DO NATIONAL PATENT LAWS STIMULATE DOMESTIC INNOVATION IN A GLOBAL PATENTING ENVIRONMENT?
A Cross-Country Analysis of Pharmaceutical Patent Protection, 1978–2002

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Abstract—This paper evaluates the effects of patent protection on pharmaceutical innovations for 26 countries that established pharmaceutical patent laws during 1978–2002. Controlling for country characteristics through matched sampling techniques to establish two proper comparison sets among 92 sampled countries and through country-pair fixed-effects regressions, this study yields robust results. National patent protection alone does not stimulate domestic innovation, as estimated by changes in citation-weighted U.S. patent awards, domestic R&D, and pharmaceutical industry exports. However, domestic innovation accelerates in countries with higher levels of economic development, educational attainment, and economic freedom. Additionally, there appears to be an optimal level of intellectual property rights regulation above which further enhancement reduces innovative activities.

I. Introduction

SINCE the 1980s, intellectual property rights (IPR) protection has become much more extensive as countries at various stages of development began to implement or extend their national patent rights.[1] The question of whether national IPR legislation could stimulate enough innovation to justify the economic, political, and social costs associated with its implementation and enforcement still provokes heated debate, and has pertinent policy implications. This paper studies whether a nation's implementation of pharmaceutical patents stimulates domestic pharmaceutical R&D expenditures and innovations, as measured by U.S. patents awarded to residents of that country. Because we cannot observe counterfactual outcomes of patent protection within countries, international comparisons provide valuable leverage for testing the hypothesis. The passage of national pharmaceutical patent laws in a number of countries in the 1980s and 1990s created a natural experiment to test the economic impact of patents. I identified these countries and comparable control countries with data available from 1978 to 2002. This study seeks to overcome data and methodological constraints that have confined previous research predominantly to single-country analyses with inconclusive results (Pazderka, 1999 and McFetridge, 1996 versus Scherer & Weisburst, 1995 and Challu, 1995).

The main findings of this study are that in the group of sampled countries the implementation of patent laws by itself does not promptly stimulate domestic innovation. However, patent laws in nations with high levels of development, education, and economic freedom do stimulate innovation. This study also provides novel empirical support for the theory that the relationship between innovation and the IPR strength has an "inverted U" shape (Gallini, 1992; Horwitz & Lai, 1996). An optimal level of IPR appears to exist, above which additional strengthening actually tends to discourage innovation.

One of the rationales for patent protection is that granting exclusive rights to innovators will enable them to reap the benefits and recoup the costs of R&D investments, increasing their incentives to innovate. The actual effect of IPR on innovation, however, remains one of the most controversial questions in the economics of technology. Secrecy was found to be much more important than patents for protecting intellectual property, in a 1994 survey of 1,478 American manufacturing firms (Cohen, Nelson, & Walsh, 2000). Patents may even be counterproductive, incurring additional application costs and promoting litigation and wasteful attempts to invent around patents (Jaffe & Lerner, 2004).[2] Patent laws could also delay spillover effects in sequential innovations, where each innovation is built upon its predecessors, by fostering high licensing fees and races for licensing (Scotchmer & Green, 1990). While a negative correlation between tightening IPR and innovation was found empirically in Bessen and Maskin (2000) and Sakakibara and Branstetter (1999), it was not supported in Kortum and Lerner (1998).

Although a series of surveys conducted in the United States (Mansfield, Schwartz, & Wagner, 1981; Levin et al., 1987) and Switzerland (Harabi, 1997) uniformly establish the importance of patents for pharmaceutical innovations relative to other industries, it is not clear how much patent protection is optimal. Theoretical models predict that more national patent protection in developing countries may not add much to R&D investment incentives, given the existing

Received for publication November 19, 2002. Revision accepted for publication May 5, 2006.

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I would like to give my special thanks to Professors Richard Caves, Josh Lerner, and Donald Rubin for their constant advice and encouragement; to Lee Branstetter, Gary Chamberlain, Richard Cooper, Dale Jorgenson, Markus Mobius, Ariel Pakes, Zorina Khan, Pierre Sauve, Dan Benjamin, Davin Chor, Gopal Garuda, Jennifer Hill, Ping Ma, Jesse Shapiro, Kia Song, Hui Xie, Stanley Watt, and NBER conferences participants for comments on various drafts; to Drs. Arvind Subramanian, Jayashree Watal, Gary Hufbauer, and Keith Maskus for their advice and references at early stages of my research; to Andrei Shleifer, Paul Beamish, Fritz Foley, and my friend Michael Katz for providing data; and to Professor Daron Acemoglu and the three anonymous referees for their invaluable comments.

[1] At least forty developing countries lacked pharmaceutical product patent protection as of the late 1980s. By the end of 1999, however, only sixteen World Trade Organization (WTO) member countries excluded pharmaceuticals from national patent protection.

[2] "Inventing around a patent" occurs when imitators attempt to avoid patent protection and licensing rules by making small modifications on the original innovation. The disclosure of technical details required in patents helps this activity.

The Review of Economics and Statistics, August 2007, 89(3): 436–453

world intellectual property regime (Chin & Grossman, 1990; Deardorff, 1992; Helpman, 1993). Counterarguments assert that additional patent laws provide a favorable local environment for pursuit of innovations by domestic inventors, who have firsthand knowledge of country-specific diseases. National patent laws would also induce domestic investors to switch from imitative activities to innovative ones. The importance of patent protection in a developing country is least controversial for treatments of diseases found only in that country. In addition, one country's national patent cannot always provide enough market incentive for innovators to devote research resources for that country. This implies that a group of countries with similar therapeutic needs could implement patent laws together, which is exactly the position the Pharmaceutical Research and Manufacturing Association of America held during the TRIPs negotiations. Although Acemoglu and Linn (2003) found that an increase in the potential market size for a drug category may augment the number of new drugs approved by the Food and Drug Administration in the United States, there is no evidence so far that research investments or innovations in tropical-disease drugs have increased significantly after developing countries implemented patent laws (Lanjouw & Cockburn, 2000). Costs of patent implementation have been identified, including the capture of national patent monopoly rights mainly by foreigners (Lanjouw, 1998; Maskus, 2000), and the legal administration and litigation costs of a patent system (UNCTAD, 1996; Love, 2001). Cumbersome legal systems may discourage R&D activities.

Very little research has been done for non-OECD countries, mainly because of the difficulty in collecting data. Furthermore, some previous studies of IPR in developing countries pooled data across industries. This is problematic because patents may have different effects in different industries (Levin et al., 1987). In standard economic analyses, the effect of patent protection on innovation is estimated simply by comparing the level of innovation in countries with and without patent laws, controlling for country characteristics usually by OLS. This study makes several contributions to the literature. First, it goes beyond cross-section studies by assembling a panel of data consisting of 92 countries over two decades. The panel structure enables me to better control for the latent innovative potential of a country and to improve the precision and reduce the bias in the patent effect estimator. The panel has the advantage of testing pre- and post-patent innovation changes within the same country. In addition, this study on multiple countries makes the results generalizable and overcomes the limitations in the previous single-country analyses.

A second contribution of my study is to employ nonparametric matching methods, which easily accommodate a rich set of control covariates that are correlated with a country's latent innovative potential and patent implementation. Although countries with patent protection, many of them developed nations, tend to have higher innovation levels, patent protection need not be the causal factor. Countries with strong patent protection may simply have a greater capacity for innovation. The factors that determine a country's innovative potential are likely correlated with national patent policies. Failing to control for this correlation would yield biased estimates of patent effects. Previous research has indeed found correlations between national patent legislation and market openness, lagged R&D expenditure, GDP per capita (Acemoglu et al. 2004), economic growth (Evenson, 1990), and the legal origin of a country's commercial laws (Lerner, 2000b). Its pharmaceutical industry's characteristics should also affect a nation's decision to implement patent laws and its innovative potential (Kaufer, 1989). Controlling for these covariates substantially mitigates the potential for omitted variable bias. OLS faces a degrees-of-freedom problem because observations with missing data are automatically dropped in estimation, while Mahalanobis matching overcomes this difficulty.

The last contribution lies in the procedure for appropriately controlling these observed country characteristics. An additive regression equation applied to the entire sample essentially controls covariates by forcing the same linear relationship on countries from the control and treated groups. Because patent and no-patent countries differ substantially in certain characteristics (tables 2, 3), standard linear regression, which assumes the same linear relationship between each control variable and the outcome variable for all observations, implies an extended extrapolation across country groups and therefore makes the resultant OLS estimates extremely sensitive to regression specifications.[3] Preliminary analyses show that OLS coefficients jump from 7.34 to −3.74 when using raw patents as response variable, and from 1.86 to −0.85 when using log of citation-weighted patents as response variable, but all statistically insignificant. Matching methods have been shown to reduce these confounding variable biases (Rosenbaum & Rubin, 1984; Heckman et al., 1996), by balancing the relevant pretreatment country characteristics of the control and treated groups. This study controls covariates through a two-step process: the first step identifies pairs of countries with similar characteristics through Mahalanobis matching, and the second step performs pairwise econometric analyses on the matched pairs. Fixed-effects regressions on matched country pairs control thoroughly for unobserved country characteristics.

[3] If there is only one control variable, then this problem can possibly be overcome by adding a set of higher-order terms of the control variable and interaction terms of the control and the patent indicator variables until the linear assumption is satisfied. However, this does not work if there is limited overlap in the covariate distributions. Moreover, when there is a large set of variables to be controlled, as is the case here, adding terms for each control variable takes away already limited degrees of freedom and becomes unfeasible. Even with a large sample, it would be difficult to model response surfaces in high dimensions, because it is especially difficult to assess linearity in a high-dimensional covariate space.

The rest of the paper is structured as follows. Section II describes the study design and the construction of the data set (supplemented by the data appendix). The methodologies are described in section III. Section IV presents the main empirical results. Finally, section V summarizes the main approach and results and makes recommendations for policies and future studies.

II. Data

A. *Design of the Study*

In answering whether national patents in developing countries stimulate domestic innovations, the ideal experiment would randomly assign a set of countries in the pool of no-patent countries to implement national patent laws at a certain time. The effects of patents on innovation could be tested simply by comparing mean innovation levels of the patent and no-patent countries.[4] Unfortunately, in reality patent reforms differ across nations in terms of both the time and the degree of implementation. Table 1 lists the year when each sampled country implemented pharmaceutical patents. They were grouped in four periods: 1978–82, 1983–85, 1986–90, 1991–95.[5] Most newly patent-granting countries had provided some degree of protection for pharmaceutical processes before they formally introduced product patents.[6] An indicator variable *PATMOD* is constructed to distinguish these countries (*PATMOD* = 1) from those that implemented patents for the first time (*PATMOD* = 0).

Secondly, although the decision to adopt the patent privilege can be regarded as exogenous to the extent that many of them are made under persistent pressures from the West, some voluntary decision-making is involved. That is demonstrated by the differences in scope[7] and timing of legislation. Country characteristics may affect both the innovation outcome and the decision to implement national patents. This endogeneity implies that the conventional method of regressing the outcome variable on the patent indicator and country covariates would very likely produce a biased estimate of the effect. There is no sound instrumental variable to address this concern. Instead, this study applies a matching method to form country pairs for which patent treatment can be considered randomly assigned within each pair. I define treatment as the implementation of national pharmaceutical patent laws (dummy variable *PAT* = 1) during the reference period, and the control as no change in patent law (*PAT* = 0). Two control groups are defined in order to make the most use of the sample size available. One control group consists of countries that never had patent protection prior to the next reference period, the other of countries that had patent protection before the reference period. Each new-patent country is paired with one country from the never-patent group and another country from the always-patent group. Fixed-effects regression analyses are then carried out separately on these two sets of matched pairs, where OLS linear assumptions are better satisfied due to the more balanced covariates. The two-way comparison based on these two control groups can help to detect the potential bias arising from the country-specific factors in the matched pairs.

TABLE 1.—MATCHING PAIRS AND TIMING OF REFORMS—MATCHED WITH THE MAHALANOBIS METHOD

Year of Patent Laws	New-Patent Countries	No-Patent Countries	Always-Patent Countries
Period 1 (1978–82)			
1983	Denmark	Norway	Sweden
Period 2 (1983–85)			
1986	Taiwan	Hungary	Hong Kong
1987	Canada	Norway	Netherlands
1986	Korea	Thailand	Singapore
1987	Austria	Finland	Australia
Period 3 (1986–90)			
1993	Brazil	Argentina	Korea
1991	Chile	Uruguay	Panama
1991	China	India	Korea
1992	Spain	Argentina	Belgium
1995	Finland	Slovenia	Australia
1992	Greece	Poland	Singapore
1992	Hungary	Romania	Israel
1992–1993	Indonesia	Egypt	Philippines
1991	Mexico	Argentina	Korea
1992	Norway	Slovenia	Australia
1992	Portugal	Romania	Hong Kong
1992–1993	Thailand	Colombia	Philippines
Period 4 (1991–95)			
1996	Bolivia	Paraguay	Zimbabwe
1996	Colombia	Egypt	Philippines
1997	Ghana	Jordan	Kenya
1996	Iceland	Slovenia	Luxembourg
1996	Peru	Guatemala	Algeria
1996 or 1997	Turkey	Iran	South Africa
1997	Romania	Bulgaria	Chile
1996	Ecuador	Tunisia	El Salvador
1996	Venezuela	Costa Rica	Chile

This table provides information about the timing of reforms in the countries that started to implement their domestic pharmaceutical patent protections during 1980–1997, and the corresponding matched countries that never had pharmaceutical patent laws in the contemporary period or always had pharmaceutical patent laws even prior to the contemporary period. Patent implementation years are obtained by referencing the legal documents of each country's intellectual property rights office.

[4] This is computationally equivalent to regressing the innovation outcome variable on the binary variable of patent protection. Controlling for all other country covariates is unnecessary for obtaining an unbiased estimate because of randomization, but it assists in obtaining greater precision of the experimental estimates.

[5] Because the OECD R&D expenditure data (innovation outcome variables) are only available up until 1999, the countries that switched patent laws in 1999 will not be examined. Some countries hesitate about whether to patent. The values for the control variables in the previous several years could be as important as the values in the year before legislation in affecting a country's decisions. In addition, some control variables, such as average years of schooling and economic freedom indices are available only at five-year intervals. I therefore use the averaged values over the previous three to five years. This also helps to smooth out any outlier values in a particular year. The lagged one-year values are also used in robustness checks, and results are similar.

[6] The only exceptions are Brazil, China, Chile, Korea, Indonesia, Mexico, Peru, Romania, Taiwan, Thailand, and Turkey.

[7] For instance, China first implemented national patent laws in 1983, but excluded the pharmaceutical sector until 1992.

B. *Selection of the Outcome Variables and Construction of the Control Variables*

Following previous cross-country analyses of inventive activities, this study uses citation-weighted U.S. pharmaceutical patent awards (listed by application dates) as the main innovation proxy. Patent data are listed by country of residence of the first listed innovator. This information provides a uniform base for comparison, because U.S. patent law has treated applications from different countries in a nondiscriminatory and consistent manner since the 1880s.[8] Papers by Evenson, Griliches, Pakes, and others (Griliches, 1984) suggest that patent counts and R&D expenditure are highly correlated in cross section. Studies also show concordances in the shifts of R&D expenditure and patenting level (Kaufer, 1989). In the OECD data set, containing reliable R&D data, the correlation between the difference in the log of U.S. patents awarded to a country in consecutive years and that of its R&D expenditures is around 0.8. Thus, "to a first approximation, one can use patent data as an indicator of technological activity in parallel with or in lieu of R&D data" (Griliches, 1984, p. 14). Mansfield (1986) finds in his 1981–1983 survey of 100 U.S. firms that around 82% of patentable inventions in pharmaceuticals were patented.

Although patents awarded are good indicators of innovations, the value of innovations is not accurately measured by patent counts, because of the existence of asymmetric information between innovators and patent offices. The citation weights could serve to overcome such problems (Hall, Jaffe, & Trajtenberg, 2001). The NBER patent database contains the number of citations made to each patent granted by the U.S. patent office from 1960 to 2002. Following Trajtenberg (1990), I calculate the citation-weighted patent counts by summing $(1 + c_i)^{0.6}$ over all the pharmaceutical patents awarded to a country in a given year, where c_i is the citation made to patent i.

Not all foreign innovations are patented in the United States. The innovator's decision to apply for a patent in the United States depends on many factors, including geographic distance from the United States, market potential of their invention in the United States, and so forth. Because these factors are also related to trade between an innovator's country of residence and the United States, their bias might be corrected by controlling for pharmaceutical exports to the United States. Given that the United States market is the world's largest, innovations of more than local significance tend to be patented in the United States if they are patented at all (Scherer & Weisburst, 1995).[9] Since the cost and standard of patent filing are high, U.S. patent data are expected to capture only substantial innovations,[10] and it serves as a natural selection of only important innovations, appropriate for this research. This also helps to make the levels of innovation comparable across years, because any given country's important innovations would be patented in the United States both before and after the implementation of domestic patents. The country-specific propensity to patent in the United States is further controlled by the construction of an "innovative potential" variable, a categorical variable indicating at what level the country has been awarded U.S. patents in all industries except pharmaceuticals.[11] In addition, this study tests the change in U.S. patents due to national patent laws, instead of absolute numbers of patents. Other advantages and concerns of using the U.S. patent data and the corresponding robustness checks are discussed in appendix I.B (appendices I.B–III are available at http://www.nber.org/nyiqian/patentappend.pdf).

Pharmaceutical R&D expenditures, an alternative measure of innovation, are available only for 23 OECD countries. I therefore apply regression models to only these countries when testing the relationship between patent implementation and R&D expenditures (section IIIBb). Data on R&D personnel for the OECD countries are also used as another proxy for innovation. For robustness checks, I imputed R&D values for the non-OECD countries using a regression model as described in appendix I.C, and carried out analyses on these imputed values. Pharmaceutical exports to the United States are used as a final innovation measure in the appendix.

C. *Control Variables for Latent Innovative Potential*

In order to obtain unbiased estimated coefficients of the key independent variables (*PAT* and *PATMOD* as specified in section IIA), one would hope to control for countries' different innovative potentials. Economists have speculated widely on country characteristics that might relate to latent

[8] U.S. pharmaceutical patent law has not changed much in the period I am examining, except for two modifications in 1995. The U.S. extended the duration of pharmaceutical patents from seventeen years to twenty years and modified the interference (when multiple patent applications make similar or identical claims) rule. After 1995, innovative activities in foreign countries also count as valid evidence for establishing the first invention date in cases of interference. Although the probability of having interference cases is very low—there were thirteen interference cases declared out of 2,000 applications in 1999 (USPTO, 2000, interview of Paul Harrison)—the threat of litigation can still have important implications. This may partly explain the generally increasing trend of foreign patenting in the United States. Fortunately, this change does not influence the international comparative analyses this study carries out, because it affects innovations from all foreign countries equally.

[9] Putnam (1996) shows that around 63.9% of international patents in 1975 (those patents filed in at least two countries) are patented in the United States. Based on the data collected in this study, the number of U.S. patent awards is about three times that of the European Patent Office (EPO) patent applications on average for a particular country and year. The ratio of number of patents awarded in the United States to that in the domestic country is calculated to be in the range of 0.83 and 11, using the U.S. Patent and Trademark Office (USPTO) and World Intellectual Property Organization (WIPO) data for a particular country and year. The U.S. patent counts are bigger than the domestic patent counts in some cases, possibly because it takes longer to process patent applications in these countries than in the United States.

[10] The flip side is that this estimate loses information on new innovations that might be locally successful.

[11] The pharmaceutical patents are excluded to avoid interference with the pharmaceutical patents outcome variable.

innovative potential and the decision to implement domestic patent law. GDP, GDP per capita PPP, GDP growth rates, and educational attainment are the obvious confounding characteristics. While I leave the details of the control covariates to the appendix, this section motivates some nonobvious control variable constructions.

A measure of economic freedom is included to indicate a country's market and trade freedoms and legal and financial systems' developments. As Acemoglu, Johnson, and Robinson (2004) have pointed out, economic institutions influence the investments of physical and human capital and technologies, the organization of production, and in turn innovative activities. The economic freedom index is also correlated with a country's patent implementation decision, since protection of IPR rights is a component for maintaining market order. In robustness checks, I further control for the origin of the country's legal system. Lerner (2000b) found that countries with British and French commercial law legal origins are more likely to have national patent laws, and British legal origin is also found to be conducive for appropriating the returns on investment (La Porta et al., 1996).

Relevant pharmaceutical industry characteristics differ across countries and could affect both the outcomes of innovation and the decision to implement patent legislation, as reflected by the fact that some countries decide to exclude the pharmaceutical industry from their national patent laws. I use the sector's employment level to normalize industry size across different countries. Because the transfer of technology from abroad could have an impact on domestic innovation and countries' decisions of patent implementation, estimates of technology transfer through foreign direct investment (FDI) are also included. The most relevant data would be the total FDI received in a country's pharmaceutical industry, which is not available. By including both U.S. and Japanese FDI, geographic proximity in FDI locations could be controlled for to some extent.

It is worth emphasizing that this study uses the lagged (pre-patent period) values for all the control covariates, because they are likely to be affected by national patent implementation.

D. *Interaction Variables for the Conditional Importance of Patent Implementation*

Countries at different development levels differ in other latent factors that could affect their R&D or U.S. patent-filing responses to domestic patent protection. One such notable factor is technology infrastructure. Maskus (2000, p. 202) suggests that developed countries and many high-income developing countries have already built extensive systems for promoting national technological change. I interact log GDP per capita PPP with *PAT* to test the effects of patent implementation conditional on a country's level of development. Interaction variables between log education and *PAT,* and between log economic freedom and *PAT,* respectively, are also included to test the hypothesis that human capital and open markets are complementary factors to patent protection in stimulating innovation (Maskus, 2000). The interaction term of the price control policy and *PAT* tests the linkages between patent protection and other industry policy. To test the validity of the theory that there is an optimal level of IPR strength, I construct several variables: the squared term of the log IPR composite score (Ginarte & Park, 1997), the interaction term of this log composite score with *PAT,* as well as the quintile dummies of the IPR score in robustness checks.

III. Methodology

A. *Matched Sampling*[12]

Grouping countries with similar characteristics according to a single country variable, as done by Ginarte and Park (1997), balances the countries on this particular variable but does not help to eliminate biases due to disparities in other variables. The challenge is to find a composite score that encompasses all the country characteristics that are deemed to be important both for the probability of implementing domestic patents and for innovative activity in the country. Each new-patent country can then be matched to a no-patent (or always-patent) country by ordering the values of this composite score among all the no-patent (or always-patent) countries and finding the country whose score is the closest to that of the new-patent country to be matched. The propensity score method[13] and the Mahalanobis matching method are two ways to calculate this composite score. Such a nonparametric matching method is used instead of Heckman's procedure mainly because the decision to implement patenting is too complicated and idiosyncratic to model. An important diagnostic check for the effectiveness of a matching method is the covariate balance—the degree of similarity in country characteristics between the no-patent (or always-patent) and new-patent countries—within matched pairs (Rosenbaum & Rubin, 1984). Both propensity scores and Mahalanobis distances can be thought of as instruments for covariate balance. As long as the country characteristics are similar after matching, it does not matter which method is adopted to achieve such balance. It is also important to recognize that the matching procedures do not involve the outcome variable at all, so that there is no chance of biasing results in favor of one patent condition over the other during matching.

[12] Matched sampling is a method for selecting units from a large pool of potential controls to form a reduced control group that has similar distributions of observed covariates to a treated group (Rosenbaum & Rubin, 1985).

[13] This study attempted to calculate propensity scores—the probability of patent law implementation based on the countries' characteristics—with partially missing data. Unfortunately, the serious missing data problem in the initial data set requires estimating a large number of parameters, which are not supported by the sample size. This method is applied in robustness checks when all the data are assembled after using the Mahalanobis method.

TABLE 2.—MEAN CHARACTERISTICS COMPARISON OF NEW-PATENT AND ALWAYS-PATENT COUNTRIES

	New-Patent Countries		Always-Patent Countries		*t*-statistic	
	Before Matching	After Matching	Before Matching	After Matching	Before Matching	After Matching
Country-Level Covariates						
GDP (in billions of 1995 constant USD)	148.99	145.60	422.80	162.94	−3.11***	−29
	(164.29)	(158.50)	(1,080.06)	(264.18)		
Real GDP growth	3.44	3.97	2.47	4.63	1.65*	−.82
	(2.85)	(2.81)	(3.90)	(3.02)		
GDP per capita PPP	7,201.05	7,102.51	9,396.01	8,486.38	−2.18***	−.90
	(4,946.28)	(5,264.23)	(6,518.03)	(5,974.89)		
Economic Freedom	6.07	6.21	6.46	6.86	−1.26	−1.69*
	(1.49)	(1.31)	(1.85)	(1.43)		
Legal Origin of U.K.	.12	.15	.45	.44	−4.72***	−2.47**
	(.33)	(.36)	(.50)	(.51)		
Legal Origin of France	.39	.48	.31	.41	.92	.54
	(.50)	(.51)	(.46)	(.50)		
Legal Origin of Socialist	.27	.11	.09	0	2.27**	1.68*
	(.45)	(.32)	(.28)	0		
Legal Origin Scandinavian	.12	.15	.05	.04	1.24	1.41*
	(.33)	(.36)	(.21)	(.19)		
Price Control Indicator	0.52	0.74	0.54	0.70	−.28	.30
	(0.51)	(0.45)	(0.50)	(0.47)		
Education	6.84	6.81	7.35	7.60	−1.04	−1.31
	(2.21)	(2.15)	(2.71)	(2.17)		
IPR Score	2.47	2.55	3.24	3.12	−4.32***	−2.67**
	(.85)	(.80)	(.64)	(.54)		
Innovative Potential	2.58	2.70	3.19	3.07	−2.36**	−1.23
	(1.30)	(1.07)	(1.71)	(1.00)		
Industrial-Level Covariates						
Employment	29.98	28.07	36.09	11.87	1.43*	1.11
	(76.30)	(73.60)	(60.90)	(17.53)		
Output (in millions of USD)	1,094.94	1,046.10	4,819.99	1,136.58	−3.48***	−.18
	(1,283.19)	(1,213.58)	(10,559.58)	(2,317.89)		
Pharmaceutical Exports to the U.S.	7.29	8.71	43.58	8.37	−4.35***	.09
	(12.37)	(13.23)	(106.97)	(14.70)		
Number of subsidiaries of U.S. MNE	5.45	6.52	6.74	6.85	−.78	−.14
	(8.50)	(8.97)	(9.75)	(8.56)		
Number of subsidiaries of Japanese MNE	1.30	1.59	1.46	2.41	−.26	−.76
	(2.88)	(3.12)	(4.52)	(4.64)		
Indicator for missing variable "Employment"	.24		.40		1.76**	
	(.44)		(.49)			
Number of observations	33	26	176	26		

This table provides descriptive statistics for the data obtained from World Trade Analyzer, World Bank *WDI,* and UNIDO *Industrial Property Statistics.* The economic freedom index comes from the Fraser Institute, legal families from La Porta et al. (1996), and the education proxy from Barro and Lee (2000). The price control dummy equals 1 if a country has pharmaceutical price control policy, and is drawn from Danzon (1997) and Economist Intelligence Unit reports. The numbers of subsidiaries of U.S. and Japanese MNE are provided by Prof. Fritz Foley and Paul Beamish. I constructed the "innovative potential" categorical variable using the data from the USPTO. It equals 6 if the U.S. patent awards (in all industries except the pharmaceuticals in a year) surpass 1,000, 5 if patent count is under 1,000 but greater than 100, 4 if it is under 100 but greater than 6, 3 if it is between 6 and 1, and 1 if no patent is awarded at all.

Author's calculations from the sample data of the four reference periods prior to national patent implementation, where control covariates are used. Standard deviations are in parentheses. The industrial-level employment and output variables are only observed for all countries in the reduced matched sample. The statistics are calculated for the observed values. The *t*-statistics are obtained by regressing the covariate on the patent implementation indicator and a constant within the subclass. They reduced significantly after matching, indicating better covariate balances across the new-patent (treatment) and always-patent (control) groups. Significance levels: * = .10, ** = .05, *** = .01.

The main advantage of using Mahalanobis matching is its greater flexibility and accuracy in matching individual countries, which results in country pairs that are most suitable for pairwise statistical analyses. It also helps to get around the problem of missing data by matching in two passes: the first pass matched on the variables with no missing observations; and the second pass matched on all the characteristics after filling in the missing data with various national abstracts (appendix III). This method matches the points in a multidimensional space according to the distances between two points (Rosenbaum & Rubin, 1985). In this study, the coordinates of the multidimensional space are the matching variables, and the points to be matched are the sampled countries. The distance between any two countries is calculated as a function of the differences in the matching variables (appendix III). The Mahalanobis method collapses the set of country covariates into a scalar distance score. Table 1 lists the matched countries. Each match is done by finding the country in a control group that has the minimum Mahalanobis distance to the new-patent country. Countries that long had patent protection have statistically significantly higher average levels of incomes, GDP per capita PPP, pharmaceutical outputs, and exports in the previous period than those in the new-patent countries (table 2); the variable values of the new-patent countries are again higher than those of the no-patent countries (table 3). Comparing the *t*-statistics of the

TABLE 3.—MEAN CHARACTERISTICS COMPARISON OF NEW-PATENT AND NO-PATENT COUNTRIES

	New-Patent Countries		No-Patent Countries		*t*-statistic	
	Before Matching	After Matching	Before Matching	After Matching	Before Matching	After Matching
Country-Level Covariates						
GDP (in billions of 1995 constant USD)	148.99	145.60	76.04	67.31	2.38**	2.43**
	(164.29)	(158.50)	(112.48)	(72.82)		
Real GDP growth	3.44	3.97	2.97	2.73	.81	1.64*
	(2.85)	(2.81)	(3.33)	(2.37)		
GDP per capita PPP	7,201.05	7,102.51	4,248.35	5,727.53	3.21***	1.12
	(4,946.28)	(5,264.23)	(3,203.33)	(3,531.82)		
Economic Freedom	6.07	6.21	5.18	5.67	2.90***	1.54*
	(1.49)	(1.31)	(1.41)	(1.30)		
Legal Origin of U.K.	.12	.15	.07	.12	.92	.35
	(.33)	(.36)	(.26)	(.33)		
Legal Origin of France	.39	.48	.54	.50	−1.56*	−.13
	(.50)	(.51)	(.50)	(.51)		
Legal Origin of Socialist	.27	.11	.29	.31	−.21	−1.77*
	(.45)	(.32)	(.46)	(.47)		
Legal Origin Scandinavian	.12	.15	.05	.08	1.24*	.81
	(.33)	(.36)	(.21)	(.27)		
Price Control Indicator	0.52	0.74	0.66	0.76	−1.46*	−.16
	(0.51)	(0.45)	(0.48)	(0.44)		
Education	6.84	6.81	5.49	6.48	2.92***	.58
	(2.21)	(2.15)	(1.83)	(1.88)		
IPR Score	2.47	2.55	2.02	2.15	2.46**	1.97**
	(.85)	(.80)	(.68)	(.58)		
Innovative Potential	2.58	2.70	2.02	2.27	2.35**	1.67*
	(1.30)	(1.07)	(.88)	(.78)		
Industrial-Level Covariates						
Employment	29.98	28.07	22.40	15.47	.47	.84
	(76.30)	(73.60)	(43.78)	(26.16)		
Output (in millions of USD)	1,094.94	1,046.10	649.34	668.26	2.37**	1.38*
	(1,283.19)	(1,213.58)	(862.73)	(722.29)		
Pharmaceutical Exports to the U.S.	7.29	8.71	1.93	1.68	2.45**	2.67**
	(12.37)	(13.23)	(5.22)	(3.39)		
Number of subsidiaries of U.S. MNE	5.45	6.52	3.48	2.77	1.49*	1.93**
	(8.50)	(8.97)	(6.89)	(4.31)		
Number of subsidiaries of Japanese MNE	1.30	1.59	.36	.31	2.86***	1.90**
	(2.88)	(3.12)	(1.38)	(1.19)		
Indicator for missing variable "Employment"	.24		.50		−2.78***	
	(.44)		(.50)			
Number of observations	33	26	159	26		

This table provides descriptive statistics for the data obtained from World Trade Analyzer, World Bank *WDI,* and UNIDO *Industrial Property Statistics.* The economic freedom index comes from the Fraser Institute, legal families from La Porta et al. (1996), and the education proxy from Barro and Lee (2000). The price control dummy equals 1 if a country has pharmaceutical price control policy, and is drawn from Danzon (1997) and Economist Intelligence Unit reports. The numbers of subsidiaries of U.S. and Japanese MNE are provided by Prof. Fritz Foley and Paul Beamish. I constructed the "innovative potential" categorical variable using the data from the USPTO. It equals 6 if the U.S. patent awards (in all industries except the pharmaceuticals in a year) surpass 1,000, 5 if patent count is under 1,000 but greater than 100, 4 if it is under 100 but greater than 6, 3 if it is between 6 and 1, and 1 if no patent is awarded at all.

Source: Author's calculations from the sample data of four reference periods prior to patent implementation, where control covariates are used. Standard deviations are listed in parentheses. The industrial-level employment and output variables are only observed for 39 out of the 85 sampled countries. The statistics are calculated for the observed values. Significance levels are referenced for each variable according to their degree of freedom: * = .10, ** = .05, *** = .01. The *t*-statistics are obtained by regressing the patent implementation indicator on each covariate and a constant. They reduced significantly after matching.

covariates before and after matching, we clearly see that the covariates are much more balanced after matching.

B. Regression Models

(a) Regressions on the Entire Matched Sample. Although this study attempts to match on and control for an extensive list of variables that are correlated with a country's innovative potential, biases may still exist due to incomplete controls. This problem is addressed by using a panel data regression method (Rubin & Thomas, 2000). The formal regression models are estimated on these two groups of matched pairs (set 1: no-patent and new-patent pairs, and set 2: always-patent and new-patent pairs) separately in addition to pooling together the two control groups:

$$\begin{aligned}\log RESPONSE_{i,j,t+n} &= \beta_{0,i} + \beta_1 \times PAT_{i,j} + \beta_2 \\ &\times PATMOD_{i,j} + \beta_3 \times \log COVARIATES_{i,j} + \beta_4 \\ &\times D_t + \beta_5 \times \log RESPONSE_{i,j,t} + \varepsilon_{i,j,t+n}\end{aligned} \quad (1)$$

and

$$\begin{aligned}\log RESPONSE_{i,j,t+n} &= \beta_{0,i} + \beta_1 \times PAT_{i,j} + \beta_2 \\ &\times PATMOD_{i,j} + \beta_3 \times INTERACT_{i,j} + \beta_4 \\ &\times \log COVARIATES_{i,j} + \beta_5 \times D_t + \beta_6 \\ &\times \log RESPONSE_{i,j,t} + \varepsilon_{i,j,t+n},\end{aligned} \quad (2)$$

where $RESPONSE_{i,j,t+n}$ is the outcome variable of each country j of pair i in the reduced sample in period (or year)

$t + n$ (n years after patent implementation). A similar definition applies to $RESPONSE_{i,j,t}$ for period (or year) t. For the first specification, the outcome variable is the citation-weighted U.S. patent awards after the new patent implementation.[14] In the alternative specifications for robustness checks, I use raw U.S. patent counts, the citation-weighted U.S. patents whose citation numbers are half of a standard deviation above the mean (the main innovations), and pharmaceutical exports as the outcome variables. $\beta_{0,i}$ consists of the pair-specific effects. *PAT* and *PATMOD* are as defined in section IIA. *INTERACT* is the vector of interaction variables specified in section IID. *COVARIATES* refers to a vector of control variables. The full model controls for log of pharmaceutical exports to the U.S., log GDP per capita PPP, log IPR composite score of Ginarte and Park (1997) and its squared term, log average years of schooling, log economic freedom, log Japanese and U.S. foreign affiliate counts, log innovative potential, a dummy for price control policy, and log pharmaceutical industry employment. D_t stands for the five dummies for each of the periods (for example, D_t takes on value 1 if pair i is matched when examining the period t, and the other four period dummies for pair i have value 0). The regression residual is denoted by ε_i.[15] In robustness checks, log GDP, log GDP growth, and UK legal origin are added as control covariates.

(b) Regressions on the Sample of OECD Countries. In testing the impacts of national patent protection on R&D incentives, I mainly used the sample of 23 countries whose actual pharmaceutical R&D expenditures are observed. As a preliminary step, I carried out a series of dynamic panel regressions of OECD countries' R&D in logs on the control covariates, period dummies, and the country fixed effects, yielding statistically insignificant coefficients on the patent change indicator variable (-0.59 with standard deviation 0.34). I then adhered to the previously outlined study design to avoid relying on implicit assumptions of linearity imposed by OLS regression models. Due to the small sample size of the OECD countries, I employed only one control group—countries that did not change their pharmaceutical patent laws during a particular period t—to form a basis of comparison for the new-patent countries. I also did not define pairs here. Table 4 shows that there are a few outlier countries whose income, pharmaceutical output, and employment levels are much higher than the majority of other countries: the United Kingdom, France, Germany, Italy, Japan, and the United States. These outlier observations were removed from the sample, significantly improving the covariate balances (table 4).

One would ideally like to run separate regressions for each period. However, this is not possible given that only a few OECD countries changed domestic patent laws in each period. I therefore stacked the observations of the four periods to form a panel, and the panel method was again applied, but taking the period-specific effects as the fixed effects.

$$\log R\&D_{j,t+n} = \beta_0 + \beta_1 \times PAT_j + \beta_2 \times PATMOD_j + \beta_3 \times INTERACT_j + \beta_4 \times \log COVARIATES_j + \beta_5 \times D_t + \beta_6 \times \log R\&D_{j,t} + \varepsilon_{j,t+n}, \quad (3)$$

where β_0 is the constant term. $INTERACT_j$ and $COVARIATES_j$ are similar to those in model 1. $R\&D_{j,t+n}$ is the post-patent R&D expenditures of country j of period $t + n$ in the sample.

(c) Robustness Regressions. In order to obtain robust results, regressions based on three different likelihood functions are employed: the normal regression, the least absolute value (LAV) regression,[16] and the Huber regression. Minimizing Bayes (average) risk and *minimax* (which minimizes maximum risk) are two main approaches in classical decision theory. The Huber regression does exactly the latter by assuming a least favorable distribution for the data within a class of distributions, and obtains the MLE from this Huber distribution.[17] The LAV and Huber regressions are particularly good at avoiding influences due to outliers in the outcome variable. If the distribution is exactly normal, then least square is the maximum likelihood, and the standard normal regression provides better estimates than the other regressions. All three regressions are therefore performed in

[14] The regression model with the number of U.S. patents after national patent legislation as response variable and the U.S. patent counts of the previous year (or period) on the right side is in effect taking the difference of the two U.S. patent awards variables and testing the effects of patent implementation on the increment of U.S. patent awards.

[15] Limited by the sample size and by the fact that some countries with similar characteristics tend to implement national patent laws in the same period, some countries are matched to more than one other country and therefore appear more than once in the sample. The observations in model 1 are then not entirely independent of each other; this biases the t-statistics upward. An alternative model is used to test robustness:

$$\log RESPONSE_{j,t+n} = \beta_0 + \beta_1 \times PAT_j + \beta_2 \times PATMOD_j + \beta_3 \times INTERACT_j + \beta_4 \times \log COVARIATES_j + \beta_5 \times D_t + \beta_6 \times \log RESPONSE_{j,t} + \varepsilon_j \quad (2')$$

Model 2′ resembles model 2, except that β_0 is simply the constant term instead of the linear combination of pair dummies in model 2. It is employed so that each country appears in the regression only once. However, the limitation of model 2′ is that it assumes a common linear relationship between the outcome variable and the control variables for the entire covariate space, which may not actually apply for the covariates across different pairs. This model is only useful for robustness tests.

[16] LAV regression, also known as the minimum L1-norm regression, assumes a Laplace distribution for the data, and obtains the MLE through minimizing the absolute value of the deviation of data points from the median.

[17] The Huber distribution is a type of contaminated normal distribution, where a random variable (the outcome variable, for instance) is drawn from a standard normal distribution with probability $(1 - \varphi)$ and from an alternative distribution (such as Cauchy or Laplace) with probability φ. In the regression analyses of this study, this parameter is determined through several iterations to find the value that is most suitable to describe the data distribution.

TABLE 4.—MEAN CHARACTERISTICS COMPARISON OF THE NEW-PATENT COUNTRIES AND COUNTRIES WITH NO PATENT LAW CHANGES IN THE OECD COUNTRIES

	New-Patent Countries		No-Change Countries		*t*-statistics	
	Complete Sample	Balanced Sample	Complete Sample	Balanced Sample	Complete Sample	Balanced Sample
Price control	0.24	0.24	0.11	0.17	1.83**	0.90
	(0.43)	(0.43)	(0.32)	(0.38)		
U.S. subsidiary counts	7.24	7.24	14.61	10.05	−4.06***	−1.55*
	(10.87)	(10.87)	(12.10)	(9.46)		
Japanese subsidiary counts	0.12	0.12	1.91	0.58	−5.59***	−5.77***
	(0.33)	(0.33)	(5.53)	(0.87)		
Employment in Pharms	11.53	11.53	51.89	11.61	−10.73***	−0.04
	(10.89)	(10.89)	(53.81)	(9.50)		
Output in pharms	1,228.23	1,228.23	8,128.28	1,501.44	−8.22***	−1.07
	(1,427.97)	(1,427.97)	(13,348.67)	(1,459.25)		
GDP growth	2.93	2.93	2.50	2.48	1.84**	1.86**
	(1.46)	(1.46)	(1.24)	(1.32)		
Economic freedom	6.76	6.76	7.36	7.28	−3.78***	−3.16***
	(0.90)	(0.90)	(1.28)	(1.23)		
GDP	179.46	179.46	983.70	209.85	−8.71***	−1.23
	(145.15)	(145.15)	(1,561.53)	(143.47)		
GDP per capita PPP	12,061.55	12,061.55	13,689.39	13,320.63	−2.22**	−1.66*
	(4,365.54)	(4,365.54)	(4,991.05)	(4,874.86)		
UK Legal Family	0.07	0.07	0.31	0.30	−5.00***	−4.42***
	(0.26)	(0.26)	(0.46)	(0.46)		
French Legal Family	0.48	0.48	0.34	0.34	1.70**	1.64*
	(0.51)	(0.51)	(0.47)	(0.47)		
Socialist Legal Family	0	0	0	0		
	(0)	(0)	(0)	(0)		
German Legal Family	0.02	0.02	0.14	0.04	−3.78***	−0.44
	(0.15)	(0.15)	(0.35)	(0.19)		
Scandinavian Legal Family	0.43	0.43	0.21	0.33	2.70***	1.21
	(0.50)	(0.50)	(0.41)	(0.47)		
Average Years of Schooling	8.03	8.03	8.80	8.85	−2.16**	−2.25**
	(2.23)	(2.23)	(1.78)	(1.77)		
IPR index	2.77	2.77	3.60	3.40	−7.33***	−5.40***
	(0.70)	(0.70)	(0.62)	(0.65)		
Innovative Potential	3.33	3.33	3.92	3.57	−1.82**	−1.19
	(0.98)	(.98)	(0.51)	(0.79)		
No. of obs.	42	42	304	196		

This table provides descriptive statistics for the data obtained from World Trade Analyzer, World Bank *WDI,* and UNIDO *Industrial Property Statistics.* The economic freedom index comes from the Fraser Institute, legal families from La Porta et al. (1996), and the education proxy from Barro and Lee (2000). The price control dummy equals 1 if a country has pharmaceutical price control policy, and is drawn from Danzon (1997) and Economist Intelligence Unit reports. The numbers of subsidiaries of U.S. and Japanese MNE are provided by Prof. Fritz Foley and Paul Beamish. I constructed the "innovative potential" categorical variable using the data from the USPTO. It equals 6 if the U.S. patent awards (in all industries except the pharmaceuticals in a year) surpass 1,000, 5 if patent count is under 1,000 but greater than 100, 4 if it is under 100 but greater than 6, 3 if it is between 6 and 1, and 1 if no patent is awarded at all. The balanced sample does not include U.S., U.K., Japan, Germany, France, and Italy.

Source: Author's calculation from the sample data of OECD countries in the four reference periods prior to national patent implementation, where control covariates are used. The statistics are calculated for the observed values. The *t*-statistics is obtained by regressing the covariate on the patent implementation indicator and a constant within the subclass. Significance levels: * = .10, ** = .05, *** = .01.

order to obtain robust results. These three types of regressions all assume linearity between the outcome variable and each control variable. This assumption is tested with scatter plots between the log outcome variable and each of the log country covariates.

IV. Results

OLS provides some preliminary tests for whether patent laws stimulate domestic innovation. I regress the U.S. pharmaceutical patent awards on an indicator variable that takes on value 1 if a country had a pharmaceutical patent law in year t and 0 otherwise, the U.S. patent awards for all products except pharmaceuticals, and country dummies. The resulting coefficient on the patent implementation indicator is statistically insignificant (0.10 with standard deviation 0.41). The OLS regression estimates rely heavily on the assumed linear relations between the response variable and the independent variables. The matched sampling combined with pairwise regression methodology effectively controls for a wide range of variables indicating innovative potential and effectively reduces sensitivity to the linearity assumption. In this section, I present the regression results on the matched pairs obtained from the Mahalanobis matching in section IVA. I then discuss the results obtained using R&D outcomes in the OECD countries in section IVB. Section IVC summarizes the key robustness checks for potential biases due to small samples and omitted variables.

A. Using Citation-Weighted U.S. Patents as Innovation Proxy

I carried out regression analyses on the two sets of matched pairs following models 1 to 2 specified in section IIIB. I first test the effects of national patent law on the change in the log of U.S. pharmaceutical patents awarded to domestic innovators after the patent legislation (model 1). I use the log of citation-weighted U.S. patent awards for a particular year after the establishment of the national laws as the response variable. Specifically, three years (abbrevi-

TABLE 5.—LOG CITATION-WEIGHTED PATENT COUNTS IN NO-PATENT AND NEW-PATENT COUNTRIES

	Response Variables (log citation-weighted USP in different years)					
Covariates	Forward 10th years	Forward 10th years	Forward 10th year-base year	Forward 10th year-base year	Forward 5 to 10 years average	Forward 5 to 10 years average
PAT Implementation	−.22	.76	−.25	−.21	−.61	.42
	(.30)	(1.80)	(.42)	(.34)	(.37)	(.33)
PATMOD	−.69	−.55	−.41	−.08	−.06	.16
	(.64)	(.58)	(.60)	(.51)	(.63)	(.51)
PAT × log GDPpcPPP		.68**		1.14***		1.39*
		(.25)		(.34)		(.91)
PAT × log Freedom		.18		1.86**		1.91
		(.48)		(.81)		(1.75)
PAT × log Education		.38**		.10		.56**
		(.19)		(.32)		(.25)
PAT × log IPR score		−.28		−.68		.10
		(.50)		(.76)		(.45)
PAT × Price Control		−.30		−.58		−.53
		(1.72)		(.74)		(.81)
Log GDP per capita PPP	.54**	.92*	.56*	.79	.33*	.63
	(.22)	(.58)	(.33)	(.83)	(.19)	(.72)
Log Economic Freedom	.64	.62	1.50*	.71	1.37*	.17
	(.76)	(1.37)	(.91)	(.82)	(.74)	(1.44)
Log Education	.55**	1.08	.28	1.95**	1.10**	1.89*
	(.21)	(.80)	(.80)	(.85)	(.41)	(1.01)
Log IPR Score	.02	.24	.40	.59	.25	.39
	(.73)	(.81)	(.58)	(.79)	(.87)	(.90)
Log IPR squared	−.12		−.15*		−.09	
	(.10)		(.09)		(.08)	
Price Control	−.39	−.48	−.15	−.38	−.26	−.35
	(.33)	(.52)	(.52)	(.82)	(.34)	(.72)
Log Innovative Potential	.10	.35	.91*	1.43**	1.86**	.39
	(.45)	(.57)	(.52)	(.64)	(.63)	(.58)
Log Labor	−.11	−.07	−.27*	−.30	−.10	−.15
	(.13)	(.13)	(.14)	(.22)	(.17)	(.16)
Log Pharmaceutical Exports to the U.S.	.32*	.21	.03	.03	.41**	.24
	(.17)	(.25)	(.28)	(.43)	(.18)	(.18)
Log Number of U.S. MNE subsidiaries	−.08	.04	−.10	−.03	.22	.53**
	(.16)	(.27)	(.26)	(.44)	(.20)	(.24)
Log Number of Japanese subsidiaries	−.03	.10	−.08	−.08	−.07	.32
	(.25)	(.40)	(.43)	(.71)	(.19)	(.36)
Log base-year citation-weighted patents	.43**	.30**			.47*	.33
	(.14)	(.14)			(.25)	(.23)
Pair (Year) fixed effects	Y	Y	Y	Y	Y	Y
# of Obs.	52	52	52	52	52	52
R-square	.94	.95	.87	.87	.92	.95

Regression results from different regression specifications are tabulated in different columns. The dependent variable of each specification is listed in each column header. The *PAT* Implementation dummy is a dummy equal to 1 in the years starting from domestic patent implementation identified in table 1. The *PATMOD* dummy is a dummy equal to 1 if the country had pharmaceutical process patents prior to patent implementation as listed in section IIA. Macrodata obtained from World Trade Analyzer, *WDI,* and UNIDO *Industrial Property Statistics.* The economic freedom index comes from the Fraser Institute, legal families from La Porta et al. (1996), and the education proxy from Barro and Lee (2000). The price control dummy equals to 1 if a country has pharmaceutical price control policy, and is drawn from Danzon (1997) and Economist Intelligence Unit reports. The numbers of subsidiaries of U.S. and Japanese MNE are provided by Prof. Fritz Foley and Paul Beamish. I constructed the "innovative potential" categorical variable using the data from the USPTO. It equals 6 if the U.S. patent awards (in all industries except the pharmaceuticals in a year) surpass 1,000, 5 if patent count is under 1,000 but greater than 100, 4 if it is under 100 but greater than 6, 3 if it is between 6 and 1, and 1 if no patent awards. *PAT* × *X* refers to the interaction variable of *PAT* dummy and the covariate *X*, where *X* is log of GDP per capita PPP, economic freedom index, education, or IPR index, or the price control dummy. Heteroskedasticity-consistent standard errors that correct for clustering at the pair level appear in parentheses.

ated as three-year forward), four-year forward, up to ten-year forward, are the markers used as alternative years for the outcome variables in a series of regressions. The average of U.S. patent awards five to ten years post-reform is also used because the U.S. patent awards may be subject to year-to-year fluctuations. I report results using the individual year specifications as well, because averaged data can erode important trends. Year dummies are controlled for in the corresponding regressions to account for the differences in citations due to year truncations (Hall et al., 2001). A seemingly unrelated regression procedure is adopted to obtain GLS estimators in all these regression specifications, and no coefficient on *PAT* and *PATMOD* is found to be statistically significant at the 5% level. Table 5 lists the regression results for the new-patent and no-patent matched country pairs, using log ten-year forward citation-weighted patents, the difference between log ten-year forward and log base-year citation-weighted patents, and the average of log five- to ten-year forward citation-weighted patents as alternative dependent variable specifications. Table 6 records the estimations from the always- and new-patent country pairs, with the same set of alternative specifications. Neither a country's pharmaceutical patent law nor its modification of initial process protection has a statistically significant impact on the patent outcome (rows 1 and 2 in tables 5 and 6).

Although patent implementation alone does not significantly impact the number of patents received from the USPTO, it nonetheless may have effects conditional on a

TABLE 6.—LOG CITATION-WEIGHTED PATENT COUNTS IN ALWAYS-PATENT AND NEW-PATENT COUNTRIES

Covariates	Response Variables (log citation-weighted USP in different years)					
	Forward 10th years	Forward 10th years	Forward 10th year-base year	Forward 10th year-base year	Forward 5 to 10 years average	Forward 5 to 10 years average
PAT Implementation	.12	.16	−.30	−.32	−.04	.42
	(.23)	(.37)	(.50)	(.53)	(.25)	(.41)
PATMOD	−.12	−.09	−.11	−.07	−.33	−.33
	(.33)	(.31)	(.64)	(.61)	(.27)	(.31)
PAT × log GDPpcPPP		.40*		.87**		.49**
		(.22)		(.32)		(.24)
PAT × log Freedom		1.34*		2.15*		.34
		(.87)		(1.13)		(.90)
PAT × log Education		.16		.39**		.06
		(.14)		(.19)		(.11)
PAT × log IPR score		−1.77**		−1.21		−.50
		(.76)		(.94)		(.43)
PAT × Price Control		−.03		−.41		−.31
		(.47)		(.87)		(.51)
Log GDP per capita PPP	.54**	.35*	.57*	.46	.24	.40
	(.25)	(.21)	(.29)	(.62)	(.30)	(.34)
Log Economic Freedom	.43	.35	1.89	2.63**	.10	.30
	(.76)	(1.05)	(1.42)	(1.20)	(.56)	(.73)
Log Education	1.66**	1.98*	.22	1.69	1.20*	.64**
	(.72)	(.99)	(1.01)	(1.11)	(.68)	(.28)
Log IPR Score	.03	.70	.12	1.83	.30	.95
	(.25)	(.64)	(.60)	(1.51)	(.27)	(.62)
Log IPR squared	−.05**		−.02		−.01	
	(.02)		(.09)		(.04)	
Price Control	−.04	−.11	−.56	−.19	−.18	−.34
	(.28)	(.35)	(.55)	(.96)	(.27)	(.43)
Log Innovative Potential	.40	.78	1.62**	2.50**	1.21**	1.33**
	(.38)	(.69)	(.82)	(1.03)	(.48)	(.66)
Log Labor	.13	.15	.42	.18	.10	.12
	(.14)	(.20)	(.46)	(.43)	(.23)	(.22)
Log Pharmaceutical Exports to the U.S.	.11	.12	.12	.03	.18	.20*
	(.13)	(.11)	(.47)	(.28)	(.11)	(.12)
Log Number of U.S. MNE subsidiaries	−.07	−.06	−.38	.08	−.20	−.25
	(.10)	(.18)	(.38)	(.34)	(.21)	(.24)
Log Number of Japanese subsidiaries	.47**	.44	−.25	−.003	.27	.18
	(.16)	(.20)	(.31)	(.50)	(.17)	(.20)
Log base-year citation-weighted patents	.10	.11			.77***	.81***
	(.08)	(.15)			(.09)	(.13)
Pair (Year) fixed effects	Y	Y	Y	Y	Y	Y
# of Obs.	52	52	52	52	52	52
R-square	.96	.97	.76	.88	.97	.97

Regression results from different regression specifications are tabulated in different columns. The dependent variable of each specification is listed in each column header. The *PAT* Implementation dummy is a dummy equal to 1 in the years starting from domestic patent implementation identified in table 1. The *PATMOD* dummy is a dummy equal to 1 if the country had pharmaceutical process patents prior to patent implementation as listed in Section IIA. Macrodata obtained from World Trade Analyzer, *WDI,* and UNIDO *Industrial Property Statistics.* The economic freedom index comes from the Fraser Institute, legal families from La Porta et al. (1996), and the education proxy from Barro and Lee (2000). The price control dummy equals to 1 if a country has pharmaceutical price control policy, and is drawn from Danzon (1997) and Economist Intelligence Unit reports. The numbers of subsidiaries of U.S. and Japanese MNE are provided by Prof. Fritz Foley and Paul Beamish. I constructed the "innovative potential" categorical variable using the data from the USPTO. It equals 6 if the U.S. patent awards (in all industries except the pharmaceuticals in a year) surpass 1,000, 5 if patent count is under 1,000 but greater than 100, 4 if it is under 100 but greater than 6, 3 if it is between 6 and 1, and 1 if no patent awards. $PAT \times X$ refers to the interaction variable of *PAT* dummy and the covariate *X*, where *X* is log of GDP per capita PPP, economic freedom index, education, or IPR index, or the price control dummy. Heteroskedasticity-consistent standard errors that correct for clustering at the pair level appear in parentheses.

country's innovative potential. To explore such effects, variables interacting the patent implementation indicator with country characteristics are included in the regressions in the second round of analyses, following model 2 in section IIIBa. Columns 2, 4, and 6 in tables 5 and 6 show that patent protection demonstrates some importance conditional on a country's development levels, economic freedom, and education. I now discuss the results on these three interaction effects one by one.

In the regressions using the citation-weighted U.S. patents as outcome variables, the GDP per capita PPP and *PAT* interaction variable bears positive signs, and the coefficients are statistically significant at the 5% or 10% levels (row 3 in Tables 5 and 6). This suggests that patents are important for innovation conditional on a country's development level. A more developed country with pharmaceutical patents is likely to have more innovations compared to a similarly developed country without patents, or a less developed country with patents. The statistically significant coefficient on this interaction term indicates that the patent-reform effect on the log citation-weighted U.S. patents awarded ten years after the reform doubles, on average, with a unit increase in log GDP per capita PPP (coefficient = 0.68 in column 2 of table 5: $e^{.68} = 1.97$). The coefficients on the log GDP per capita PPP term itself are positive in all regressions and significant in some specifications (tables 5 and 6).

No firm conclusions can be established about the conditional importance of patent protection given a country's

education attainment or economic freedom for the citation-weighted patent outcomes, due to the varying significance levels in coefficients on the two interaction variables across various regression specifications. However, all these coefficients are positive, and many are statistically significant at the 5% or 10% levels (rows 4 and 5 in tables 5 and 6). In addition, the positive coefficients on the main effects of log education and freedom are statistically significant in many specifications as well. All these demonstrate the importance of education attainment and economic freedom for a nation's innovation level.

The positive coefficients on the log IPR score and the negative coefficients on its squared term (tables 5 and 6) shed lights on the theory pioneered by Gallini (1992) that the relationship between patent strength and innovation adopts an "inverted U" shape. The interaction of log IPR and the patent reform dummy also takes on negative coefficients in most specifications and significant at the 5% level in predicting the citation-weighted patent outcome ten years after patent implementations in the new-patent and always-patent groups (table 6). These results relate to the theories that competition sometimes can induce innovation (Aghion et al., 2002; Qian, 2005). The variable interacting the price control dummy with the patent reform dummy takes on negative coefficients throughout all specifications, although not statistically significant. Together with the negative coefficients on the price control dummy, the results indicate a negative relationship between price control policies and the patent outcomes. This finding is in agreement with others' (Grabowski & Vernon, 1992; Danzon, 1997) that price control policy tends to impair domestic innovation.

In most of the regression equations in tables 5 and 6, the coefficients on the "innovative potential" variable are positive and statistically significant at the 5% or 10% level. This illustrates the importance of a country's innovative potential in explaining the innovation differences between countries. While the true innovative potential of a country is obviously not directly observed, apparently, it can be partly captured in the variable constructed.

The country's base-year pharmaceutical exports to the United States have positive coefficients, statistically significant in several regressions. The incentive to patent in the United States is largely determined by the market potential innovators see and seek in that country. In addition, because trade between the two countries is a function of geographic distance, linguistic differences, and other variables that could affect foreign innovators' propensity for patenting in the United States, controlling for trade values helps to control for these indirect variables. In fact, innovators in a given country are more likely to seek U.S. patents if, historically, their country has exported more pharmaceuticals to the U.S. market.

In all the fixed-effects regressions, the F-statistics for the group of pair dummies, $\beta_{0,i}$, are statistically significant at the 5% level, and many of them are significant even at the 1% level. This importance of pair-specific effects indicates the methodological significance of the matching technique. The coefficients on the other control variables are mostly insignificant at the 5% level.

B. Using R&D Expenditures and Personnel as Innovation Proxies

(a) Results on the Main Patent Implementation Dummy. U.S. patent awards can be considered an estimate of innovation outputs, while R&D expenditures provide an estimate of innovation inputs. It is likely that the stimulus from patent protection could impact R&D much sooner than it would U.S. patent grants. On average, the patent-granting process takes one to two years (USPTO, 2000, interview of Paul Harrison), not counting the time needed for drug development. The R&D response to domestic patent laws is found to be immediate (Lo, 2004). R&D expenditures for one year and one period after national patent reforms (the periods are defined in section IIA and table 1), and the difference between R&D two years after patent reform and R&D in the base-year are specified as alternative dependent variables in the regression model 3 in table 7. For robustness checks, one-year, two-year, and one-period forward R&D expenditures and one-period forward R&D personnel (RSE) are specified as alternative outcomes.[18] To address the concern that patent implementation may be endogenous, R&D outcomes of one or two years prior to patent legislation are also adopted. All these specifications with different dependent variables but same set of independent variables are carried out as a system of seemingly unrelated regressions. In addition, regressions with R&D one period forward are carried out separately on the pairs of the non-OECD countries in the appendix. Estimates of patents' effects remain null for all these specifications. Row 1 in table 7 shows the statistically insignificant coefficients on the patent dummy in the main specifications. The *PATMOD* variable is disregarded because all the OECD countries, except Turkey, had process patents prior to their national product patent legislation.

Most regressions yield no statistically significant coefficient on *PAT.* The only statistically significant positive coefficient on the patent implementation indicator appears in the Huber regression of R&D two-year forward for the OECD countries.[19] This finding alone is insufficient to reject the null hypothesis that patent implementations have not generally stimulated R&D incentives, given all the other

[18] R&D expenditure is available from 1978 to 1997 for most sampled OECD countries, with 1998 data available only for five countries. Therefore, R&D observations of three-year forward are too sparse to obtain accurate estimates on the main patent implementation variable. RSE data is too few to carry out individual year specifications.

[19] A residual plot reveals an outlier in the data: Turkey experienced a drop in R&D expenditure from $10.09 million in 1992 to $0.74 million in 1994. While the standard normal and LAV regressions were likely skewed by this "influential" outlier, Huber regression successfully fits the optimal line for the remaining data points that tend to have similar R&D trends.

TABLE 7.—LOG R&D EXPENDITURES IN THE OECD COUNTRIES

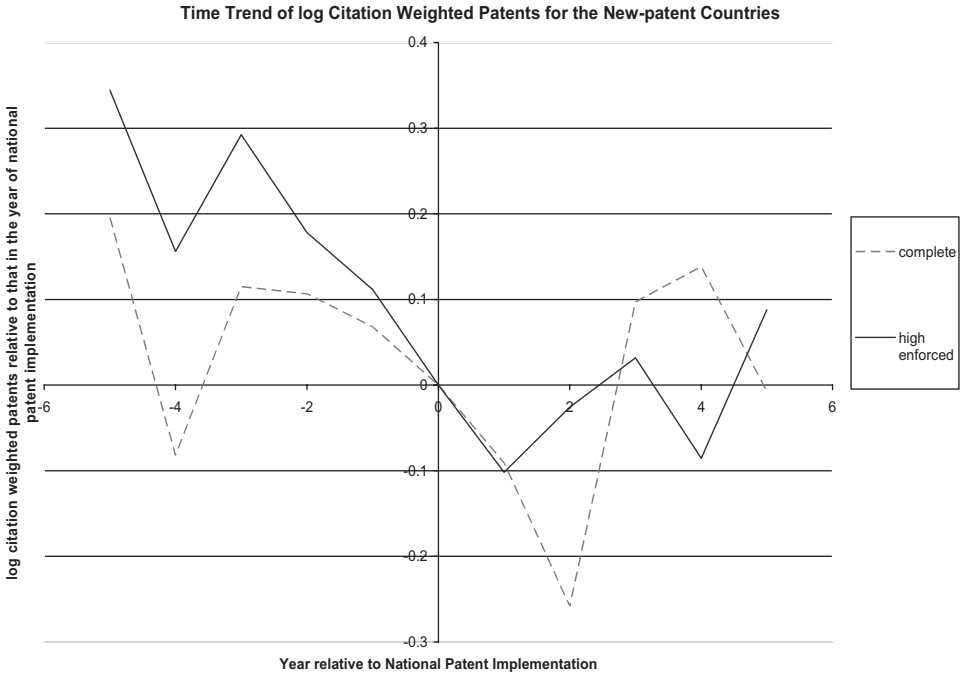
Covariates	Response Variables (log R&D)					
	Forward 1-period	Forward 1-period	Forward 1-year	Forward 1-year	Forward 2-base year	Forward 2-base year
PAT Implementation	.26	−.51	.01	−1.50	−.04	.43
	(.18)	(1.09)	(.09)	(2.26)	(.04)	(.96)
PAT × log GDPpcPPP		1.52***		.76**		.59*
		(.52)		(.25)		(.35)
PAT × log Freedom		.87***		.12**		.15*
		(.26)		(.06)		(.09)
PAT × log Education		.32**		.29***		.55**
		(.13)		(.08)		(.20)
PAT log IPR score		−.27**		−.36**		−.29**
		(.11)		(.17)		(.12)
Log GDP per capita PPP	.74*	.65	.08	.06	.82**	.51
	(.43)	(.81)	(.32)	(.35)	(.41)	(.76)
Log Economic Freedom	.09	.24	.18	.14	.37***	.17
	(.24)	(.32)	(.26)	(.29)	(.08)	(.25)
Log Education	4.97***	.06	1.46**	2.16*	.48	.19
	(1.24)	(.48)	(.63)	(1.36)	(.35)	(.42)
Log IPR Score	.79**	−.001	.18	.16	.88	.09
	(.38)	(.43)	(.27)	(.24)	(1.77)	(.30)
Log IPR squared	−.23***		−.06**		−.13**	
	(.05)		(.03)		(.06)	
Log Innovative Potential	.04	.18	.11	.10**	.09	.19
	(.48)	(.47)	(.22)	(.01)	(.13)	(.25)
Log Pharmaceutical Exports to the U.S.	.12**	.04	.05**	.04	.20***	.35
	(.05)	(.06)	(.02)	(.03)	(.04)	(.46)
Log Number of U.S. MNE subsidiaries	.06**	.04	.02	.01	.21***	.60
	(.03)	(.07)	(.02)	(.03)	(.05)	(.60)
Log Number of Japanese MNE subsidiaries	.02	.14	.10	.11	.53***	.13
	(.11)	(.17)	(.07)	(.09)	(.10)	(.14)
Price Control Indicator	−.13	−.08	−.03	−.07	−.16**	−.04
	(.09)	(.12)	(.05)	(.11)	(.07)	(.11)
Log Labor	−.01	.08	.16	−.02	.23	.07
	(.09)	(.14)	(.09)	(.07)	(.18)	(.13)
Log base-year R&D	.86***	.97***	.98***	.99***		
	(.11)	(.13)	(.05)	(.06)		
Country & period FE	Y	Y	Y	Y	Y	Y
# of obs.	238	238	238	238	238	238
R-square	.98	.98	.99	.99	.48	.42

Regression results from different regression specifications are tabulated in different columns. The dependent variable of each specification is listed in each column header. The *PAT* Implementation dummy is a dummy equal to 1 in the years starting from domestic patent implementation identified in table 1. Macrodata obtained from World Trade Analyzer, *WDI,* and UNIDO *Industrial Property Statistics.* The economic freedom index comes from the Fraser Institute, legal families from La Porta et al. (1996), and the education proxy from Barro and Lee (2000). The price control dummy equals 1 if a country has pharmaceutical price control policy, and is drawn from Danzon (1997) and Economist Intelligence Unit Reports. The numbers of subsidiaries of U.S. and Japanese MNE are provided by Prof. Fritz Foley and Paul Beamish. I constructed the "innovative potential" categorical variable using the data from the USPTO. It equals 6 if the U.S. patent awards (in all industries except the pharmaceuticals in a year) surpass 1,000, 5 if patent count is under 1,000 but greater than 100, 4 if it is under 100 but greater than 6, 3 if it is between 6 and 1, and 1 if no patent awards. *PAT* × *X* refers to the interaction variable of *PAT* dummy and the covariate *X*, where *X* stands for log of GDP per capita PPP, economic freedom index, education, or IPR index, or the price control dummy. Heteroskedasticity-consistent standard errors that correct for clustering at the country level appear in parentheses. The interaction variable of patent implementation dummy and price control dummy is omitted in the regression due to lack of variation.

insignificant results obtained in a series of robustness tests in appendix II.

(b) Results from the Interaction Terms and Control Covariates. The variables interacting patent reform dummy with log of GDP per capita PPP, log economic freedom, and log education, respectively, all carry positive coefficients and are statistically significant at the 1%, 5%, or 10% levels (rows 2–4 in table 7). The main effects of the development level, education, and freedom proxies are also positive. All these imply that patent laws may have positive effects conditional on high levels of development, education, and economic freedom. Here, it is worth noting the consistently significant positive interaction effect of economic freedom and patent reforms. This result hints at the possibility that in a more integrated market such as that formed by the OECD countries, national patent law could complement a member country's open market access and favorable domestic investment policies to attract FDI and other forms of foreign technology transfers, which is empirically supported in Branstetter, Fisman, and Foley (2006). Patent laws could also help domestic companies assimilate these inward technology transfers through patent disclosures. Economic freedom can help countries with new patent systems to leverage their emerging national intellectual property advantages by facilitating exports as well. It is interesting to see the consistently significant positive effect of education levels interacted with patent reforms, suggesting that domestic patent laws could provide incentives for the high-level human capital to engage in innovative activities. As the

FIGURE 1.—TIME TRENDS OF LOG CITATION-WEIGHTED PHARMACEUTICAL PATENT COUNTS IN THE COUNTRIES THAT IMPLEMENTED NATIONAL PHARMACEUTICAL PATENT LAWS IN THE PERIOD 1978–1999.



This figure plots the trends for two groups of countries—the complete sample of countries in the treatment group, and the subsample of treatment countries that has high IP enforcement levels, as indicated by an overall IPR score (Ginarte & Park, 1997) no less than 0.66. The IPR scores take values of 0, 0.33, 0.66, and 1 among all countries.

OECD countries offer advanced education, their human capital can be productive in innovations when induced to switch out of imitations by implementing patents.

The statistically significant negative coefficients on the interaction between IPR and *PAT* (table 7, row 5) and on the squared log IPR term (table 7, row 10) support findings in the previous section that the relationship between patent strength and innovation adopts an "inverted U" shape. Most OECD countries had pharmaceutical process patents before they introduced product patents; it is likely that a country's process innovations were effectively protected if its initial national IPR protection was strong. Additional product patents then may not stimulate innovation, as Scherer (1977) and Kumar (1996) suggest. In fact, the strengthening of patent protection may block domestic initiatives to engage in "imitative" innovations, while "ingenious" innovation may not come easily and quickly. This leads to an overall decline in domestic R&D activities in the short run. An alternative explanation is that countries with a higher IPR index are more likely to enforce laws that protect intellectual property, such as trade secret laws. Domestic innovators may have alternative ways to appropriate profits from their innovations. This finding is corroborated in the time trends (figure 1) of log citation-weighted patent counts five years pre- and post-patent law implementation for the complete treatment sample of countries (dashed line) and the subset of countries that have strong IP enforcement, as indicated by the IPR index (solid line). Notice that post-implementation, the log citation-weighted patent counts dropped more for the highly enforced subsample than the complete sample. This plot mainly uses the within-country pre- and post-implementation comparison, and is susceptible to endogeneity problems of national patent implementation. It only serves to provide a visual check of the patenting trends.

Table 7 shows that the coefficients on the other control covariates carry signs and statistical significances similar to those in the previous section with citation-weighted patents outcomes. The log numbers of U.S. and Japanese MNE subsidiaries gain a few significant positive coefficients at the 1% or 5% levels, providing some evidence for positive impacts of FDI on innovations. The variable interacting price control and patent implementation is omitted from the regressions for OECD countries due to a lack of variation in the sample. The price control dummy carries negative coefficients throughout the various specifications.

C. *Checking Potential Biases due to Small Samples and Omitted Variables*

Bootstrap simulations are applied to estimate the size of the bias in the coefficients' estimates using small samples. In particular, randomly draw 78 countries among the two sets of treatment-control country pairs and execute the regression models in section IIIBa on the simulated bootstrap samples as done with the original sample. I repeat this simulation 10,000 times, and obtain a distribution for each of the regression coefficients. I then calculate the mean of

each coefficient's distribution and compare it with the coefficient estimate from the original study. The differences between the mean coefficient estimate from bootstrap samples and the coefficient estimate from the original 26 pairs is the estimate of the bias of this coefficient estimate. The biases of estimates for the main patent and the interaction variables are in the 0.01–0.03 ranges and would not alter p-values of the coefficients estimates significantly, indicating a negligible bias in the original estimates.

To check how sensitive the patent effect estimates are to other potential latent variables, I conduct statistical analyses following Rosenbaum (1999, 2002), and the estimates in this study are again robust to these alternative tests. A sensitivity analysis addresses the following concern: after matching on the observed country characteristics, how large must the residual departure from random assignment be before the qualitative conclusions are altered. I calculate the range of point estimates for the patent law effects in my study and check them against the standard sensitivity range listed in Rosenbaum (2002). The estimates in this study are shown to be insensitive to hidden biases caused by unobserved covariates. Details are available upon request.

V. Conclusions

This paper tests the effects of national pharmaceutical patent legislation on domestic innovations. It addresses two obstacles in the economic literature of technological changes: data deficiency and methodological limitations. This study constructs a database that approaches ideal experimental data, given the limitations of observational studies. In the literature of technological advances, this study is the first to adopt the matched sampling methods combined with fixed-effects panel regressions. The lack of observed counterfactual outcomes—what would have happened in the presence or absence of national patent law—for a given country necessitates international comparisons. In previous studies involving developed countries, the natural benchmarks for comparisons are other developed countries, notably OECD countries. The choice of control groups becomes much more difficult when one intends to study countries at various income and developmental levels, as is the case here. One key innovation of this study is to apply the Mahalanobis matching method to overcome the difficulties of missing data, and to match countries of similar characteristics. Fixed pair-effects regression models on the sample of matched countries control well for the various country characteristics—both observed and unobserved—which are correlated with latent innovative potential and are important for explaining innovation outcomes. This helps to improve the precision of estimates.

After controlling for a list of covariates that are likely to affect innovative potentials, I find no statistically significant relationship between national pharmaceutical patent protection and U.S. patent awards (in net and citation-weighted counts) or domestic R&D. This empirical finding is hardly surprising. Some developing countries have always had patent protection, yet domestically they do not have innovative potential and rely heavily on imports.[20] However, the interaction of national patent implementation with development level is positively related with domestic R&D expenditure and domestically originated pharmaceutical patents in the United States. The interaction of patent implementation and economic freedom and the interaction of patent implementation and education are shown to be positively related to R&D expenditure in the OECD countries. Furthermore, there appears to be an optimal level of IPR regulation above which enhanced protection is eventually associated with a decline in innovative activities. In short, for countries that have relatively low levels of development, education, and market freedom, any potential benefits from additional innovation depend ultimately on domestic macroeconomic factors and require a substantial time-discount.

It is also possible that the lack of a statistically significant increase in the U.S. patent awards after national patent legislation is linked to data limitations, as discussed in detail in appendix I.B. Patent laws may also affect innovation in dimensions other than raising its absolute number, in particular, changing the direction of innovative activity (Moser, 2003) or increasing FDI (Branstetter, Fisman, & Foley, 2006). Nevertheless, the findings in this study have important policy implications. They vindicate Maskus's (2000, p. 199) argument that "expectations that stronger IPRs alone will bring technical change and growth are likely to be frustrated." Countries with different degrees of development, general intellectual property strength, and economic freedom have varying innovative responses to national patent law. Most of these country characteristics indeed go hand in hand. Kumar (1996) finds a positive relationship between the R&D intensity of U.S. affiliates and the strength of national IPR only in developed countries, not developing ones. Many developed countries, including Germany and Switzerland, had opposed national patent legislation when they were technology importers in order to take advantage of freely accessible foreign technologies. Evenson (1990) argues that countries have no interest in strong IPR until they become significant technology exporters. Although the TRIPs allow for adjustment time,[21] it is unlikely that developing countries will transform from mere "technology importers" to even moderate "technology exporters" within this short time frame.

[20] For instance, data show that French West Africa never applied for any pharmaceutical patent from the EPO or USPTO during 1978–1999, despite its well-established national patent laws.

[21] Developing countries had a grace period of five years and the least developed had ten years.

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DATA APPENDIX

Country covariates

PAT and PATMOD—These two indicator variables are constructed for the periods in this study by cross-referencing several different sources. Among them are the Ginarte and Park (1997) patent coverage index, the WIPO documents on harmonizing patent laws, the country reports and "Super 301 list" published by the U.S. Department of Commerce, and the compiled patent laws folio at the Harvard Law library. The Ginarte and Park index covers seventy of the countries in my sample. I assigned the indicator values for the remaining 22 countries by looking up the other sources mentioned above. All sources are listed in the references section. In a few cases, where different sources provide conflicting information on when a particular country started implementing pharmaceutical patents, I gained clarification by contacting individual patent offices.

GDP, real GDP growth, and GDP per capita PPP—These three variables are available for 85 out of the 92 sampling countries. They are from the World Development Indicator (WDI) database published by the World Bank (2000). This database contains data for over 200 countries from 1960 to 2000, although the GDP per capita PPP data are only available from 1975 onwards.

Average years of schooling for total population—This education attainment variable has data for 65 sampling countries (Barro & Lee, 2000). Data are available at five-year intervals in 1960–1999.

Economic freedom—Estimated using the Fraser Institute composite index, which takes into account a number of government policies and openness factors.[22] A country with more economic freedom facilitates more trade and other economic exchanges, and therefore facilitates more innovation.

Legal family—This family of dummies identify the legal origin of the company law or commercial code of each country. The five origins are English common law, French commercial code, German commercial code, Scandinavian commercial code, and Socialist/Communist laws (La Porta et al., 1996).

Innovative potential—The variable takes value 6 if the U.S. patent awards (in all industries except the pharmaceuticals in a year) surpass 1,000; 5 if patent count is under 1,000 but greater than 100; 4 if it is under 100 but greater than 6; 3 if it is between 6 and 1; and 1 if no patent is awarded at all.[23]

Pharmaceutical industry employment and output—Extracted from the Industrial Statistics CD-ROM published by the United Nations Industrial Development Organization (UNIDO). The database lists these variables by country and by industry (as classified by the four-digit International Standard Industrial Classification codes), covering the years 1978–1999. The pharmaceutical industry is listed under the code 3522. Comprehensive as it is, the database still has many missing values. The employment and output variables are observed for only fifty of the sampling countries. Data for these two variables are augmented with the OECD Structural Analysis (STAN) database, the UN Industrial Statistics Yearbook, and national statistical abstracts of some countries. Industry output data from these extra sources are converted to U.S. dollars using the annual exchange rates published in the International Financial Statistics (IFS). The

[22] For detailed components of the index, please see http://www.fraserinstitute.ca/economicfreedom/index.asp?snav=ef.

[23] These threshold values are taken by tabulating the quartiles of the variable on total U.S. patents in all other industries.

compatibility of the data from these different sources is verified using a random sample of countries where data are available in all these sources.

US FDI—Because of confidentiality for multinational enterprises, the detailed asset and R&D data at the foreign subsidiaries in the pharmaceutical industry are not released. Instead, Dr. Fritz Foley at the BEA kindly released the U.S. foreign subsidiary counts listed by country, and he also provided me with the information that the correlations between these subsidiary counts and assets (and R&D outlays) when computed year by year lie between 0.724 and 0.934. Thus, the subsidiary counts can act as an estimate for the technology transfer from the United States to the different countries.

Japanese FDI—Similarly, I obtained the Japanese foreign subsidiary counts data in the pharmaceutical industry from Professor Paul Beamish at the University of Western Ontario. Because the United States and Japanese R&D spending per subsidiary can be quite different, I decided to keep the two counts as separate variables rather than merging them together in the regression specifications. These two variables are fully observed for all the 92 sampling countries.

Country's pharmaceutical exports to the United States—The World Trade Analyzer database produced by Statistics Canada provides a data source for the imports of the United States listed by country and by industry from 1980 to 1996. The database lists the different industries according to the Standard International Trade Classification (SITC), under which code 54 corresponds to the medicinal and pharmaceutical products. Since the database covers only the manufacturing industries, the pharmaceutical exports refer to the manufactured products. The data for the pharmaceutical exports to the United States (or, equivalently, U.S. imports) are available for all the sampling countries.

Price control—This variable is constructed by cross-referencing several sources, including the country reports published by the U.S. Department of Commerce, the Economist Intelligence Unit (EIU) database, the price control component of the Fraser Institute economic freedom index, the OECD report for the pharmaceutical industry, Danzon (1997), and other documents searched in Google.

IPR strength score—It is an unweighted sum of five component indices, including the domestic patentability of seven product categories, the membership a country has in international agreements, the duration of national patent protection, protection of losses from compulsory licensing, revocation of patents, and so on, and the enforcement evaluation of a patent system (Ginarte & Park, 1997). The inclusion of this variable also helps to control for the enforcement of national pharmaceutical patent laws, correcting possible loopholes that the simple patent coverage indicator does not account for—the lack of enforcement of national patent laws in some countries.

qIPR—It is a categorical variable that takes on values 1 to 5 for the corresponding quintiles of the IPR strength score. Five dummy variables for each quintile of IPR are then generated by tabulating the *qIPR* variable.

Appendices I.B, I.C, II, and III are included in the working-paper version and are posted on my Web page: http://www.nber.org/~yiqian/patentappend.pdf.