APPENDIX I. Data Appendix

B. US Patent Awards Data.

a. Choice of US patent awards as outcome variable over the WIPO patent counts.

There are two main patent measures available in the data I gathered. One is the annual patent application data of each country from 1975-1997, published in the Industrial Property Statistics by World Intellectual Property Organization (WIPO). The second is the annual data of the United States on patents awarded listed by industry and by country of origin from 1978-1999, collected in a "Patenting Trends in the US, 1999" CD-ROM published by the United States Patent and Trademark Office (USPTO). Both sources list data by the innovator's country of residence.

The problem with the WIPO data is that it could be difficult to control for the idiosyncratic patent system differences in different countries. The number of patent applications may not be comparable across countries. In addition, the number of domestic patent applications in a country could be a direct outcome of the domestic patent system, instead of the indirect outcome of innovation activities. For example, a country without a domestic patent system will naturally have no domestic patent applications. Non-informative changes in the patent counts also occur in the cases of patent law modifications. For instance, when Japan's patent laws changed from one-claim per patent application to allowing multi-claims in 1988, there was a significant drop in the number of patent applications that does not necessarily reflect a decrease in innovation activity.

The "Patenting Trends in the US" CD-ROM lists patent awards to innovators from ninety-three countries in total, covering the years 1978-1999. The data are listed by industry, using the Standard Industrial Classification (SIC) codes. The patents for drug and medicine are classified according to the SIC code 283. The US observation is dropped mainly because it has extremely high patent counts compared to any other countries. This is partly attributable to the fact that US patents constitute domestic patenting for US innovators. There are therefore ninety-two countries in total in the sample, and all these countries have

some propensity to file patents in the US, as reflected by a non-zero count of total US patent awards over all the years.

The data used are U.S. utility patents granted during the period 1963 to 1999 (with aggregated patent counts for 1963-1977, and year-by-year listings for patents since 1978). This CD-ROM lists patent grants by year of grant and by state or country of origin, for each product field. Patent origin is based on the residence, at the time of grant, of the first-named inventor listed on the patent. Patent awards may introduce lags in processing times, making the exact corresponding year of innovative activity unpredictable. Patent data listed by application dates are also extracted from the NBER patent database (Hall, *et. al.*, 2001), and the citation-weighted patent counts are used as alternative innovation estimates. Pharmaceutical patent applications are normally filed near the end of pre-clinical work and issued in the clinical testing stage (Scherer & Weisburst, 1995).

b. Concerns using the US patent awards as innovation measures.

One concern about the use of US patent awards is that there may be tax evasion incentives for some Multinational Enterprises to file from different countries. Such MNE patent application policies may contaminate the patent awards data. This MNE patenting complication does not influence my analyses, because the data are listed according to the country of residence of inventor and not that of assignees[1]. Suppose a US subsidiary located in China carries out innovation in pharmaceuticals: the patent award will always be listed under the entry of China as the country of origin. Only the "assignee" of the patent will differ, being either the Chinese subsidiary or the US headquarters, depending on the MNE's preference.

It would be interesting to test the different changes in the MNE's innovations in a country that changed patent laws, and the changes in the national corporations. Unfortunately, such disaggregate data are not available for the US patent awards or the R&D expenditure variable. This does not hurt the main analyses of the study, however, as any patent filings of the residents reflect the domestic innovation level. If the innovator is a

[1] Assignee refers to the person(s) or corporate to whom all or limited rights under a patent are legally transferred.

national, then producer surplus goes to the country. If the innovator is a foreigner, typically an MNE subsidiary, then the fact that the innovation takes place in the country suggests that the research laboratory is in the country, and there are potential knowledge spillovers to benefit the country. Similarly, R&D expenditure include R&D activities of both national companies and MNE and reflect domestic innovative incentives.

One may also question the validity of estimating innovation with the US patent awards considering innovators may simply change the location of patenting to domestic once a national patent law is in place. The US patent counts would then not capture these additional innovations. This may not be important given that US is the largest market in the World, and the marginal cost of filing an additional patent application is mitigated with the various international treaties since the 1950s (Notably the Patent Cooperative Treaty among the WIPO members in 1973).

There is another concern of the potential bias induced by the data. If there are no IPR agreements between a country and the United States, there might be little patenting in the US, and once such an arrangement is introduced, companies that were already innovating will start patenting their innovations in the US. This would lead to an increase in the number of US patent awards, but would not represent that patenting law stimulate domestic innovation. To address the validity of using the US patents estimate, I did a correlation plot between the R&D expenditure and the US patent awards counts for the countries where both data are available. I found that the two variables are highly correlated, with correlation coefficient equal to .8.

Although the US patent awards data act as a good estimate for innovation, the value of an innovation is not fully measured by the patent counts, because of the existence of asymmetric information between the innovators (patent applicants) and the patent offices (Cornelli and Schankerman 1999, and Scotchmer 1999). The citation weights could serve to overcome such problems (Hall, et. al., 2001). In light of this literature, I further research by bringing citation weights into the outcome variable, using the NBER patent database. It contains the number of citations made to each patent granted by the US 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 particular year, where c_i is the citation made to patent i. In addition, I generated a variable to capture the main innovations by counting up the citation weighted patents whose citations are half standard deviation above the mean number of citations received by a patent. The important innovations are patented in the US regardless of the innovator's domestic patent legislation conditions. The use of this new variable as the response variable can therefore help to tease out the national patent effects on innovation instead of the effects on patenting in the US, a concern discussed in the previous paragraph. I have also used a country's pharmaceutical exports to the US as an alternative estimate for innovation. The coefficients on the patent implementation dummy variable are statistically insignificant, and in fact negative. The interaction variable between PAT and economic freedom index takes on statistically significant positive coefficients.

C. Imputation of the R&D data

The Analytical Business Enterprise Research and Development (ANBERD) database provides R&D expenditure data listed by industry for sixteen of the largest OECD R&D performing countries: Australia, Belgium, Canada, Denmark, Finland, France, West Germany, Germany, Ireland, Italy, Japan, the Netherlands, Norway, Spain, Sweden, the United Kingdom and the United States. Industrial research & development (R&D) is defined as R&D activities carried out in the business enterprise sector, regardless of the origin of funding. While the government and higher education sectors also carry out R&D activities, industrial R&D remains the most closely linked to the creation of new products. To make the data comparable across nations over time, the ANBERD estimates are measured in current PPP$. In addition, I find R&D data for twenty-three OECD countries in the OECD Health Care CD-ROM, which includes the fifteen countries (except East Germany) found in the ANBERD. The original data is listed in national currency units. To merge this data with the ANBERD data, I converted the R&D data into PPP dollars. This was done by first converting the R&D data from national currency measure to US dollars using the current year market exchange rate published in the IFS, and then dividing the R&D at current year

US dollars by the PPP based on consumer prices published in the Penn World Table (PWT 5.6). Because the PPP index is only available from 1978-1992, the values for years after 1992 were computed by using the consumer price index published in the IFS. This study uses the equation below to impute later year PPP values: $PPP_{t+1} = PPP_t * (CPI_{t+1} / CPI_t)$, where t denotes year t. After this conversion, the data obtained from the Health Care CD-ROM is almost equal to that of the ANBERD database for the fifteen countries whose data are collected in both databases. The minimum value of the R&D spending among these fifteen countries is 1.79 million PPP$, and the maximum difference in values between R&D data from the two databases is only 91.3 PPP$.

A more crude measure of innovation than R&D expenditure may be number of R&D personnel, including scientists, engineers, technicians and any other employees involved in R&D. This variable is even less available than R&D expenditure: it is only observed for ten OECD countries from 1987-1996, with data missing in certain years. This variable is also used in one of the regression specifications to test robustness of results.

Total R&D expenditure at the country level comes from the World Development Indicator database. Fundamental and applied research and experimental development work leading to new devices, products, or processes are included in the expenditure account. There are many missing data points, especially prior to 1990. I use simple interpolation to fill in missing data in the cases where I can, since the total R&D time series tends to be smooth. I specify the model below to impute an industry level R&D for the non-OECD countries: $\log(R\&D_j) = \beta_0 + \beta_1 * \log(TOTRD_j) + \beta_2 * \log(GNP_j) + \beta_3 * \log(output_j) + \beta_4 * \log(employment_j) + \varepsilon_j$. where $R\&D_j$ is the pharmaceutical R&D of country j, $TOTRD_j$ is the country-level R&D expenditure, $output_j$ and $employment_j$ refer to those in the pharmaceutical industry of country j, and ε_j denotes the residual.

My rationale for this model starts from the conjecture that industry R&D as a share of industry output in country j can be predicted by the total R&D as a share of the GNP of the country j. (GNP is used instead of GDP because the country level R&D is measured as the percentage of GNP in the WDI database.) The share of industry R&D certainly cannot be predicted perfectly by the total R&D share, because R&D intensity and productivity in

the pharmaceutical industry differ from country to country. This provides the basis for bringing more industry-level variables into the model. Danzon (1997) points out that R&D is risky and its average cost is high in truly innovative drugs. Risky innovation increases the time and capital costs of developing drugs, which in turn raises input costs and employment level. The model specified above yields an $R^2 = .99$ for regressions on the twenty-three OECD countries in all the five periods. The US pharmaceutical company foreign affiliate counts may also help to predict the pharmaceutical R&D, but I choose not to include this variable, because the function of US FDI in the OECD countries can be very different from that in other countries. The imputation gives fifty pharmaceutical R&D observations.

The findings associated with the imputed R&D may well be capturing the change of these imputing components due to national patent legislation. My original rationale for using this variable includes testing the change in pharmaceutical industry-level variables after national patenting. However, total domestic R&D tends to have a substantial weight in predicting pharmaceutical R&D compared to the other variables in the imputation model. Regression runs using this imputed pharmaceutical R&D may potentially be testing the response of total R&D to national patent law, and lead to insignificant results. However, it is worth noting that regression on imputed R&D only constitutes a small part of the analyses, and other regression results overwhelmingly show similar insignificant coefficients on the patent indicators.

APPENDIX II. Mahalanobis Distance Calculations

The matching distance follows the standard Mahalanobis metric calculation, and takes the form $(\sqrt{(}\ (Xa - X_b)'(invcov)(Xa - X_b)\ )\ )$, where Xa and X_b denote the vectors of covariates for countries A and B respectively, and invcov denotes the inverse of the pooled variance-covariance matrix of the covariates that are observed for the country that switched policy. This pooled variance-covariance matrix is calculated in a fashion similar to that in a multivariate analysis of variance (MANOVA)[2]. The intuition of the Mahalanobis distance formula can be explained in the following way. Starting with the simple case of a two-dimensional coordinate system, the Pythagorean theorem implies that the distance between any two points is equal to the square root of $(x1-y1)^2 + (x2-y2)^2$. Further geometry extends this result to the n-dimensional space: $d(A, B) = \text{sqrt}\ [(x1-y1)^2+(x2-y2)^2 +\ldots+(xn-yn)^2]$. Simple Euclidean distance, motivated by the Pythagorean theorem, is unsatisfactory for our statistical purposes for two reasons. First, each coordinate contributes equally to the calculation of Euclidean distance. Second, the coordinates are assumed to be orthogonal to each other, which does not apply to practical cases where the covariates are correlated with each other. The inclusion of the VC matrix in the Mahalanobis formula adjusts for the above two factors (Johnson&Wichern 1992). The inclusion of the VC matrix also gives rise to another advantage of Mahalanobis matching -- it matches the interactions of the country covariates automatically, even though these interaction variables are not generated and included as additional matching covariates (Rubin 1973). Therefore, Mahalanobis matching results in a composite score for all the covariates.

One limitation of the Mahalanobis matching method is that it is not designed to match categorical variables, such as the legal families and price control variables used in this study. Inclusion of these categorical variables most likely complicates the VC calculations and makes the matching inaccurate. To overcome this difficulty and still include the important discrete variables in matching, I use the propensity score of these categorical variables as a summary statistic, which is continuous, to be one of the matching variables.

[2] In calculating the pooled variance-covariance (henceforth abbreviated as VC) matrix for the control group and the group of countries that switched policies, the two groups are centered around their own means respectively. In cases when the switched group is so small that the VC matrix is singular (when the degree of freedom is 0 or negative), then only the VC matrix of the control group is used. The final formula for calculating the pooled VC is: $((DF_t -1)*VC_t + (DF_c-1)*VC_c)/(DF_t + DF_c - 2)$, where DF stands for degree of freedom, and subscript t refers to the treatment group, and c refers to the control group.

That is, I calculate the implied probability of having national pharmaceutical patent law (the estimated propensity score), which is simply the predicted value from the logistic regression of the patent implementation indicator on the non-continuous variables. This propensity score can be perceived as a one-dimensional composite score of the discrete variables. This new variable—the propensity score—is then included as one of the matching covariates, together with all the other continuous variables.

Missing data prevent completely matching all the covariates in one pass, because different observations are missing different variables, and this complicates the calculation of the variance-covariance matrix used in the Mahalanobis distance. Therefore, I modify this method by matching in two passes. In the first pass I use only the country level variables that are observed for almost all the sampling countries. I group the observations according to their missing patterns in these covariates before matching. This first pass matching orders the countries in the two control groups according to their Mahalanobis distances to each of the new-patent countries. I keep a list of countries that are the closest or the next-closest matches to each of the new-patent countries, together with the new-patent countries, to form a reduced sample of countries. There are eighteen countries in this reduced sample that have missing data in industry level covariates. I then search for data for these countries by looking through their National Statistical Abstracts and the UN Industrial Statistics Yearbook. I was able to fill in most of the missing values so that the reduced sample is ready for the second matching pass. There are still a few countries in this reduced sample whose industry data are not found, and these observations have to be dropped out of the second pass of matching. In this second pass, I pair up the countries using all the matching covariates.

To test the robustness of the matching algorithm, I tried several specifications of matching covariates. For each specification, the key variables (such as GDP per capita PPP, pharmaceutical industry employment and exports to the US) are included with different combinations of other control variables. Several rounds of matching using different combinations of matching variables are performed until the balances of covariates are the best. I checked all the variable values for the matched pairs, and the matching seems to make practical sense.

APPENDIX III. Robustness Results

a. Robustness Checks on the R&D outcome

Instead of using R&D in the same year as the domestic patent implementation as a basis for comparison, lagged year R&D (both one-year and two-year) was used in a series of robustness regression tests. There were no statistically significant coefficients on the "PAT" or "PATMOD".

Although the majority of regression results provided no evidence to reject the null hypothesis that national patent law has no direct effect on R&D incentives, there may still be instances where some individual countries had increases in R&D. However, these increases may have been masked by the insignificant results of all the other countries within the sample. In order to detect such instances, I plotted the residuals against the predicted values for each regression run, and found no abnormal observations in most cases. The only exception has in the regression using one-period forward R&D expenditure for the OECD countries. There are two countries with high positive residuals—Canada and Norway, while a large negative residual is attributable to Turkey. This finding involving Canada corroborates that of Pazderka (1999) and McFetridge (1996), highlighting Canada's boost in R&D following its 1987 Act to abolish compulsory licensing for pharmaceuticals[3]. Norway, on the other hand, increased its domestic R&D from $9.92 million in the period of 1983-5 to $32.10 million in the next period (1986-90), although it did not have pharmaceutical product patents until 1992. A closer reading of the data reveals that R&D increased in Norway at an annual growth rate of approximately 30% after 1986, peaking in 1993, to finally plateau and decline in the late 1990s. It could be that Norwegian domestic innovators increased their R&D activities in earlier years in anticipation of the upcoming patent law. However, the implication that this response started six years ahead of the actual implementation of the law is unpersuasive. Given that the increase in Canadian R&D is in a large part due to the political commitment of the PMAC, this observation alone does not

[3] My data divulge an increase from an average annual value of $118.70 million in the period of 1986-90 to $285.90 million in the period of 1991-5. Most of the increase in Canadian R&D occurred after 1988; its domestic average R&D during the period of 1983-5 was $54.04.

provide enough evidence to reject the null hypothesis in the one-period forward R&D regression.

Regression models are also applied to the R&D scientists, technicians and engineers (RSE). This variable is only observed for ten OECD countries, and the results for these countries corroborate those obtained in the regressions of R&D expenditures (Table 12-17). Because there are very few observations, coefficients are only estimated when using period comparisons of RSE. My attempt to compare RSE changes for one-year and two-year forward fails to yield estimates on the patent implementation indicator.

b. Other Robustness Checks

Besides the already-mentioned robustness checks, random effects regression models are performed instead of fixed-effects. In addition, the constructed "innovative potential" variable may be capturing the difference between patent awards in pharmaceuticals and those in other industries due to the implementation of pharmaceutical patent protection. Therefore, I carried out robustness regressions that did not include this control variable. The regression results have been consistent over all specifications. Once again, this robustness is partly attributed to the matching procedure. The main finding in all cases is that implementation of national patent protection in the sampled countries only brings about statistically significant increases in the US patent awards to domestic innovators and in R&D expenditure, conditional on economic freedom and domestic development.

To test the overall importance of patent treatment on innovation, a propensity score "treat" is generated as a summary score of all the patent protection characteristics. I regress the patent implementation indicator variable on the process patent indicator variable, the interaction variables between the patent implementation indicator "PAT" and per capita GDP in PPP terms, between "PAT" and IPR score variable, between "PAT" and economic freedom, between "PAT" and education attainment, and between "PAT" and price control indicator. The variable "treat" is then the predicted outcome variable from this regression. Seemingly Unrelated Regression is then carried out regressing the US patent awards of

various years on "treat" and a set of country covariates. There are still no statistically significant coefficients on the "treat" variable (Table 7).

Previous literature also identified the likely importance of the inequality factor for countries' innovative potentials. In particular, countries at the top income levels tend to dominate in innovation. In light of this, I generated a dummy variable "topPPP", which takes on value 1 if a country's log(GDPpcPPP) is one standard deviation above the sample mean, and 0 otherwise. The regression results including this variable are similar to those in the other specifications, and there is no statistically significant coefficient on this inequality indicator variable at the 10% level.

Moreover, I have carried out sensitivity analyses on my regression models (testing the importance of each right-hand side variable in the regression by removing one variable at a time and check the coefficient changes in all other variables). The regression applied to the sample after matching obtains results robust to various specifications. Neither the coefficient magnitudes nor significance levels experienced memorable changes.