0.11
SizeRT	0.51	0.33	1.55	0.12
MobIn	1.00	2.11	0.47	0.64
Pat-BibSC	0.02	0.02	0.98	0.33
GovEff	-2.97	3.31	-0.9	0.37
FirmsInv	0.22	3.20	0.07	0.95
lagBwPCit	2.70	0.37	7.38	0.00

Source: Own estimations based on sample of 376 USPTO patents in nanotechnology classes 977/700-863

V. Conclusions

Currently, nanotechnologies are an emergent paradigm that is characterized by significant input in scientific knowledge flows. Widespread r&d efforts; national and international networks of researchers; and communicating vessels among governments, firms, and universities are crucial for spreading radical change to solve technological problems on the basis of the nanoscale. The diffusion of the findings of new research on nnp is essential if it is to become a dominant paradigm.

Our estimations for nanotechnology patent diffusion show that the variables identified as the nanotechnology innovation factors that affect *DifNani* are i) lag time, ii) the size of research teams, iii) the invention scope of each nanotechnology patent, and iv) technological cooperation. The marginal effects of the variations in these independent variables on *DifNan* suggest some policies for promoting the diffusion of this new paradigm. Such policies must finance and support arriving at collaborative environments to catalyze nanotechnology patents. The creation of collaborative partner networks and the association of nanoscientific research and nanotechnology development could help increase the number of inventors in teams, develop additional new ideas to extend the number of claims, and generate positive externalities for NNP growth and diffusion.

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Appendix

Table Appendix 1
Class 977: Nanotechnology*

Technological Sectors	*Class linked*
Electric & electronics	73, 250, 257, 310, 313, 324, 372, 374
Mechanical	75, 148, 420,
Chemical	117, 118, 501, 502, 506, 516, 900-963
Drugs & and medical	351, 514, 600, 601, 604, 606, 607, 623
Computers and communications	385
Biotechnology	800-899
Nanoestructure	700-799
Others	428

Source: USPTO patents in nanotechnology classes 977/700-863

* At least one physical dimension 1-100 nm and special property, function or effect uniquely attributable to the nano-sized dimension

TABLE APPENDIX 2
POISSON MODEL

Difnan	Coef.	Std. Err.	z	P>z
ClNano	0.01	0.00	16.94	0.00
A	0.00	0.00	-0.46	0.65
GTI	0.21	0.05	4.51	0.00
CoopTec	-0.23	0.08	-2.71	0.01
SizeRT	0.04	0.01	4.84	0.00
MobIn	0.26	0.04	6.13	0.00
Pat-BibSC	0.00	0.00	5.29	0.00
GovEff	-0.82	0.06	-12.86	0.00
FirmsInv	-0.47	0.06	-7.98	0.00
lagBwPCi	0.14	0.01	15.84	0.00
_cons	2.31	0.07	32.87	0.00
(1/df) Pearson = 35.09493				
AIC	9016.06			
BIC	9059.167			

Source: Own estimations based on sample of 376 USPTO patents in nanotechnology classes 977/700-863

Table Appendix 3
Negative binomial regression

Difnan	IRR	Robust Std. Err.	z	P>z
ClNano	1.01	0.00	2.74	0.01
A	1.00	0.00	-0.04	0.97
GTI	1.00	0.47	0.00	1.00
CoopTec	0.91	0.50	-0.17	0.87
SizeRT	1.04	0.06	0.72	0.47
MobIn	1.37	0.34	1.28	0.20
Pat-BibSC	1.00	0.00	0.32	0.75
GovEff	0.44	0.19	-1.86	0.06
FirmsInv	0.63	0.26	-1.11	0.27
lagBwPCi	1.36	0.14	3.05	0.00
cons	7.93	4.12	3.99	0.00
/lnalpha	0.90	0.08		
alpha	2.46	0.20		
AIC	2452		BIC	2499
Number of obs = 372				
Wald chi2(10) = 19.80				
Prob > chi2 = 0.0312				
Pseudo R2 = 0.0135				

Source: Own estimations based on sample of 376 USPTO patents in nanotechnology classes 977/700-863

Table Appendix 4
Generalized Poisson regression

Difnan	IRR	Std. Err. Robust	z	P>z
ClNano	1.02	0.00	7.52	0.00
A	1.00	0.00	-0.53	0.59
GTI	1.04	0.16	0.24	0.81
CoopTec	0.66	0.17	-1.57	0.12
SizeRT	1.05	0.03	1.55	0.12
MobIn	1.10	0.22	0.48	0.63
Pat-BibSC	1.00	0.00	0.98	0.33
GovEff	0.76	0.23	-0.91	0.36
FirmsInv	1.02	0.31	0.07	0.95
lagBwPCi	1.29	0.04	8.47	0.00
_cons	4.78	1.74	4.30	0.00
/atanhdelta	1.29	0.05		
delta	0.86	0.01		
Likelihood-ratio test of delta=0:		chi2(1) = 6622.59	Prob>=chi2 = 0.0000	
Number of obs = 372				
Wald chi2(10) = 179.38				
Prob > chi2=	0			
Pseudo R2 = 0.0502				
AIC	2395.466		BIC	2442.493

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