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The Impact of Stronger Property Rights in Pharmaceuticals on Innovation in Developed and Developing Countries

by
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Abstract

An instrumental variable econometric model is specified to investigate how changes in a country's patent protection for pharmaceutical innovations are related to patent awards from the U.S. Patent and Trademark Office to the country's applicants. We use a new measure of patent protection for pharmaceutical innovations, the PIPP Index, to account for cross-country variation in pharmaceutical protection. Using GMM and other IV estimators, we find that stronger pharmaceutical patent protection in the applicant's home country does not increase the number of U.S. pharmaceutical patents awarded to developed and developing country inventors.

Keywords**:** Patent, pharmaceutical, GMM, instrument, innovation, TRIPS

JEL**:** O1; O31; O34;

1. Introduction

Over the last 30 years, virtually every country has substantially strengthened its patent system. Changes in the patent systems of developing countries have taken place partly because of changes in the size and structure of their own economies and partly because of diplomatic pressure exerted on them by the European Union and the United States. This diplomatic activity culminated in 1995 with the establishment of the World Trade Organization and the Agreement on Trade-Related Aspects of Intellectual Property Rights (TRIPS). TRIPS obligated WTO members to substantially strengthen and harmonize patent rights.

There is controversy regarding how stronger patent rights affect innovation and welfare in both developing and developed countries. The conventional economic rationale for stronger patent rights is that they stimulate inventions of new products and technologies (Arrow 1962; Nordhaus 1969; Scherer 1972), promote domestic and foreign investment (Maskus 1998; Javorcik 2004), facilitate technology transfer, and improve the availability of essential medicines (Giacotto *et al.* 2005; Vernon 2005). The conventional arguments were challenged by the "North-South" general equilibrium models of patent protection in which increases in patent protection in the developing South reduce innovation in the developed North under plausible assumptions and parameter specifications (e.g., Deardorff 1992; Helpman 1993; Grossman and Lai 2004; Parello 2008).[1]

A large empirical literature has arisen to examine the relationship between patent strength and innovation in both developed and developing countries, e.g., Maskus and Yang 2001; Chen and Puttitanun 2005; Allred and Park 2007; Branstetter et al. 2006 and 2011, and

[1] See Park (2008) for a survey of the literature relating stronger IPRs to national and international innovation.

Lerner 2009. Virtually all papers since the late 1990s have used the Ginarte-Park Patent Index as a measure of the strength of a country's patent system and have typically acknowledged that patent strength is likely to be endogenous, affected by a country's flow of innovations and its level of economic development. Most studies have, however, been unable to effectively control for the endogeneity of the patent index, as they have been unable to identify strong and valid excluded instrumental variables. Moreover, while the use of an index measuring the overall strength of a country's patent system is appropriate for an economy-wide analysis of innovation, it is less appropriate for studies of innovation in particular industries as the strength of patent protection typically varies substantially across industries. This problem is particularly acute for studies of the pharmaceutical industry, as IPRs protecting pharmaceutical innovations in both developed and developing countries have frequently been weaker than the patent protection provided to innovations in other industries.

Our study is the first to use an industry-specific index of patent protection to estimate the cross-country effects of patent protection on innovation. We utilize the recently developed Pharmaceutical Intellectual Property Protection (PIPP) Index to undertake a cross-country analysis of the effect of a country's patent protection for pharmaceutical innovations on pharmaceutical patents awarded by the United States Patent and Trademark Office to the country's researchers (Liu 2008; Liu and La Croix 2008 and 2011). Our empirical research uses a panel of 92 developed and developing countries with complete data over four 5-year intervals in the 1985 to 2000 period. Since the PIPP Index is endogenously determined and subject to measurement errors, we recognize that an OLS estimate of the coefficient on the PIPP Index will be attenuated. To remedy these problems, our analysis employs two instrumental variables—WTO-Cases and USTR Listings[2]—to identify the effect of the PIPP Index on pharmaceutical innovations patented by developed and developing country residents in the United States.

We report results from three estimation techniques: pooled two-stage least squares (2SLS), Limited Information Maximum Likelihood (LIML), and pooled Generalized Method of Moments (GMM). Results from each of these models generally reveal a positive estimated coefficient on the PIPP Index for both the developed and developing country samples, which is, however, statistically insignificant at the 10 percent level.

2. Literature Review

Until recently, most empirical studies of the effects of stronger patent rights on R&D and patent awards analyzed either firm-level data for a specific country or national data for a sample of developed countries (Comanor and Scherer 1969; Griliches and Mairesse 1984; Goto and Suzuki 1989; Giaccotto et al. 2005; Branstetter et al. 2006). The focus on analyzing data samples from developed countries was due to four factors: (1) The relatively small amount of R&D activity in developing countries, (2) their weak patent laws and facilitating organizations, (3) a lack of reliable data on inputs to and outputs from R&D activities within developing countries, and (4) the absence of a quantitative measure of the scope and strength of each country's patent protection for specific industries. The last point is particularly important, as national patent laws continue to differ substantially across countries even after the harmonization of patent laws resulting from the 1995 TRIPS Agreement (Maskus, 2000; La Croix and Liu, 2008).

Ginarte and Park's (1997) index of national patent rights provided researchers with

2 We discuss the two instrumental variables in detail in Section 3.

the first comprehensive measure of the strength of a country's patent laws, incorporating measures of the patent law's scope, the nature of the property rights provided, treatment of foreign applicants and patent holders, and public and private enforcement provisions. The Ginarte-Park Patent Index's coverage of both developing and developed countries facilitated an extension of earlier research on the determinants of R&D and innovative outputs in developed countries to developing countries (Lai and Yan 2007; Chen and Puttitanun 2005). Chen and Puttitanun (2005) found that within their sample of 65 developing countries, increases in the Ginarte-Park Index were negatively related to R&D activity. Allred and Park (2007) found that "[p]atent protection has an inverted-U relationship with foreign patent filings (that is, stimulates international diffusion of innovation up to some point) in developed countries, but no significant relationship in developing countries" (p. 895).

A natural extension of studies of the effect of patent strength on overall economic innovation is to examine how the effect of patent strength for innovations in particular industries affects innovation within those industries. This is particularly important for industries in which product development is lengthy, uncertain, and expensive, and imitation by competitors is quick and cheap. The chemical and pharmaceutical industries are the most prominent examples (Taylor and Silberston, 1973; Scherer 1977; Mansfield 1986; Levin et al. 1987; Tocker 1988). The empirical literature studying the effect of increased patent protection for pharmaceutical innovations on patenting behavior has three strands: case studies of a single country that examine changes in aggregate or industry-level innovation data; regression analysis of pooled cross-sections of matched country pairs; and panel regression analysis of country-level data using instrumental variables to account for endogeneity and measurement error. We discuss each of the three strands of research below.

Case studies have found that the impact of country decisions to award pharmaceutical product patents differs considerably across countries. Kawaura and La Croix (1995, Table V) found that after Japan's introduction of a pharmaceutical product patent in 1975, annual pharmaceutical process patent applications to the Japanese Patent Office declined from 3,373 in 1975 to an average of 970 in the 1978-1982 period, whereas applications for pharmaceutical product patents jumped to an average of 1,818 in the 1978-1982 period. La Croix and Kawaura (1997) found that the introduction of pharmaceutical product patents in Korea in 1986 led to a 74 percent decline in the value of Korean pharmaceutical companies listed on the Korea Stock Exchange. McFetridge (1997) and Pazderka (1999) investigated how Canadian pharmaceutical R&D expenditures changed after pharmaceutical product patents were instituted in 1987, and both found positive and statistically significant effects. Scherer and Weisburst (1995) found that Italy's transition in 1977 to pharmaceutical product patents was not associated with a significant increase in R&D expenditures by domestic pharmaceutical manufacturers.

Qian's (2007) econometric study of the impact on pharmaceutical product patents represents the second strand of the literature. It addresses the endogeneity of patent law provisions by using Mahalanobis matching methods to create several smaller samples of matched countries. Qian's econometric analysis uses 5-year and 3-year averaged data for 85 countries from 1980 to 1999 to estimate the impact of instituting pharmaceutical product patents on the citation-adjusted pharmaceutical product patents awarded to each country's residents by the USPTO. After controlling for country-specific factors and industry-level variables that could affect innovative potential, the estimated coefficient on the bivariate pharmaceutical product patent variable is not statistically significant at the ten percent level.

However, estimated coefficients for interaction terms between the bivariate pharmaceutical product patent variable and the log of per capita GDP (positive and statistically significant at the 10 or 5 percent level in all three specifications), the log of average years of schooling of the population (positive and statistically significant at the 5 percent level in two of three specifications), and the log of the Frasier Institute's Economic Freedom of the World Index (positive and significant at the 5 percent level in one of three specifications). Qian concludes that "…patent laws in nations with high levels of development, education, and economic freedom do stimulate innovation [in new pharmaceutical products]" (p. 436).

The third strand of the literature uses instrumental variables to overcome the bias associated with using OLS to estimate the coefficient for the measure of patent strength. Maskus and Penubarti (1995) found that an early index of patent protection—the Rapp and Rozek Index (Rapp and Rozek 1990)—was endogenously determined. They found a positive relationship between the Rapp-Rozek Index and GNP per capita as well as a more tentative U-shaped relationship between the Index and GNP. Ginarte and Park (1997) and Maskus (2000) provided econometric analyses of the determinants of the Ginarte-Park Patent Index. Ginarte and Park's (1997) central finding from their empirical analysis was that "more developed countries tend to provide stronger [patent] protection" (p. 283). Maskus (2000) extended Ginarte and Park's research by adding more countries to their sample and the square of log GDP per capita to the regression specification. He identified a U-shaped, statistically significant relationship between the log of GDP per capita and the Ginarte-Park Patent Index.[3]

Chen and Puttitanun (2005) built a two-sector open economy model of innovation within a developing country. Domestic firms in the import sector imitate the technology

[3] Lerner (2002a) found results similar to those in Maskus (2000).

used by a developed country exporter, while in the non-traded goods sector, some firms are capable of developing new technologies to produce new products while other local firms imitate their technologies and products. By introducing innovation by developing country firms into a growth model incorporating quality ladders and product cycles, Chen and Puttitanun were able to model the tradeoff faced by firms in developing countries between imitative and innovative activities.

Chen and Puttitanun tested their model using panel data spanning 64 developing countries and six five-year data aggregates covering the 1975-2000 period. They specified a triangular system of two simultaneous equations, one for patent protection and one for domestic innovation. Estimating the system using 2SLS and with pooled first-differenced data, they found that an increase in patent strength (as measured by the Ginarte-Park Patent Index) on innovation (as measured by patents awarded to country residents by the U.S.P.T.O.) is positive in each of the four specifications and statistically significant at the five percent level in two of four specifications. A first-stage regression on the Ginarte-Park Patent Index points to an inverted U-shaped relationship between the Index and GDP per capita.

Branstetter et al. (2011) investigates whether an increase in the strength of a country's patent system (as measured by the Ginarte-Park Index) is associated with an increase in the scale of activities by U.S. multinational enterprises (MNEs) in the country. They identify 16 countries that significantly strengthened their patent system over the 1980s and 1990s and estimate the impact of these changes on U.S. MNE foreign direct investment, technology transfer, employment compensation, and R&D spending (p. 28). Their econometric findings reveal substantial and statistically significant increases (at the five percent level) in all of these activities. Moreover, their results indicate that "any decline in indigenous innovation is more than offset by an expanded range of goods being produced by MNEs and other firms" (p. 28).

A recent study by Lerner (2009) uses methodologies that are closely related to those used in this study. Lerner investigates how 177 major changes in 60 large countries' patent laws between 1850 and 1999 affected the propensity of each country's residents to file patent applications for their inventions in the United Kingdom. His decision to focus on international patenting activity in the United Kingdom was driven by the availability of long data series on patent applications in the United Kingdom as well as by its "relatively constant patent policy" (p. 343). Controlling for changes in the overall propensity to patent over time and using a weighted least squares estimator, Lerner finds that the impact of a positive change in patent protection depends on the country's initial level of patent protection. Countries with weak initial patent protection that implemented a substantial positive change in patent protection had statistically significant (at the five percent level) *increases* in UK patent applications from their researchers, while countries with strong initial patent protection that implemented a positive change had statistically significant (at the five percent level) *decreases* in UK patent applications from their researchers. Instrumenting for positive changes in patent protection did not appreciably change these results (Lerner, 2009, p. 347).

3. Econometric Issues and Data

This article focuses on estimating the effect of an increase in a country's patent protection for pharmaceutical innovations on the flow of pharmaceutical innovations patented in the United States by the country's researchers. Our base econometric model is a recursive model,

$$Patent_{i,t} = f(PIPP_{i,t}, \quad X_{i,t} \quad \varepsilon_{i,t}) \tag{1}$$

$$PIPP_{i,t} = g(X_{i,t}, \quad I_{i,t}, \quad \mu_{i,t}) \tag{2}$$

where $Patent_{it}$ is our measure of the flow of new pharmaceutical innovations developed by residents of country i at time t (discussed in detail below), $PIPP_{it}$—the Pharmaceutical Innovation Patent Protection Index—is an index measuring the strength of patent protection for pharmaceutical innovations in country i at time t, X_{it} is a vector of control variables and I_{it} is a vector of excluded instrumental variables in the first-stage regression.

Our measure of a country's flow of pharmaceutical innovations is the number of pharmaceutical patents awarded by the USPTO to the country's residents and corporations. This is a standard measure of the source of international innovations that has been widely used by other researchers analyzing cross-country innovation rates as well as innovation in specific industries e.g., Comanor and Scherer (1969), Basberg (1987), Pavitt (1988), Griliches (1990), Chen and Puttitanun (2005), Yi (2007), Allred and Park (2007), and Park (2008). A central reason to use patents issued by one of the world's two largest economies is that the process of patent review and standards for issuing a patent are held constant across applicants from different countries.[4] The raw patent data are available over the 1963-2004 period from databases compiled by the USPTO (2007) and the National Bureau of Economic Research (Hall et al. 2001). We assign a patent application or patent award to the country of residence reported for the first listed applicant. Since our regression analysis uses data at five-year intervals, we sum annual data on patents awarded to residents of a particular

[4] This, however, assumes that U.S. patent examiners do not discriminate with respect to the nationality of the applicant.

country for the observation year and the previous four years, e.g., the 1985 observation is the sum of patent awards from 1981 to 1985.

To measure the strength of a country's provision of property rights in pharmaceutical innovations, we use the Pharmaceutical Intellectual Property Protection ($PIPP_{it}$) Index (Liu and La Croix 2011). Ranging over the interval [0, 5], $PIPP_{it}$ provides virtually complete annual data for 154 countries from 1960 to 2005. It aggregates three types of information for each country: (1) the range of pharmaceutical innovations for which the country provides intellectual property protection; (2) provisions of the country's statute and case law limiting the duration of pharmaceutical patent rights and increasing the ability of a pharmaceutical patent holder to enforce rights; and (3) the country's participation in international agreements that allow a pharmaceutical innovation developed in one country to receive protection in other member countries. We emphasize that the PIPP Index measures the provisions contained in each country's statutory and case laws governing pharmaceutical innovation and does not measure whether its patent laws were actually enforced.[5]

Our regression estimates include country-specific controls for output per capita; the stock of human capital; and legal, governance, and regulatory institutions and policies, some of which are correlated with $PIPP_{it}$. The endogeneity of $PIPP_{it}$ implies that the estimated OLS coefficient on $PIPP_{it}$ will be biased. A typical solution to this problem is to identify excluded instruments for $PIPP_{it}$.

Two variables stand out as candidates for excluded instruments: (1) The designation of countries by the Office of the U.S. Trade Representative for diplomatic pressure due to weak intellectual property rights and (2) WTO disputes brought under the TRIPS Agreement.

[5] For each five-year interval, $PIPP_{it}$ is the average of the interval year and the four previous years e.g., a country's PIPP score for the 1981-1985 interval is the average of PIPP scores from 1981 to 1985.

The USTR variable provides a measure of pressure from the U.S. government on the foreign country's government to upgrade its IPR statutes to provide additional depth and scope of protection for intellectual property and to devote more resources to public enforcement of these laws. Countries targeted by the USTR for IPR violations are reported in its Special 301 Report, which has been published annually from 1984.[6] The Report lists countries for which the USTR has concluded that the country's IPR statutes and/or enforcement of these statutes fail to meet US standards. USTR pressure tends to have roots in complaints from U.S. firms (and industry associations) holding U.S. patents or other protected intellectual property that are sold, licensed, embodied in their exports, or used in plants of their foreign affiliates. The correspondence between a country's listing in the Special 301 Report and the pressure actually brought to bear by the U.S. government varies somewhat, due to strategic importance, recent favors to the U.S. government, or a small internal market that reduces the value of IPR enforcement by the country to U.S. firms.

The USTR explicitly regards the Special 301 process as an instrument to pressure countries into increasing their levels of patent protection. In 2003, the USTR stated[7] that it

> … intercede[s] directly in countries where piracy is especially prevalent or governments are exceptionally tolerant of piracy. Among our most effective tools in this effort is the annual "Special 301" review mandated by Congress in the 1988 Trade Act.
>
> This tool has vastly improved intellectual property standards around the world. Publication of the Special 301 list warns a country of our concerns. And it warns potential investors in that country that their intellectual property rights are not likely to be satisfactorily protected. The listing process itself has often helped win improvements in enforcement. In many cases, these actions lead to permanent improvement in the situation. At times, however, we must use the sanction authority granted to us for worst case offenders.

[6] The USTR did not publish a Special 301 Report in 1988.

[7] USTR, 2004. Fact Sheet: The Work of USTR—Intellectual Property, as quoted in Taylor and Cayford (2004, 372).

We use the USTR Special 301 listing of a country in a given year as an instrument for the PIPP Index. A USTR Special 301 Report listing for a country should be correlated with establishment and strengthening of the country's patent laws due to the U.S. trade sanctions and diplomatic pressure that would otherwise be triggered and the large costs they could impose on the country. A USTR Special 301 listing of a country is, however, unlikely to directly affect the incentives of a foreign country's pharmaceutical firms and researchers to develop pharmaceutical innovations except through the indirect channel of the strength of protection provided to pharmaceutical innovations by the country's patent system.

According to the USTR Special 301 Reports, countries are grouped in one of three categories, in increasing order of severity: Watch List (WL), Priority Watch List (PWL), and Priority Foreign Country (PFC). To be on the WL simply indicates the USTR's registration of deficient policies and practices in IP protection. PWL status indicates a greater concern about IP protection from the United States and signals heightened U.S. vigilance. PFC status shows even higher concern than PWL. Before 1998, the USTR Special 301 also included some countries in "Other Observations," which was considered as being less serious than being included on the Watch List. The USTR also has a "306 monitoring" category that is less serious than a PFC listing bur more serious than a PWL listing.

Following previous research, we code the annual USTR variable as 5 for PFC countries, 4 for 306 monitoring countries, 3 for PWL countries, 2 for WL countries and 1.5 for other observations. Countries not listed in the annual USTR Special 301 report receive a value of 1. We use a two-year lag because of the time required for a foreign government to respond to the Special 301 listing, change enforcement practices, and draft and enact new IPR legislation.[8]

Our second candidate to serve as an instrumental variable is $WTO\text{-}Cases_{it}$. A member of the World Trade Organization (WTO) can initiate a dispute with the WTO's Dispute Settlement Body when it believes that the policies or actions of another member country are violating the WTO Agreement. A country, if listed as a respondent to a dispute involving patent provisions in the TRIPS Agreement, is assigned an annual value of 1 from the year in which the WTO case was initiated until the year in which it is resolved; otherwise the value is zero. There are 11 such cases, all of which were initiated before 2005. In each of the cases, either the United States or an EU member brought a TRIPS Agreement-related complaint against eight other members of the WTO. The argument for using WTO cases brought under TRIPS as an instrumental variable closely parallels the argument for using Special 301 listings as an instrument: A WTO IPR case puts pressure on the targeted government to strengthen its IPR statutes and enforcement, including those related to pharmaceutical patent protection, yet should not directly affect the incentives of a country's pharmaceutical firms and researchers.

Our first-stage regression includes several control variables. Following earlier studies of the Ginarte-Park Patent Index (1997), we include $ln(GDP)_{it}$ and $[ln(GDP)_{it}]^2$, the country's population to control for scale effects ($\ln Population_{it}$), and a proxy for the pharmaceutical industry's human capital stock—the percent of the country's population with some tertiary education—to control for innovative capacity ($\ln TerEducation_{it}$).[9] Ginarte and Park (1997)

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[8] Thus, USTR in 1985 is the average of the annual 1979-1983 USTR observations.

[9] Real GDP per capita is from the World Development Indicators (WDI) database 2005. Population data are from the World Development Indicator (WDI) database. GDP_{it} and $Population_{it}$ are calculated as five-year averages.

and Maskus (2000) used secondary school enrollment rates provided by Barro and Lee (2000). We have chosen to use data on educational attainment rather than enrollment due to the development by Lutz et al. (2007) of a sophisticated new data on educational attainment that covers both developed and developing countries. We use data on tertiary educational attainment because workers in developed countries' pharmaceutical industries are more likely to have some college education than the typical resident. For example, 43 percent of employees in Canada's pharmaceutical industry had B.A. degrees in 1996[10], and 33 percent of employees in the chemical industry in European Union (EU) countries had a tertiary level education in 2005 compared with 23 percent of employees in the total EU labor force.[11]

To control for the quality of a country's institutions and policies governing markets, firms, international trade, money, and the government fisc, we follow Chen and Puttitanun (2005) and Yi (2007) and include the Economic Freedom of the World Index ($EconFreedom_{it}$) in our regression specifications. The Index aggregates five categories measuring the size of government expenditures, taxation, and enterprises; openness to international trade; access to sound money; regulation of business, trade, and credit; and legal structure and security of property rights (Frasier Institute 2005). It covers 123 countries and was reported at five-year intervals from 1970 to 2000 and annually from 2000.[12] We expect a positive relationship between $EconFreedom_{it}$ and $PIPP_{it}$ because specialized patent

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[10] Human Resources and Skills Development, Government of Canada, 2011. Pharmaceutical and Medicine Industry, Employment. Available at http://www.hrsdc.gc.ca/eng/hip/hrp/sp/industry_profiles/pharmaceutical_medicine.shtml. (last access on August 20, 2011)

[11] EU Employment data are from http://www.eds-destatis.de/en/downloads/sif/np_05_44.pdf. (last access on August 20, 2011). We have been unable to identify adequate educational attainment for employees in pharmaceutical industries in developing countries.

[12] In their econometric analysis, Ginarte and Park (1997) used a different index of institutions and policies, the Heritage Foundation's Market Freedom Index.

protection for pharmaceutical innovations requires complementary legal, regulatory, and governance institutions for pharmaceutical patents to be enforced and well functioning labor, capital, and product markets for firms to undertake innovation and bring pharmaceuticals to market.

The dependent variables in both the first- and second-stage regressions have two properties that could affect choice of estimators. First, the dependent variable in the second-stage regression—the annual number of USPTO pharmaceutical patents granted to a country's residents—is non-negative count data. Second, our dependent variable in the first-stage regression—$PIPP_{it}$—is restricted to the interval [0, 5]. To account for these characteristics, we use a GMM estimator as our benchmark specification. Two advantages of GMM are that it is robust to misspecifications and that in the presence of heteroskedasticity, the GMM estimator is more efficient than the simple IV estimator (Baum, et al. 2003, 2007).[13] In general, if both structural equations are identified and there are no restrictions on the structural parameters, then 2SLS, GMM and Limited Information Maximum Likelihood (LIML) should produce the same estimates. A LIML estimator (obtained from large sample asymptotic expansions) is median unbiased on the assumption that a maximum likelihood estimation will have better properties in some well-defined sense. This is because it uses more information than a GMM estimator. Thus, we estimate the two regressions using both GMM and LIML estimators.[14]

Our data set covers 25 developed and 66 developing countries. We classify a country as developed (developing) if its real GDP per capita was greater (less) than US$10,000 in

[13] If the data are not heteroskedastic, then the GMM estimator is no worse asymptotically than the IV estimator.

[14] We pool our five-year aggregate samples rather than run a panel analysis, because fixed effect panel analysis does not support an endogenous right-hand-side variable that is used to test a hypothesis.

2000. Table 1 displays summary statistics from developed and developing countries data sets. Figure 1 compares the average PIPP Index value for developed and developing countries

<Table 1 and Figure 1 are here>

from 1980 to 2005. In the early 1980s, average values of the PIPP Index were very low—less than .0.6--for both developing and developed countries. Only when a first draft of what would become the TRIPS Agreement began to circulate among WTO members in 1990 did average PIPP values for developing countries start to increase substantially. Increases in average PIPP values for both developed and developing countries did not, however, lead to convergence of the two series. In 1981, the gap between average PIPP values in developing and developed countries was just 0.32, but over the next 16 years it would increase to its historical maximum, 2.20. From there, it fell to 1.86 in 2000 and 1.59 in 2005.

We found a similar pattern for the number of pharmaceutical patent awards to residents of developed and developing countries. Figure 2 shows that in 1985 the average number of patent grants was 132 for residents of developed countries and just 3.74 for residents of developing countries. By 2000, the average number of patent grants had increased for both sets of countries, to 358 for developed countries and 16 for developing countries.

< Figure 2 here>

4. Econometric Results

We begin with an examination of results from second-state regressions in which the PIPP Index enters directly rather than instrumental variables for the index. We run the following pooled OLS regression specification with and without time dummies for both developed and developing countries:

$$Patent_{it} = \beta_0 + \beta_1 PIPP_{it} + \beta_2 \ln(GDP) + \beta_3 \ln(Population_{it}) + \beta_4 \ln(TerEducation_{it}) + \beta_5 \ln(EconFreedom) + \alpha_t + \varepsilon_{it}$$

where α_t is a vector of time dummy variables and ε_{it} is an error term. Results are reported in Table 2. Estimated coefficients on $PIPP_{it}$ for developing countries are positive in specifications without time dummies (column 1) and with time dummies (column 2) and are all statistically insignificant at the ten percent level. Estimated coefficients on $PIPP_{it}$ for developed countries are negative in the specifications without time dummies (column 3) and with time dummies (column 4) but, once again, are both statistically insignificant at the ten percent level. The results parallel those obtained by Lerner (2009), who finds that an increase in the strength of a country's patent laws has a positive and statistically significant correlation with U.K. patents issued to the country's residents when the country's initial level of patent protection is weak and a negative and statistically significant effect when its initial level of patent protection is strong. The remainder of this paper is dedicated to investigating instrumental specifications of the PIPP index that could allow us to account for both endogeneity and measurement errors that could bias estimated coefficients and standard errors for $PIPP_{it}$ in the OLS specifications reported in Table 2.

4.1 Results from First-Stage Regressions

Results for developing countries from the first-stage regressions are reported in Table 3. Column 1 reports pooled OLS results. The estimated coefficients of $ln(GDP)_{it}$ are negative

[Table 3 here]

but statistically insignificant at the ten percent level, while the estimated coefficients of $(lnGDP_{it})^2$ are positive and statistically insignificant at the ten percent level. Similarly, when we add time dummies or use tobit estimators (see columns 2, 3 and 4), estimated coefficients on $ln(GDP_{it})$ and $(lnGDP_{it})^2$ continue to be statistically insignificant. These results indicate that the higher rank of GDP per capita should not be included in the model for developing countries in the first-stage estimation.

The estimated coefficient on $\ln(TerEducation_{it})$ is negative and statistically significant at the five percent level. In our discussion above (section 3.2), we noted there is no definitive prediction for the coefficient of school attainment because higher school attainment increases the demand for patents by increasing R&D capabilities but decreases it by increasing the ability to imitate innovations developed both inside and outside of the country. The estimated coefficient on $ln(EconFreedom_{it})$ is positive and statistically significant at the five percent level.

The estimated coefficient for the $USTR_{it}$ instrumental variable is positive and statistically significant. The effect of being listed one step higher level in classification schemes used by the USTR Special 301 Report increases a country's pharmaceutical patent protections by 0.52. The estimated coefficient for the second instrumental variable, $WTO\text{-}Cases_{it}$, is also positive and statistically significant at the five percent level.

Column 2 reports OLS estimates with time dummies. Estimated coefficients for all control variables and instruments have the same sign as those estimated in the OLS model without time dummies (column 1). The coefficients of $\ln(GDP)_{it}$ and $(\ln GDP_{it})^2$ are statistically insignificant at the ten percent level. The estimated coefficients for the 1990, 1995 and 2000 time dummies are all positive and statistically significant at the 5 percent level. This is consistent with increases in the strength of patent laws in developing countries in these periods. However, estimated coefficients for both instruments, $USTR_{it}$ and *WTO-*

Cases$_{it}$, become statistically insignificant at the ten percent level. In other words, the instruments are not valid when we add time dummies to the regression. Because neither instrumental variable is statistically significant, we cannot apply instrumental estimation methods to the second stage with this specification of the first-stage equation.

Columns 3 and 4 report Tobit estimates with and without time dummies for comparison purposes. Although we cannot use the predicted results from the Tobit model in the second-stage regressions, we use Tobit estimates to determine whether our first-stage OLS estimates are robust to specification changes. Estimated coefficients show the same signs, magnitudes, and statistical significance as the OLS results (reported in columns 1 and 2).

Because the OLS results reported in columns 1 through 4 show that the U-shaped relationship between $\ln(GDP_{it})$ and $PIPP_{it}$ may not exist, we exclude $(lnGDP_{it})^2$ from our next specification. Moreover, $WTO\text{-}Cases_{it}$ is statistically insignificant at the ten percent level in all specifications. Sagan's J statistic (11.324 with *p*-value of .001) for the second step of our instrumental variables rejects the null hypothesis, which indicates that the instrument $WTO\text{-}Cases_{it}$ may not be valid. Thus, we exclude it from our specification for developing countries. Results from this revised specification are reported in column 5 and 6. The estimated coefficient on $\ln(GDP_{it})$ becomes positive and statistically significant at the five percent level, and the magnitude and statistical significance of estimated coefficients for all other covariates do not change appreciably.

<Table 4 here>

Results from first-stage regressions using our developed country sample are reported in Table 4. Column 1 reports results from the pooled OLS model. Estimated coefficients for

$\ln(GDP_{it})$, $(\ln GDP_{it})^2$ and $\ln(TerEducation_{it})$ are statistically insignificant at the ten percent level. The estimated coefficient of $\ln(EconFreedom_{it})$ is positive and statistically significant at the five percent level.

The estimated coefficient for the instrumental variable $USTR_{it}$ is positive and statistically significant at the five percent level and the estimated coefficient for the instrumental variable $WTO\text{-}Cases_{it}$ is also positive and statistically significant at the 5 percent level. Column 2 reports results when we add time dummies to the specification. The estimated coefficients for the time dummy variables are all positive and statistically significant at the five percent level. This likely reflects the upgrading of patent laws during these periods. Both instruments are statistically insignificant at the ten percent level and are considered to be invalid.

Since both $\ln(GDP_{it})$ and $(\ln GDP_{it})^2$ were statistically insignificant in our initial OLS regressions, we rerun OLS regressions excluding $(\ln GDP_{it})^2$ without time dummies (column 3) and with time dummies (column 4). We find that the estimated coefficient of $\ln(GDP_{it})$ is positive and statistically significant in both specifications. We infer from these results that the relationship between $\ln(GDP_{it})$ and $PIPP_{it}$ is positive and linear rather than *U*-shaped.[15] Column 4 reports OLS estimates with time dummies after excluding the higher order GDP term; the estimated coefficient on $\ln(GDP_{it})$ becomes positive and statistically significant at the five percent level. However, both instruments are, however, statistically insignificant in the specification with time dummies. Thus, the results with time dummies for both the developing and developed countries need to be carefully interpreted.

[15] For a full discussion of the relationship between the PIPP Index and GDP, see La Croix and Liu (2009).

In columns 5 and 6, we report Tobit estimates with and without time dummies for comparison purposes. All estimated coefficients show the same signs and statistical significance as the OLS results in column 3 and 4, respectively.

4.2 Instrumental Variable Estimates of the Effects of the PIPP Index on USPTO Patents

Table 5 reports instrumental variable estimates of the effects of stronger patent protection using the developing countries sample. Column 1 reports estimates from the two-step recursive model in which ln($Population_{it}$) does not enter the first-stage equation. The estimated coefficients for ln(GDP_{it}), ln($TerEducation_{it}$) and ln($EconFreedom_{it}$) are also statistically insignificant at the ten percent level. The only estimated coefficient that is statistically significant (at the five percent level) is ln($Population_{it}$), our proxy for scale effects. The estimated coefficient on $PIPP_{it}$ is statistically insignificant at the ten percent level.

<Table 5 here>

Column 2 reports results using the GMM estimators with two instruments, $USTR_{it}$ and $WTO\text{-}Cases_{it}$. The GMM estimation includes ln($Population_{it}$) in the first-stage as well as the second-stage regressions. Estimated coefficients for control variables are statistically insignificant except those for ln($Population_{it}$) (at the 5 percent level) and ln(GDP_{it}) (at the 10 percent level). The estimated coefficient on $PIPP_{it}$ is positive and statistically insignificant. Column 3 reports results from specifications with time dummy variables included in both stages. The estimated coefficient for $PIPP_{it}$ more than doubles in size, from 3.01 to 7.81 but remains statistically insignificant.

Several standard tests of the validity and strength of instrumental variables are, however, not supportive of the two-instrument GMM specification with time dummy variables. The value of Anderson's Canonical Correlations test is 4.33 (column 3), indicating that the null hypothesis of model identification is rejected. The Hansen J statistic provides a test for overidentifying restrictions in an IV-GMM model, and its value (1.96 in column 3) rejects the null hypothesis, informing us that the model's estimates are invalid. We also utilize the Cragg-Donald Wald F-statistic to test whether the *USTR* instrument is weakly correlated with the endogenous variable (Cragg and Donald 1993). Since the F-statistic (2.12) is lower than the rule of thumb value provided by Staiger and Stock (1997), we conclude that the instruments are weak. In response to these concerns, we re-estimate both specifications without *WTO-Cases* and report results in columns 4 and 5.

Column 4 reports a model specification without time dummies and with only the *USTR* instrument. Since the Cragg-Donald F-statistic (29.08) is higher than the rule of thumb value (10.0) provided by Staiger and Stock (1997), we conclude that the model is exactly identified. The estimated coefficient for $PIPP_{it}$ increases substantially compared to the two instrument specification (from 3.08 to 5.68) but is once again statistically insignificant. Column 5 reports a specification with time dummy variables and with only the *USTR* instrument. The diagnostic tests are similar to those the two-instrument specification with time dummies, leading us to conclude that the instrument is weak and the estimates are invalid. In any case, the estimated coefficient for $PIPP_{it}$ in this specification is once again statistically insignificant. In sum, regardless of the number of instruments used, estimation technique, or inclusion of time dummies, the estimated coefficient for $PIPP_{it}$ is statistically insignificant in all specifications for developing countries.

<Table 6 here>

Table 6 reports several instrumental variable estimates for the developed countries sample. Column 1 reports estimates from the two-step recursive model, and the results are similar to those for developing countries. Estimated coefficients for ln(*Population*$_{it}$) and ln(*GDP*$_{it}$) are statistically significant at the five percent level and coefficients of ln(*EconFreedom*$_{it}$) and ln(*TerEducation*$_{it}$) are statistically significant at the ten percent level. The estimated coefficient for the PIPP index is much higher than the estimated coefficient from the recursive model for developing countries (105.55 vs. 3.08) but remains statistically insignificant.

Column 2 reports results using the GMM estimator with two instruments, *USTR*$_{it}$ and *WTO-Cases*$_{it}$. The GMM estimation includes ln(*Population*$_{it}$) in the first-stage as well as the second-stage regressions. The estimated coefficients for the control variables display the same signs and statistical significance as in in the recursive model. The estimated coefficient for the PIPP Index is positive and slightly smaller in magnitude than the estimated coefficient in the recursive specification (105.55 vs. 111.87), but continues to be statistically insignificant. Diagnostic tests are supportive of the two-instrument specification. The Hansen J statistic (.08) is consistent with validity of both instruments. Since the Cragg-Donald Wald F statistic value (17.07) is higher than rule of thumb value provided by Staiger and Stock (1997), this indicates that the instrumental variables are strongly correlated with the endogenous variables.

Column 3 reports results from specifications with time dummy variables included in both estimation stages. The signs of the estimated coefficients for the control variables are consistent with those from the recursive specification and the GMM specification without time dummies (columns 1 and 2), but estimated coefficients for ln(*TerEducation*$_{it}$) and ln(*EconFreedom*$_{it}$) become statistically insignificant. The Hansen J statistic (.21) is still consistent with validity of both instruments but the value of the Cragg-Donald Wald F statistic value (5.31) is much lower than rule of thumb value (10.0), indicating weak instruments. The estimated coefficient for $PIPP_{it}$ turns negative but remains statistically insignificant. In sum, regardless of the estimation technique or inclusion of time dummies, the estimated coefficient for $PIPP_{it}$ never become statistically significant in any regressions using the developed country sample.

5. Summary of Results and Checks for Robustness

<Table 7 and Table 8 here>

Tables 7 and 8 summarize the results obtained for the estimated coefficient for the PIPP Index using the different estimation methodologies for developing and developed countries, respectively. Table 7, column 1, summarizes estimated coefficients for the PIPP Index obtained from our earlier regression analyses of the developing country sample. Recursive estimates yield the smallest estimated coefficients and are statistically insignificant at the ten percent level. The estimated coefficients obtained using GMM/LIML with and without time dummies are larger but also statistically insignificant.

Our first robustness check on our baseline results is obtained by using an alternative measure of innovation in the pharmaceutical industry as the dependent variable: Pharmaceutical product patent applications filed with the USPTO by researchers residing in country *i*. Results obtained from estimates using patent applications are displayed in Table 7, column 2. Estimated coefficients for $PIPP_{it}$ are not statistically significant at the ten percent level for any specification. Adding time dummies to each of the estimation models does not substantially change the regression results.

Table 8, column 1 reports the estimated coefficients for $PIPP_{it}$ using the same estimation methods that we utilized for developing countries. Again, the estimated coefficients for $PIPP_{it}$ obtained via GMM and LIML methods were higher than estimated coefficients obtained via OLS. The only noticeable difference in the regression estimates for the developed and developing country samples are that the estimated coefficients for $PIPP_{it}$ are much higher than those for developing countries, albeit statistically insignificant at the ten percent level in both samples. Once again, these results persist when we use patent applications rather than patent grants as the dependent variable in our regression analysis (Table 8, column 2).

A second robustness test is to run all regression specifications using Lutz et al.'s measure of secondary school attainment rather than their measure of tertiary school attainment. In the first-stage regressions, we found one substantial change: the estimated coefficient on $(GDP_{it})^2$ was positive and statistically significant at the five percent level. However, the estimated coefficients on $PIPP_{it}$ in the second-stage regressions remained statistically insignificant at the ten percent level (Tables 7 and 8, column 3).

As a third robustness test, we ran regressions using the Barro and Lee (2007) measures of tertiary educational attainment. Using these measures increases the number of developed and developing countries in the samples from 23 to 24 and from 51 to 68, respectively. Again, we found no differences in estimated coefficients on $PIPP_{it}$ in second-stage regressions (Tables 7 and 8, column 4). As a fourth robustness test, we ran regressions that replaced the *EconFreedom* control variable with a standard (albeit flawed) proxy for economic openness, the share of imports and exports in GDP. We find once again statistically insignificant estimated coefficients for $PIPP_{it}$ (Tables 7 and 8, column 5). For a fifth robustness test, we ran regression specifications using both $PIPP_{it}$ and $(PIPP_{it})^2$ in the second-stage regressions.[16] Regression results reveal that estimated coefficients for both orders of $PIPP_{it}$ and their instruments are statistically insignificant at the ten percent level for both developed and developing country samples.

In sum, estimated coefficients on $PIPP_{it}$ in both developed and developing country specifications survive changes in the dependent variable (patent applications vs. patent grants), alternative measure of covariates (education, openness, and economic freedom), and regression estimation techniques.

6. Conclusion

With the aid of a newly developed index measuring the strength of a country's patent protection of pharmaceutical innovations, the PIPP Index, we conduct econometric analysis to evaluate whether and how stronger patent protection affects international innovation in pharmaceutical products. Since OLS recursive estimates of the impact of $PIPP_{it}$ could be biased due to endogeneity and measurement error, we investigate how estimated coefficients for $PIPP_{it}$ might change when we use a recursive estimation model or a GMM model with instrumental variables to account for these problems.

Numerous specifications of a first-stage regression on the PIPP Index found no evidence for a *U*-shaped relationship between GDP per capita and the PIPP Index for either the developing or developed country samples. In the second-stage regressions, we used a variety of specification and econometric methods and found that an increase in the PIPP

[16] These results are available upon request from the authors.

Index was associated with a positive but statistically insignificant response in the flow of U.S. patent grants in both developed and developing country samples.

Our results differ from those reported in Chen and Puttitanun (2005), who found a statistically significant and positive relationship between the Ginarte-Park Patent Index and USPTO patent grants to residents of developing countries.[17] Our results are not inconsistent with their results, as they use a sample of patents covering all industries, while we investigate data from a single industry. Our results provide a note of caution regarding the extension of regression results from an aggregate sample of industrial patents to a particular industry.

Qian (2007) analyzed the impact of establishing process and product patents in pharmaceuticals on USPTO patent grants and found that the impact of a dummy variable for protection of pharmaceutical product patents was statistically insignificant. Qian also found that estimated coefficients on interaction terms between three socioeconomic variables and the pharmaceutical product patent dummy variable were positive and statistically significant in several specifications. There are a number of reasons why our results might differ. First, we use a different, more comprehensive measure of patent strength rather than a binary variable that only captures whether a country provides a pharmaceutical product or process patent. Second, Qian used a much smaller matched \sample to account for endogeneity of patent protection, while we used a larger unmatched sample and utilized instrumental variable methods to account for endogeneity. Moreover, we note that Yi's matching methods do not produced matched data sets that are balanced with respect to control and treated observations. Since balancing is a necessary condition for applying propensity score models, it is unclear whether Yi's application of matching methods can resolve the endogeneity problem. By contrast, we have identified instrumental variables for the PIPP Index that are

[17] Their empirical analysis does not include results from a developed country sample.

both valid and strong, two necessary conditions for applying instrumental variable methods. However, one weakness of our study and a strength of Qian's study is that we are unable to consider interaction terms between the PIPP Index and socioeconomic variables, as this would require separate instruments for each of the interaction terms.

We were not surprised by our estimates with respect to developing countries, as it seems unlikely that developing countries would have a comparative advantage in developing new pharmaceutical products. Our findings for developed countries are, however less expected, and we identify two factors that could potentially be raising standard errors on the estimated coefficient for $PIPP_{it}$. First, measurement errors in both the dependent variable and the PIPP Index may be responsible for raising the standard errors of the developed country estimates. Our primary dependent variable--counts of USPTO pharmaceutical patent awards--is clearly not perfectly correlated with the market value of a country's pharmaceutical innovations. The PIPP Index is also measured with error, as it incorporates measureable features of both statute and case law, but does not directly measure whether these laws are adequately enforced.[18] Second, most researchers in small countries develop pharmaceuticals to be marketed in a global market. They are, therefore, more likely to focus on the average income-weighted patent protection provided to pharmaceuticals by all countries in the world market rather than on pharmaceutical patent protection in their own country. Increases in patent protection for pharmaceuticals in their own country may have more of an influence on the timing of new pharmaceutical launches in the country rather than on the extent of resident pharmaceutical R&D activities.

[18] Some of the measurement error in the PIPP Index has been corrected via our use of instrumental variables. We note also that USTR listing are made on the basis of inadequate legal provisions, which are measured by the PIPP Index, and on the basis of a country's actual enforcement activities, which are not directly measured by the PIPP Index.

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Table 1. Description of Data, 1985 to 2000

	Developed Countries (25 countries) Mean (standard deviation)				Developing Countries (68 countries) Mean (standard deviation)			
Variable	1985	1990	1995	2000	1985	1990	1995	2000
PIPP Index (0-5 values)	1.86 (1.27)	2.54 (1.08)	3.18 (0.70)	3.37 (0.56)	0.45 (0.76)	0.72 (0.78)	1.15 (0.80)	1.75 (0.79)
USPTO Patents (no.)	431.48 (1098.2)	635.28 (1650.7)	915.92 (2589.2)	1766.00 (5542.5)	3.44 (17.64)	3.82 (18.12)	4.38 (17.08)	6.69 (20.04)
GDP/Capita (thousands)	15.71 (6.24)	18.08 (7.14)	19.84 (7.74)	22.45 (8.38)	1.55 (1.49)	1.74 (1.57)	1.72 (1.56)	1.90 (1.77)
Population (millions)	32.46 (51.90)	33.51 (54.19)	34.68 (56.65)	35.81 (59.24)	49.82 (156.91)	56.27 (169.63)	58.70 (177.77)	63.12 (189.53)
Tertiary. Educational Attain. (%)	13.29 (5.49)	15.38 (5.90)	17.59 (6.36)	20.97 (7.09)	4.78 (4.24)	5.66 (4.78)	6.54 (5.28)	7.76 (6.01)
Secondary Educational Attain. (%)	63.35 (26.65)	68.24 (24.33)	72.80 (22.86)	77.05 (20.22)	25.86 (22.15)	30.23 (22.53)	34.65 (24.56)	38.99 (25.19)
Economic Freedom	6.84 (0.89)	7.31 (0.73)	7.44 (0.70)	7.62 (0.61)	4.86 (0.96)	5.10 (0.89)	5.57 (0.94)	6.05 (0.77)
USTR Spec. 301 Score (1-5 values)	0 (0)	0.64 (0.45)	1.37 (0.50)	1.46 (0.56)	0 (0)	0.21 (0.40)	1.37 (0.73)	1.48 (0.65)
WTO-Cases (no.)	0 (0)	0 (0)	0 (0)	0.29 (0.22)	0 (0)	0 (0)	0 (0)	0.02 (0.09)

Note: Developed countries (GDP per capita in 2000 less than US$10,000) listed from lowest to highest per capita GDP: Korea, Portugal, New Zealand, Greece, Cyprus, Spain, Italy, Australia, France, Belgium, Singapore, Germany, Finland, Canada, Netherlands, Austria, UK, Ireland, Sweden, Denmark, Switzerland, USA, Japan, Norway, Luxembourg

Developing countries (GDP per capita in 2000 less than US$10,000) listed from lowest to highest per capita GDP: Malawi, Niger, Chad, Rwanda, Nepal, Madagascar, Uganda, Mali, Togo, Ghana, Central Africa, Tanzania, Zambia, Benin, Bangladesh, Nigeria, Kenya, Haiti, India, Pakistan, Zimbabwe, Ivory coast, Cameroon, Ukraine, Nicaragua, Indonesia, Sri Lanka, China, Philippine, Bolivia, Honduras, Syria, Ecuador, Morocco, Paraguay, Egypt, Bulgaria, Iran, Romania, Guatemala, Jordan, Russia, Colombia, Thailand, Peru, El Salvador, Dominican, South Africa, Lithuania, Latvia, Belize, Brazil, Mauritius, Slovak Republic, Malaysia, Panama, Turkey, Costa Rica, Croatia, Estonia, Gabon, Poland, Hungary, Chile, Czech Republic, Mexico, Uruguay, Argentina

Table 2. OLS estimates for developed and developing country samples

Dependent Variable: Pharmaceutical Patents Granted by the Unites States Patent and Trade Office

	(1) Developing	(2) Developing	(3) Developed	(4) Developed
PIPP	0.87	0.71	-13.39	-105.49
	(1.55)	(1.71)	(56.40)	(77.91)
ln(GDP)	3.36**	3.42**	652.55**	731.75**
	(1.62)	(1.69)	(164.20)	(170.55)
ln(Population)	2.89**	2.88**	326.18**	345.06**
	(0.81)	(0.81)	(38.68)	(40.10)
ln(TerEducation)	0.72	0.63	229.81	161.89*
	(1.50)	(1.62)	(138.86)	(143.63)
ln(EconFreedom)	0.68	0.22	-763.66	-653.98
	(6.37)	(7.03)	(655.70)	(662.29)
Intercept	-48.78**	-48.17**	-8068.67**	-9026.14**
	(16.13)	(16.36)	(1795.97)	(1873.83)
Time dummies	No	Yes	No	Yes
Adj. R^2	.07	.06	.55	.55

Note: Standard errors are in parentheses. * and ** denote 10% and 5% levels of statistical significance, respectively.

Table 3. First-stage regressions for developing country sample

	Dependent Variable: PIPP Index					
	(1) OLS	(2) OLS	(3) Tobit	(4) Tobit	(5) OLS	(6) OLS
ln(GDP)	-0.87	-0.39	-1.01	-0.47	0.11*	0.16**
	(.65)	(0.63)	(0.72)	(0.69)	(0.06)	(0.06)
$(\ln(GDP))^2$	0.07	0.04	0.08	0.05		
	(0.05)	(0.04)	(0.05)	(0.05)		
ln(TerEducation)	-0.32**	-0.36**	-0.36**	-0.40**	-0.35**	-0.37**
	(.06)	(.06)	(.07)	(.06)	(0.06)	(0.05)
ln(EconFreedom)	0.46*	0.10	0.43	0.01	0.44	0.08
	(0.27)	(0.27)	(0.30)	(0.30)	(0.27)	(0.27)
USTR	0.29**	0.09	0.35**	0.13	0.28**	0.05**
	(0.06)	(0.09)	(0.07)	(0.09)	(0.06)	(0.08)
WTO-Cases	-1.47	-1.51	-1.54	-1.57		
	(0.96)	(0.94)	(1.04)	(1.01)		
Year 1990	2.68	0.09	3.05	0.11		0.11
	(2.22)	(.13)	(2.44)	(0.15)		(0.13)
Year 1995		0.32*		0.35*		0.38**
		(0.17)		(0.19)		(0.17)
Year 2000		0.79**		0.87**		0.83**
		(0.18)		(0.20)		(0.18)
Intercept		1.36		1.59	-0.59	-0.47**
		(2.14)		(2.34)	(0.48)	(0.47)
R^2 (or pseudo R^2)	.22	.30	.10	.14	.21	.29
χ^2			63.72	88.71		
			[0.00]	[0.00]		
F Statistic	11.55	11.33			16.11	14.07
	[0.00]	[0.00]			[0.00]	[0.00]

Note: Standard errors in parentheses and *p*-values in square brackets. * and ** denote 10% and 5% levels of statistical significance, respectively.

.

Table 4. First-stage regressions for developed country sample

Dependent Variable: PIPP Index						
	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) Tobit	(6) Tobit
ln(GDP)	-.76	1.70	1.15**	0.96**	1.26**	1.06**
	(6.02)	(5.48)	(0.25)	(0.23)	(0.26)	(0.23)
$(\ln(GDP))^2$	0.10	-0.04				
	(0.31)	(0.28)				
ln(TerEducation)	-0.27	-0.35	-0.26	-0.36*	-0.31	-0.40*
	(0.23)	(0.21)	(0.23)	(0.21)	(0.23)	(0.21)
ln(EconFreedom)	2.58**	1.71*	2.49**	1.74*	2.62**	1.82*
	(1.08)	(1.00)	(1.04)	(.96)	(1.03)	(.94)
USTR	0.52**	-0.22	0.52**	-0.21	0.55**	-0.19
	(0.12)	(0.19)	(0.12)	(0.19)	(0.12)	(.18)
WTO-Cases	1.76**	0.58	1.77**	0.58	1.73**	0.56
	(0.55)	(0.75)	(0.55)	(0.75)	(0.54)	(0.72)
Year 1990		0.88**		0.87**		0.92**
		(0.26)		(0.26)		(0.25)
Year 1995		1.64**		1.64**		1.66**
		(.36)		(0.36)		(0.35)
Year 2000		2.08**		2.07**		2.09**
		(0.47)		(0.47)		(0.45)
Intercept	-4.99	-14.33	-14.02**	-1.85**	-15.26**	-11.89**
	(28.58)	(25.97)	(2.35)	(2.23)	(2.43)	(2.26)
R^2(or pseudo R^2)	.56	.65	.56	.65	.26	.33
χ^2					80.26	102.82
					[0.00]	[0.00]
F-Statistic	18.80	17.88	22.77	2.34		

Note: Standard errors in parentheses and *p*-values in squared brackets. * and ** denote 10% and 5% levels of statistical significance, respectively.

Table 5. Instrumental variable estimates for developing country sample

Dependent Variable: Pharmaceutical Patents Granted by the Unites States Patent and Trade Office	(1) Recursive	(2) GMM without time dummies	(3) GMM with time dummies	(4) GMM without time dummies	(5) GMM with time dummies
PIPP	2.57	3.08	7.81	5.68	28.49
	(5.38)	(5.71)	(21.33)	(4.79)	(32.49)
ln(GDP)	3.14*	3.84**	3.06	3.16*	-0.33
	(1.70)	(1.83)	(3.46)	(1.64)	(5.43)
Ln(Population)	2.73**	2.28**	2.38**	3.08**	3.88**
	(0.84)	(0.93)	(1.17)	(0.83)	(1.92)
ln(TerEducation)	1.28	1.01	-2.88	1.94	10.29
	(2.17)	(1.78)	(7.50)	(1.89)	(11.79)
ln(EconFreedom)	-0.93	-4.01	-2.54	-3.85	-2.71
	(7.99)	(4.46)	(5.72)	(7.70)	(7.50)
Intercept	-45.05**	-40.70**	-48.91**	-46.53**	-47.22**
	(18.27)	(8.57)	(9.96)	(16.38)	(21.60)
Anderson Canonical LM statistic		29.16 .[.00]	4.33 [.11]	26.63 [.00]	2.40 [.12]
C-D Wald F statistic		15.03	2.12	29.08	2.34
Hansen's J statistic		1.16 [.28]	1.96 [.16]	not applicable	not applicable
Pagan-Hall general test		23.63 [.0001]	11.96 [.001]	6.97 [.22]	6.42 [.60]
Instruments		USTR, WTO-Cases	USTR, WTO-Cases	USTR	USTR

Note: Standard errors in parentheses and *p*-values in square brackets. * and ** denote 10% and 5% levels of statistical significance, respectively.

Table 6. Instrumental variable estimates for developed country sample

Dependent Variable: Pharmaceutical Patents Granted by the Unites States Patent and Trade Office

	(1) Recursive	(2) GMM without time dummies	(3) GMM with time dummies
PIPP	111.87	105.55	-56.52
	(95.85)	(88.52)	(246.41)
ln(GDP)	504.69**	487.09**	655.29**
	(187.66)	(157.28)	(320.54)
ln(Population)	314.45**	289.73**	78.40**
	(36.37)	(42.41)	(61.90)
ln(TerEducation)	247.60*	251.62*	165.44
	(138.14)	(138.89)	(136.39)
ln(EconFreedom)	-1192.38*	-1095.31*	-657.05
	(697.24)	(787.44)	(800.13)
Intercept	-5968.52**	-5716.55**	-8159.25**
	(2141.87)	(2139.48)	(4107.23)
Anderson Canonical LM statistic		31.16	11.17
		[.00]	[.004]
C-D Wald F statistic		17.07	5.31
Hansen's J statistic		.08	.21
		[.77]	[.65]
Pagan-Hall general test		25.99	.22.30
		[.0002]	[.01]
Instruments		USTR, WTO-Cases	

Note: Standard errors are in parentheses and *p*-values are in square brackets. * and ** denote 10% and 5% levels of statistical significance, respectively

Table 7. Comparison of estimated coefficients for PIPP Index in developing country sample

	(1)	(2)	(3)	(4)	(5)
Dependent Variable	Patent Awards	Patent Applications	Patent Awards	Patent Awards	Patent Awards
Robustness Test	Baseline Control Variables	Baseline Control Variables	Lutz et al. Secondary Education	Barro-Lee Tertiary Education	Openness (rather than EconFreedom)
(1) Recursive Estimates	2.57 (5.38)	5.45 (5.97)	3.53 (5.10)	0.53 (6.71)	5.04 (4.74)
(2) GMM/LIML without time dummies	5.68 (4.79)	8.22 (5.48)	3.98 (4.94)	3.11 (5.60)	3.49 (5.21)
(2) GMM/LIML with time dummies	28.49 (32.49)	42.30 (33.31)	45.26 (45.89)	13.72 (15.48)	32.40 (37.01)

Note: Standard errors in parentheses.

Table 8. Comparison of estimated coefficients for PIPP Index in developed country sample

Dependent Variable	(1) Patent Awards	(2) Patent Applications	(3) Patent Awards	(4) Patent Awards	(5) Patent Awards
Robustness Test	Baseline Control Variables	Baseline Control Variables	Lutz et al. Secondary Education	Barro-Lee Tertiary Education	Openness (rather than EconFreedom)
(4) Recursive Estimates	111.87 (95.85)	70.72 (79.11)	121.18 (99.21)	107.39 (101.56)	140.59 (101.44)
(5) GMM w/o time dummies	109.65 (106.44)	68.58 (86.79)	123.69 (111.66)	99.57 (115.39	239.64 (171.55)
(6) GMM with time dummies	-167.23 (224.59)	-97.86 (185.78)	-162.56 (227.34)	-83.32 (224.37)	-140.51 (362.33)

Note: Standard errors in parentheses.

Figure 1. Average PIPP Index for Developed and Developing Countries, 1981 to 2005

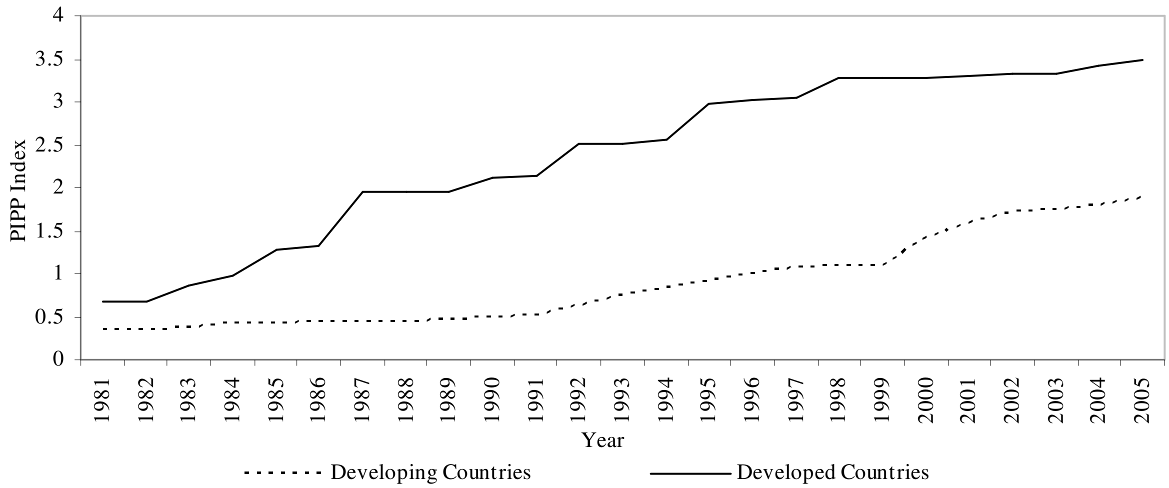
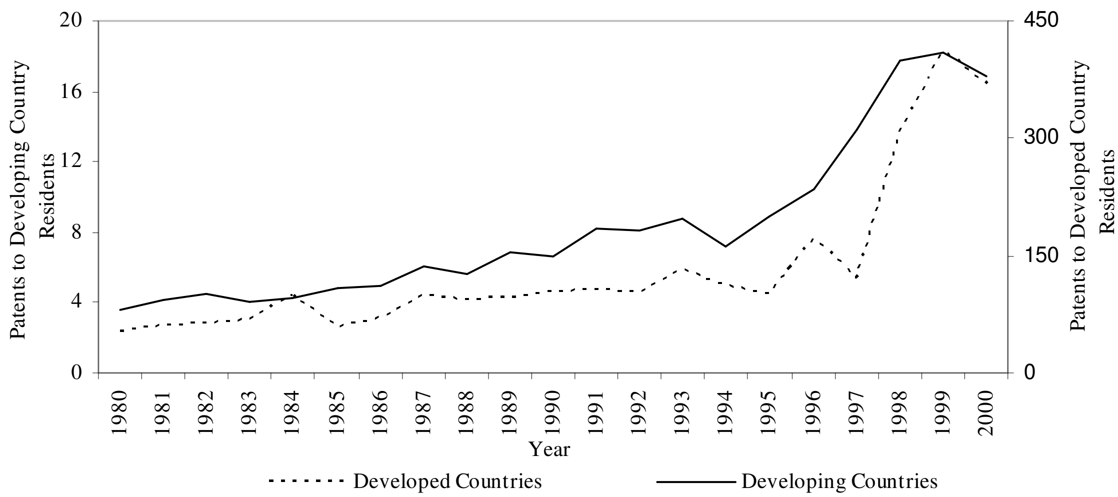


Figure 2. USPTO Pharmaceutical Patent Grants to Residents of Developed and Developing Countries, 1980 to 2000



Appendix Table 1: Robustness regressions for developing country sample: GMM with time dummies

	(1) Patent Applications as Dep. Variable	(2) Replace Lutz w/Barro-Lee TerEeducation	(3) Replace Lutz TerEducation w/ SecEducation	(4) Replace EconFreedom w/Openness
PIPP	42.30	13.72	45.26	32.40
	(33.31)	(15.48)	(45.89)	(37.01)
ln(GDP)	-2.29	2.69	.76	-.96
	(5.52)	(2.23)	(3.22)	(6.34)
ln(Population)	4.16**	3.42**	5.41	2.30
	(1.95)	(1.38)	(3.34)	(2.13)
ln(TerEducation)	14.31			13.83
	(11.93)			(15.36)
ln(SecondEdu)			17.63	
			(14.01)	
ln(B&L edu)		4.07		
		(3.18)		
ln(EconFreedom)	1.39	-3.26	-1.79	
	(13.87)	(10.15)	(14.54)	
ln(Openness)				-6.66
				(10.69)
Intercept		-46.03	-33.92	-42.66
		(22.10)	(37.00)	(30.15)
Anderson Canonical	2.40	3.67	1.22	1.36
LM statistic	[.12]	[.06]	[.27]	[.24]
C-D Wald F Statistic	2.34	3.57	1.18	1.32
Hansen's J Statistic	Not applied	Not applied	Not applied	Not applied
Instruments	USTR	USTR	USTR	USTR

Appendix Table 2: Robustness regressions for developed country sample:
GMM with time dummies

	(1) Patent Applications as Dep. Variable	(2) Replace Lutz w/Barro-Lee TerEeducation	(3) Replace Lutz TerEducation w/ SecEducation	(4) Replace EconFreedom w/Openness
PIPP	-24.15	46.04	-21.75	-5.62
	(200.63)	(248.71)	(264.55)	(221.54)
ln(GDP)	525.16**	552.36**	734.64**	573.37*
	(257.62)	(271.43)	(355.32)	(295.87)
ln(Population)	271.50**	335.07**	318.95**	248.58
	(62.98)	(95.21)	(82.91)	(143.61)
ln(TerEducation)	113.03			168.01
	(111.54)			(114.26)
ln(SecondEdu)			-130.46	
			(157.68)	
ln(B&L edu)		115.18		
		(88.00)		
ln(EconFreedom)	-505.07	-509.07	-259.31	
	(659.91)	(651.01)	(694.29)	
ln(Openness)				-272.56
				(333.05)
Intercept	-6616.49**	-7418.10**	-9301.72**	-8191.83**
	(3332.69)	(3578.19)	(4691.13)	(3466.87)
Anderson Canonical LM statistic	11.17 [.004]	10.97 [.004]	10.50 [.005]	13.91 [.001]
C-D Wald F Statistic	5.31	5.19	4.97	6.69
Hansen's J Statistic	.19 [.66]	0.31 [.57]	0.36 [.55]	0.10 [.75]
Instruments	USTR, WTO-Casea	USTR, WTO-Cases	USTR, WTO-Cases	USTR, WTO-Cases

Appendix Table 3. Robustness regressions for developing country sample: GMM without time dummies

	(1) Patent Applications as Dep. Variable	(2) Replace Lutz w/Barro-Lee TerEeducation	(3) Replace Lutz TerEducation w/ SecEducation	(4) Replace EconFreedom w/Openness
PIPP	8.22	3.11	3.98	3.49
	(5.48)	(5.60)	(4.94)	(5.21)
ln(GDP)	3.13*	2.93	2.10	3.57
	(1.88)	(2.06)	(1.59)	(1.98)
ln(Population)	2.97**	2.75**	2.79	3.34
	(.95)	(.97)	(.85)	(1.11)
ln(TerEducation)	1.66			1.75
	(2.17)			(2.46)
ln(SecondEdu)			4.33	
			(1.93)	
ln(B&L edu)		1.95		
		(1.72)		
ln(EconFreedom)	-2.26	-2.58	-2.33	
	(8.81)	(9.40)	(7.64)	
ln(Openness)				.78
				(3.21)
Intercept	-49.54**	-40.12	-28.86	-42.66
	(18.75)	(18.59)	(17.92)	(30.15)
Anderson Canonical	26.63	20.34	22.31	25.67
LM statistic	[.00]	[.00]	[.00]	[.00]
C-D Wald F Statistic	29.08	21.94	23.89	28.35
Hansen's J Statistic	Not applied	Not applied	Not applied	Not applied
Instruments	USTR	USTR	USTR	USTR

Appendix Table 4. Robustness regressions for developed country sample:
GMM without time dummies

	(1) Patent Applications as Dep. Variable	(2) Replace Lutz w/Barro-Lee TerEeducation	(3) Replace Lutz TerEducation w/ SecEducation	(4) Replace EconFreedom w/Openness
PIPP	67.73 (74.42)	98.12 (97.85)	118.89 (101.02)	285.03 (185.63)
ln(GDP)	437.92** (128.29)	537.97** (151.61)	605.71** (177.29)	276.79 (213.55)
ln(Population)	253.10** (36.77)	327.89** (55.03)	289.54** (45.90)	40.93 (148.73)
ln(TerEducation)	159.18* (96.43)			272.97** (122.63)
ln(SecondEdu)			-90.00 (120.82)	
ln(B&L edu)		129.41 (86.09)		
ln(EconFreedom)	-804.23 (646.01)	-705.95 (676.78)	-594.58 (683.82)	
ln(Openness)				-810.65* (461.45)
Intercept	-5256.23** (1801.04)	-6936.31** (1995.59)	-7291.27** (2517.12)	-4439.80* (2532.01)
Anderson canonical LM statistic	31.16 [.00]	26.79 [.00]	29.62 [.00]	22.04 [.00]
C-D Wald F Statistic	17.06	14.37	16.083	11.50
Hansen's J Statistic	.02 [.89]	.03 [.87]	.09 [.76]	.42 [.52]
Instruments	USTR, WTO-Cases	USTR, WTO-Cases	USTR, WTO-Cases	USTR, WTO-Cases