INTERNATIONAL TRANSFER OF SOLAR TECHNOLOGY

By

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To my grandparents James Robert Spear and Margaret Spear, whose love and support made this work possible

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This dissertation investigates the relationship between patent quality and the international transfer of solar technology. Using data from 84 countries, I also explore whether strengthening a country's intellectual property rights (IPR) laws increases patent filings in this sector. In addition, this research examines patent filings as a measure of technology transfer, as well as the structure of the international solar market. I find a generally positive and statistically significant relationship between patent quality and the international transfer of solar technology. The analysis also shows that—contrary to other research—IPR laws alone generally have no effect or a negative effect on technology transfer in this sector when a quality measure is included. Finally, results demonstrate that climate affecting the intensity of sunlight alone does not determine solar technology inflows. Rather, infrastructure, IPR laws, and human capital combined with this indicator are important.

CHAPTER 1
INTRODUCTION

Much discussion has recently been focused on the concept of international environmental technology transfer, and in particular the role of patents in both measuring and facilitating these flows. Key questions emerge: Which patents are likely to be filed abroad, and what characteristics do they share? What do countries with high patent inflows look like? Do patent flows behave differently depending on the sector being examined or income level of the country where patenting occurs? In this dissertation, I investigate the relationship between patent quality and international technology transfer, specifically as it relates to solar technologies. Using patent flows as a measure of technology diffusion, I hypothesize that solar patents of higher quality, as indicated by a weighted measure of forward citations, are more likely to be filed abroad than their lower-quality counterparts. I also hypothesize that the strength of a country's intellectual property rights (IPR) laws will increase patent filings in this sector as well.

This research adds to the literature in several key ways. First, I examine data disaggregated at the technology level. While much research has been done on the relationship between intellectual property and technology transfer at the aggregate level, "there is an urgent need for increased availability of reliable and objective data on climate technologies, particularly on IPR-related aspects" (Latif and Maskus, et al., 2011). Other scholars have previously pointed out the need to examine data in this area that is disaggregated by national income level and sector, including Kumar (1996), Lall (2003), and Basberg (1987). Unlike many previous studies, I conduct a disaggregated analysis using a dataset of solar patents filed from the United States in 84 countries between 1952 and 2011. The results here will allow me either to confirm that solar patent flows behave in line with aggregate patent flows and with those in other sectors, or to explore why patenting patterns in this sector may be different.

Second, I examine the structure of the international solar market. Outlining the buyers, sellers, and major national and business players in the industry can help better explain the results of the data analysis. Third, I examine to what extent patent filings represent technology diffusion via a literature review of the topic. To confirm that higher-quality patents are more likely to be filed internationally is important because it indicates that only more valuable technology will potentially be used internationally. However, a patent filed abroad—even a high-quality one—does not necessarily mean that the technology embodied in that patent will be used in the country where it is filed, or used in a way that will spill over outside the company or research institution that files it. Finally, this research offers a new perspective on the relationship between intellectual property rights and the international transfer of solar technologies by considering quality as an additional variable of interest, which has not been studied before to my knowledge.

This issue is especially salient now, as world leaders have met recently at several climate conferences to negotiate steps to curb global warming. At the 2011 Durban conference, both developed and developing countries committed themselves to formulating a legally-binding agreement to reduce climate-change-causing emissions, and Kyoto Protocol policies were extended (WRI, 2011). They also made progress on providing financing for poorer nations to access climate-change-mitigating technologies, and facilitating technology transfer is important in this context. Thus, solar technology transfer, an alternative energy likely to see more production as carbon emissions are reduced under Kyoto, is an important area of research.

Quality is a fundamental aspect of the IPR–technology transfer question. Theory predicts that higher-quality technologies are more likely to be diffused internationally (Eaton and Kortum, 1994; Eaton and Kortum, 1995, Kortum and Lerner, 1997). How is quality best measured? For many years, beginning especially in the 1980s, scholars have used patent citations for this purpose. Researchers like citations because they provide a clear path showing how innovation “moves” between people, firms, industries, and countries. Citations can be indicative of a product’s quality because the more often a patent is cited, the higher the probability that it is a useful or valuable development. Quality measures are crucial because they are the only way to determine whether patents are important or of any value. In the past, researchers have used raw patent counts to measure technology transfer, but if those patents are of low quality or do not represent any real innovation, then it is not accurate to say that technology is actually being transferred. Finding a way to measure patent quality allows researchers to capture true flows of technology more accurately.

I use a weighted measure of forward patent citations to gauge patent quality. I hypothesize that, per theory, patent quality should be positively correlated with more technology diffusion. I find a positive, statistically significant relationship between the two across a range of specifications. To my knowledge, this is the first study examining specifically the relationship between patent quality and the propensity to patent as it relates to solar technology. The results here are the first empirical confirmation that, when it comes to international technology transfer in the solar sector, quality matters.

IPRs are also important for green technologies since this sector requires large initial R&D investments; innovators need to be able to reap profits from their initial outlays to succeed (Latif and Maskus, et al., 2011). In addition, IPRs' importance can vary across technologies; some sectors that produce easily imitated products (e.g., pharmaceuticals) find IPR strength to be a vital requirement, while other, less-imitable, industries (e.g., traditional manufacturing) may be less concerned with protecting intellectual property.

I expect that because of the large R&D investment required and the advanced technology often needed to develop and produce solar-energy products, a strong IPR system should be positively correlated with patent flows. The only research, to my knowledge, examining the relationship between IPR laws and solar international technology transfer (ITT) (Dechezleprêtre, 2011) found that stronger IPR laws have a positive, statistically significant effect on solar technology flows. However, I find the opposite result; my results show that when a variable controlling for patent quality is added to the analysis, IPR laws have a negative, statistically significant effect, or no effect at all. In addition, these effects may differ depending on the level of economic development; in countries with strong IPR laws and high levels of economic development, robust patent protection may actually make it harder for technologies to be patented. This research offers an indication that the effect of IPR laws on technology flows of solar patents may be different for highly-developed nations than when examining poor and rich nations together.

The dissertation proceeds as follows: Section 2 explores the structure of the international solar market. Section 3 presents a brief review of the literature related to patents, patent quality, and patent citations. Section 4 examines the reliability of patents as measures of technology transfer. Section 5 explains the theoretical underpinnings of the analysis, as well as an econometric model drawn from the theoretical model. Section 6 details how the variables are constructed and the sources of data. Section 7 presents and analyzes the empirical results for a subset of 16 OECD nations. Section 8 presents and analyzes results for all 84 high- and lower-income nations.[1] Finally, Section 6 offers concluding remarks.

[1] I define income according to the World Bank. One exception is the inclusion of Zimbabwe, whose per capita GDP puts it in the low-income category, according to the bank.

CHAPTER 2
THE STRUCTURE OF THE INTERNATIONAL SOLAR MARKET

The structure of the international solar market may help shed light on global technology flows in this area, and what drivers are likely to be significant in encouraging international diffusion of this type of technology. First, it is important to review the main types of solar technologies and their potential capacities. Then, several facets of the global solar market can be explored, including the degree of concentration in the industry; its cost structure; ease of and barriers to entry; availability and pricing of substitutes; the market for inputs; and the demand side of the market. Finally, the future of solar energy can be analyzed with projections of production and consumption.

Types and Capacities of Solar Technologies

Solar technology can be broadly divided into four types: collection, concentration, photovoltaics, and heating/cooling (Steiner, 2009). Solar-collector technologies collect sunlight through such mechanisms as plates, troughs, towers, and dishes. Concentrated solar power, or CSP, uses mirrors or lenses to concentrate sunlight. Solar photovoltaics, or PV, refers to technology that converts sunlight into energy. Solar heating and cooling use either passive design (e.g., reflective roofs) or active design (e.g., solar-powered AC units) to reduce the use of fossil fuels in heating and cooling buildings. There are also smaller sub-sectors in solar-powered vehicles, but the technological development there is insignificant compared with the rest of the industry. Finally, nanotechnologies are also beginning to be used in the solar sector, but these developments are truly on the frontier of knowledge; therefore, little information about nano-solar advancements is currently available. The oldest form of solar technology is solar thermal power, a mode of solar collection that peaked in the 1970s. Since then, solar PV has grown rapidly, particularly in the 1990s (Steiner, 2009). Currently, solar PV and CSP constitute the most important subsectors of the industry.

Worldwide, solar capacity has increased by more than 1,500 percent between 1992 and 2003 (WIPO, 2009). Germany, Japan, and the United States account for 85 percent of total capacity. Despite this expansion, solar energy comprises a very small percentage of total energy use globally, 0.02 percent (Sharma, 2011); fossil fuels provide almost 80 percent of the world's energy, with nuclear power coming in second at 13 percent (Byrne, 2010). Nonetheless, use of solar technologies is growing. For example, as of 2000, 1.1 million developing-world homes used solar PV or lanterns; 10 million homes used solar water heating; and more than 25 countries had policies in place to regulate independent power production (Holm, 2005). By 2010, 70 million homes worldwide used solar water heating (UNEP, 2010), while about 3 million homes used small PV installations (Sawin, 2010). Overall, use has doubled every two years (Sharma, 2011).

In particular, the PV sector has grown quickly, at 35 percent per year on average since 2000 according to some (Poullikkas, 2010). Other estimates are even more impressive, showing 60 percent average annual growth since 2000 (Sawin, 2010). Thanks to this growth, the industry earned almost $40 billion of revenue worldwide (Sharma, 2011). Investors are also noticing the solar industry's potential: 2010 saw $2.3 billion worth of venture capital and private equity investment, a compound annual growth rate of almost 60 percent between 2004 and 2010 (U.S. DOE, 2011). Total investments added up to almost $80 billion in 2010, with Germany comprising 45 percent of the total (Hopwood, 2011). (Table 2-1)

Concentrated solar power (CSP) is also an important subsector, and capacity has been expanding there as well. Spain is the top installer of CSP technologies (just over 55 percent of the global total), followed by the United States (almost 39 percent) and Iran (5 percent) (US DOE, 2011).

Degree of Concentration

It is important to note that different solar technologies compete in different types of markets. For example, large-scale PV and CSP projects may compete with grid-connected utilities, while smaller, off-grid, standalone solar power installations more likely compete with diesel and other types of generators (Timilsina, 2011). Likewise, there are markets for both commercial and residential installations, as well as other consumer products (toys and electronics) and government products (traffic lights, road signs). Markets and their incentives differ widely across the world. European and Asian nations tend to have very centralized policies and incentives, while the United States features sometimes overlapping federal, state, and local policies (Barker, 2011).

As measured by patent filings, Japanese companies dominate solar technology development, including Canon, Sanyo Electric, Sharp, Matsushita Electric, and Kyocera (WIPO, 2009). Specifically, in the solar PV sector, 15 firms control 49 percent of the market (REN21, 2012). (Table 2-2)

The fact that the majority of the world's top solar PV firms are located in China reflects a fundamental shift in the market: While Europe remains the top consumer of solar energy and products, production has shifted, and continues to shift, to Asia. In addition to Chinese companies, Taiwanese and Indian production are also expected to become more significant (REN21, 2012).

Together, China and Taiwan produce almost half of all solar PV cells worldwide (Sharma, 2011), but Europe is also a large solar exporter (Groba, 2011). After China, the world's top PV producers are Japan, Germany, Taiwan, and the U.S. In China's PV market, exports are extremely important, accounting for 95 percent of total production. PV production growth in China has been astounding: The country produced one-third of the world's solar cells in 2008 but currently produces almost 60 percent (Choudhury, 2012). China also provides 77 percent of total global solar water heater production. Chinese production is not very concentrated, with 900 PV manufacturers. Meanwhile, new policies (e.g., feed-in tariffs) are expected to spur further development of both China and India's domestic PV cell markets (Platzer, 2012). Overall, there were about 500 firms worldwide in the PV sub-sector in 2009 (Kirkegaard, 2010). More recently, others have estimated the existence of more than 1,000 firms globally (Platzer, 2012). In overall solar manufacturing, six of the top-10 companies are Chinese; European and Japanese producers have been pushed out of the top (Choudhury, 2012).

In the area of concentrated solar power, the top two markets are the United States and Spain (OECD/IEA, 2011). Outside the main markets in Asia, Europe, and the U.S., other emerging economies are seeing growth in their CSP industries, helped along by governments, NGOs, and multinational organizations, as well as favorable weather conditions. These up-and-coming CSP countries include Chile, India, Morocco, Saudi Arabia, South Africa, and the UAE (González, 2012).

The CSP subsector is more concentrated than the PV market. The CSP industry is marked by vertical integration, with companies participating in everything from R&D to production and operation of facilities (REN21, 2012). Key companies involved in this sector include Abengoa (Spain), BrightSource Energy (United States), GE (United States), and AREVA (France). In the solar heating sector, five of the largest Chinese firms[1] have played major roles in the market. In Europe, meanwhile, mergers and acquisitions in the face of the recent economic downturn have further consolidated the market (REN21, 2012).

Cost Structure

Costs play an integral role in how the international solar market operates, and overall the trend is clear: They have been declining across the board for all types of solar technologies. Nonetheless, these technologies have not yet reached cost parity with traditional energy sources; moreover, the initial capital investments required remain high ($100-200 million for a 100MW plant, Susman, 2008), even while maintenance costs are low (Byrne 2010). Capital costs were even higher for solar PV in the 1970s, however, at $30-35 per watt, compared with $4-5 per watt today (Timilsina, 2011). Despite the decrease, initial capital requirements are often cited as a barrier to the technology being used more widely (Sharma, 2011). Nonetheless, projections show that investment costs may be reduced between 30 percent and 40 percent over the next 10 years (OECD/IEA, “Deploying Renewables,” 2011).

Although costs are also falling in the CSP subsector, they are not as competitive as in the PV sector (OECD/IEA, “Deploying Renewables,” 2011). At the consumer level, solar PV prices have dropped to $2 per watt (compared to around $1 or less for traditional energies), representing a 50-60 percent decline (UNEP, 2010). In the U.S., solar PV operation costs have fallen an average of 3.6 percent yearly in the last 10

[1] Linuo New Materials, Sangle, Micoe, Himin, and the Sunrain Group.

years (Kahn, 2009). Many PV manufacturers have been seeking to reduce costs by expanding output; it is estimated that for every doubling of output, costs can be reduced by 18 to 20 percent (Susman, 2008). Costs are estimated to fall by 10 percent per year until 2020, meaning that solar's per watt cost could reach $1, or close to parity with fossil fuels. Another pricing advantage in the solar market, particularly when considering international trade in solar-related products, is that in general, tariffs are very low in this sector worldwide—approximately 8 percent in developing nations and near zero or zero in developed nations (Algieri et al., 2011).

The European Photovoltaic Industry Association predicts that the cost of solar electricity will drop by half in the next 10 to 15 years; analysts expect price parity with traditional electricity in five to 10 years, meaning that solar PV will become even more competitive (QMS Partners, 2009). The current and expected price drops in solar PV are due in part to the extreme competition engendered by the supply-demand imbalance in the market (to be discussed subsequently), as well as from technological improvements and economies of scale (McCrone, 2012, *Solarbuzz*, 2010).

Ease of Entry and Barriers to Entry

Currently, the biggest factors affecting entry are government support and high capital costs. This is due to the fact that, while prices have been falling swiftly and steadily, the solar market is not yet developed enough to survive on its own. Indeed, generous government subsidies have recently come to an end in Europe, and that, combined with the economic downturn, has forced companies to consolidate and made new entrants less likely.

Along with the need for public support comes the issue of grid integration. Even if solar energy reaches consumer price parity with traditional electricity generation, and even if investment costs fall to a level where government subsidies are no longer necessary, integrating solar energy into existing grids or building new ones requires additional government monies and support (Johansson et al., 2012). The CSP subsector faces challenges in addition to investment costs and grid integration. Because of the large tracts of land needed for solar panels to collect energy, the NIMBY (Not in My Backyard) phenomenon can also be an issue (Johansson et al., 2012).

Availability and Pricing of Substitutes

In many cases, substitutes for solar energy may also be complements. Hybrid energy systems—where renewable energy is used to supplement traditional fossil-fueled generation, or several different types of renewable energies are used together to produce energy depending on conditions—are growing in popularity (REN21, 2012). Nonetheless, while solar energy is gaining overall market share, other renewables, especially hydro and wind power, are more popular forms of renewable energy (OECD/IEA, “Deploying Renewables,” 2011).

Hydro power comprises almost 84 percent of the world’s renewable energy and has grown as an energy source by 50 percent since 1990 (OECD/IEA, “Deploying Renewables,” 2011). Wind power is the world’s second-most-used renewable-energy source, with production having increased by a massive 870 percent between 2000 and 2009 (OECD/IEA, “Deploying Renewables,” 2011). As with solar power, China has taken a lead in developing many of these new hydro and wind energy projects.

Perhaps one of the reasons that water and wind power have become more widespread is due to their competitive pricing. Given favorable conditions—where the resource is readily and steadily available and where the market is sufficiently developed—both renewable sources of energy are either price-competitive with, or very close to becoming price-competitive with, energy generated from traditional fossil fuels (OECD/IEA, “Deploying Renewables,” 2011).

A recent study found that the international demand for solar PV products is both income and price elastic (Algieri et al., 2011). The authors find that income elasticity is higher than price elasticity and conclude that foreign income is therefore a major factor in increasing solar exports. As hybrid energy systems continue to increase in popularity, and as prices for solar modules and energy continue to fall, it seems that competition from more the traditional and well-developed renewable sources of water and wind will be less of a factor.

Input Market

Perhaps the most important current issue in the international solar market is the gross supply-demand imbalance that has plagued the PV market in recent years. In the early 2000s, pro-solar policies in countries like Germany, Spain, Japan, Italy, and the United States drove up demand for solar cells, which are made from solar-grade polysilicon (Hayward, 2011). The spike in demand for solar-grade polysilicon quickly led to a supply shortage. Attracted to the newly high profit margins in the sector, in 2008, many producers entered the market (Kirkegaard, 2010). Due mostly to large, cheap Chinese manufacturers, production increased rapidly, and the polysilicon market was quickly oversupplied. Consequently, polysilicon prices dropped precipitously, 40 percent per year; this bolstered demand but also significantly reduced profit margins (Aanesen, 2012). The financial ramifications of this glut are large: One analyst estimated that as of 2011, production equipment worth about $8 billion was “sitting on suppliers’ order books” (Colville, 2011).

The fallout of the supply-demand imbalance is still being felt, and the market is changing rapidly as it adjusts. Prices remain depressed as of late 2012. While global solar demand is expected to increase in the coming years, the increases will be smaller since several of the programs encouraging solar production and consumption in Europe and the United States have expired or are set to expire. Moreover, some Chinese and Taiwanese firms are trying to reduce costs via expansion to take advantage of economies of scale, adding even more to the oversupply. Due to all of these factors, the solar PV sub-sector seems to be moving toward consolidation, with recent rounds of bankruptcies, mergers, and partnerships (Platzer, 2012). However, consolidation has been occurring mostly in the West, as Asian manufacturers continue to expand individually (Choudhury, 2012).

Demand

Europe dominates demand in the global solar market, mostly driven by generous feed-in tariff policies (Byrne, 2010). [2] Countries like Germany, France, Italy, and the Czech Republic encourage solar production via such programs, and as a result, 77 percent of world demand for PV technology has come from Europe. Demand in the United States has been positively influenced by a number of national and state programs, though the central approach found in some European countries is lacking. The U.S. and Europe represent more than 75 percent of global demand, with Asia representing about 25 percent (Byrne, 2010). In the U.S., more than three-quarters of sales are in California and New Jersey, both of which have incentives and policies designed to encourage solar energy production and consumption (Susman, 2008).

[2] A feed-in tariff offers set payments to renewable-energy producers.

In terms of total area of solar collectors installed worldwide, China, Germany, Turkey, and India top the list, followed by the U.S., Mexico, India, Brazil, Thailand, South Korea, and Israel (Timilsina, 2011). In terms of consumption, the top markets are Germany and Italy, although Japan may overtake Italy due to expanded incentives enacted in July 2012 (Bloomberg News, 2012). It is estimated that the most demand in OECD countries will be in rooftop solar installations, while ground installations are expected to be more prevalent in poorer nations (Aanesen, 2012).

Demand is growing, particularly in China and India, due to those nations' rapid GDP growth. Between 2007 and 2009, 70 percent of the world's growth in energy demand came from China and India. Worldwide, demand for solar energy has been growing at 35 to 40 percent per year, and similar rates are expected in the future (QMS Partners, 2009). Markets most responsible for this global demand growth are Germany, Spain, Japan, and the U.S. To a lesser extent, India, China, and South Korea have also been demand drivers (Byrne 2010).

Projections

It is estimated that with adequate policies to encourage production and consumption, solar PV could provide 45 percent of the world's energy by 2040 (Byrne, 2010). According to one estimate, solar thermal energy, a type of collector, is expected to expand 10-fold by 2030; other estimates expect the same increase by 2020, with solar thermal providing 4 percent of the world's energy by 2040 (Byrne, 2010). By 2050, 6 percent of global energy production capacity may be in CSP, increasing significantly after 2020, when analysts expect costs to fall further (Byrne 2010). Or, CSP capacity could grow by 450 percent by 2017 (OECD/IEA, 2012). CSP faces increasing competition from solar PV, as well as complications with permitting and grid connection, which will affect its future place in the market. The U.S., Spain, and China are expected to lead the increase in CSP production (OECD/IEA, 2012). Meanwhile, solar thermal technology capacity is expected to grow by 155 percent by 2017, led by China, Germany, the United States, Turkey, and India (OECD/IEA, 2012). Overall, the OECD expects that solar PV will be competitive with retail electricity before 2020 (OECD/OEA, 2011). The continued market imbalance, as well as fierce competition due to it, will continue to push prices down even further (EPIA, 2012).

Other estimates predict that by 2040, solar energy overall will supply 11 percent of the world's energy—6 percent PV, 4 percent solar heating and cooling, and 1 percent CSP (Byrne, 2010). Some projections are not as optimistic, putting global solar energy production at 2.5 percent of the total (Poullikkas, 2010). These large variances can be accounted for by differences in assumptions regarding policies, market structures, and costs. Revenue-wise, the solar PV industry could reach $100 billion by 2014 (Sharma, 2011).

As China and other Asian countries expand production, some OECD producers may be crowded out, a phenomenon that is already occurring (Groba, 2011). Meanwhile, demand for solar PV energy is expected to grow the fastest in China, India, Southeast Asia, Latin America, the Middle East, and North Africa (EPIA, 2012). In Latin America, Brazil has recently implemented new policies designed to promote solar PV. As a result, leading industry analyst publication *Solarbuzz* is predicting regional growth in Latin America in solar PV of more than 350 percent in 2012 alone. By 2016, 6 percent of global solar PV demand could be from Latin America and the Caribbean (Barker, 2012).

In the midst of the current and expected global expansion of the solar industry, uncertainty is being caused by several issues: First, subsidy and incentive cuts in countries whose previous policies drove global solar PV demand (Germany, Italy, and the U.S.) have the potential to reduce overall demand; at this point, it is too soon to know the impact of the policy changes, but analysts note that some companies are now looking for markets that can thrive without government support (Mendolia, 2012). Second, solar is facing increased competition from shale gas production, particularly in the United States (Platzer, 2012). Third, the supply-demand imbalance shows no signs of abating in 2012. In fact, Chinese producers are planning to expand capacity by 19 percent in 2012, after upping capacity by 57 percent by the end of 2011 (Choudhury, 2012).

Fourth and finally, a trade war related to the supply-demand problem is brewing between China and the United States. American solar producers have accused Chinese cell manufacturers of illegal dumping, and in May 2012, the U.S. Department of Commerce made a preliminary ruling imposing anti-dumping tariffs (Agencies, 2012). These tariffs may be a boon to U.S. producers, but they could cause the overall installation costs of PV systems to rise (Platzer, 2010). In response, China is investigating the U.S. for its solar subsidies and possible dumping and could impose tariffs of its own (Agencies, 2012). In the meantime, Chinese producers are looking to transfer production to Taiwan or South Korea to avoid the tariffs (Colville, 2011).

In this dissertation, I am examining outgoing U.S. solar technology only. As the global market analysis shows, even though the U.S. is not one of the main manufacturers of solar technology, it is, along with the Japan, the most prolific developer of solar technology in terms of patents filed, and it remains one of the major players in the global market. Based on this market analysis, and based on the fact that my dataset covers the years 1952–2011, I expect high-quality solar technology to be more important in more developed nations since that is where demand has been most concentrated until very recently.

Table 2-1. Solar PV operating capacity by country

Ranking	Country	Capacity (%)
1.	Germany	35.6
2.	Italy	18.3
3.	Japan	7.1
4.	Rest of World	6.9
5.	Spain	6.5
6.	United States	5.7
7.	China	4.4
8.	France	4.1
9.	Other EU	4.1
10.	Belgium	2.9
11.	Czech Republic	2.8
12.	Australia	1.9

Adapted from REN21. 2012. *Renewables 2012 Global Status Report* (Page 48, Figure 12). REN21 Secretariat, Paris.

Table 2-2. Market shares of world's top solar PV manufacturers

Ranking	Company	Country	Market Share (%)
1.	Suntech Power	China	5.8
2.	First Solar	United States	5.7
3.	Yingli Green Energy	China	4.8
4.	Trina Solar	China	4.3
5.	Canadian Solar	Canada	4.0
6.	Sharp	Japan	2.8
7.	SunPower	United States	2.8
8.	Hanwha-SolarOne	China	2.7
9.	Tianwei New Energy	China	2.7
10.	Hareon Solar	China	2.5
11.	LDK Solar	China	2.5
12.	JA Solar	China	2.4
13.	Jinko Solar	China	2.3
14.	Kyocera	Japan	1.9
15.	REC	Norway	1.9
16.	Other	Rest of World	51

Adapted from REN21. 2012. *Renewables 2012 Global Status Report* (Page 48, Figure 13). REN21 Secretariat, Paris.

CHAPTER 3
LITERATURE REVIEW

Little has been written about patent quality as it specifically relates to the international transfer of environmental technology. However, the literature on patent quality, patent citations, intellectual property, and technology diffusion in general is well developed. These studies attempt to answer some key questions. First, how related are citations to quality? Second, what is the best way to measure quality using citations? The literature dealing specifically with environmental technologies and IPRs examines what effect strong patent laws may have on technology inflows.

Dozens of studies have used forward patent citations to measure patent quality. However, before examining the key research in this area, it is necessary to define patent citations themselves and explore some of their characteristics. Citations come in two types: backward and forward. Every time a patent is filed, the author and patent office officials list prior art, which includes previous patents that may be similar to or relevant to the current patent-filer's technology. Let the current patent being filed = X. We can refer to all the prior art contained in X as backward patent citations of X. However, going forward, if other patents cite X as prior art, we can refer to them as forward citations of X.

A 2001 NBER analysis of worldwide patent data (of which the dataset in this study is a subset) showed that forward patent citations occur over long periods of time. Specifically, 50 percent of patents will receive citations within 10 years of filing, 25 percent more will receive citations within 20 years of filing, and 5 percent more will receive citations within 50 years or more after filing. This means that if newer patents are included in the data, they most likely will not reflect the correct forward-citation effect simply because these patents are not old enough to have received all of the citations they will likely garner (Hall et al., 2001). Van Zeebroeck (2011) offers a simpler remedy to this time issue: Count citations received by patent applications within a given period of time.

Now that we have examined patent citations and their characteristics, we can explore what previous research has discovered about their relationship to patent quality. Trajtenberg (1990) authored one of the first studies showing the positive correlation between citations and quality. Since then, patent citations have been shown to be a reliable indicator of a patent’s quality (Lanjouw and Schankerman, 2004); studies finding a positive link between forward patent citations and patent quality include Harhoff et al. (2003) and Marco (2007). In addition, many researchers use the raw count of forward patent citations to measure quality. These include: Harhoff et al. (1999), Fallah et al. (2009), and Rosenkopf and Nerkar (2011). Norback et al. (2011) use the raw count, but they weight the number of patent citations received by a linear time trend following Hall et al. (2005). Acosta et al. (2009) scale citations by year and by stock of available knowledge, i.e., stock of available patents that a patent could site, and by sector to control for time and industry differences. Weighting citation data or using other methods to account for the age of the patents can be important. Forward citations suffer from the problem of truncation because citations can continue to occur at any time in the future. This means that newer patents have fewer citations not necessarily because they are less useful but simply because they are younger. In addition, the frequency of both patenting and citing has increased, particularly in the 1980s, so it is possible that more citations may be picking up this general trend rather than anything specific to the value of a particular patent. Another problem that may arise is that technologies from different industries (e.g., computers vs. drugs) are patented and cited at different rates. Therefore, focusing on a specific sector can help ameliorate some of these problems. Indeed, Popp (2006) finds empirical support for the idea that “allowing for different behavior across technologies is important” for climate-change-mitigating technologies. Thus, one can conclude that examining data sector by sector, or technology by technology, is apt to yield the most accurate results.

Despite the fairly rich literature on patent citations and patent quality, very little empirical work has been done examining these issues for green technologies. Acosta et al. (2009) provides the first and only, to my knowledge, analysis of this kind. Examining European environmental patents and using weighted citations as a quality measure, the authors find that patents from institutions are of a higher quality than those from individuals. They also find that green patents from the United States and Japan are cited more frequently than European patents. Finally, their analysis shows that patents that can be used in multiple sectors are more likely to be cited than patents that have very specific, limited uses.

Another recent study of patent citations and environmental technology (Pillu and Koléda 2009) examines 11 energy technologies in France, Germany, Japan, the United Kingdom, and the United States to determine what factors induce innovation in this industry. The authors use patent citations to help construct a proxy for the available stock of knowledge that inventors can use to develop new innovations; they weight the stock of patents by their productivity, i.e., citations. The authors find that both high energy prices and the availability of knowledge (i.e., patent citations) encourage innovation.

The literature confirms a robust positive relationship between patent citations and patent quality. This allows us to explore another key issue: Is there also a positive correlation between patent quality and patent filings? The available research shows the answer to be “maybe.” Little research has been done on patent quality and patent flows; however, several studies have explored the relationship between patent quality and patent valuation. One of the earlier studies in this area (Scherer 1984) showed that for U.S. firms, higher-quality patents are worth more. Later studies have also confirmed that high-quality patents are also worth more, including Hirschey and Richardson (2001, 2004) and Lanjouw and Schankerman (2004). Chen and Chang (2010) find that in the U.S. pharmaceutical industry, only some indicators of quality are positively associated with firm value. Lanjouw and Schankerman (1999) find that among U.S. manufacturing firms, higher-quality patents are more likely to be renewed, and firms are more likely to sue when high-quality patents are infringed upon.

Despite the strong relationship between patent citations and patent quality, examining these two factors alone as determinants of patent flows is not enough. Researchers must also consider country and industry characteristics, which can affect technology diffusion as well. Almost all studies exploring the relationship between intellectual property and technology diffusion use a set of independent variables to control for national factors that may affect the decision to patent (Branstetter et al., 2006, 2007; Evenson and Kanwar, 2001; Javorcik, 2004; Kanwar, 2009; and Maskus et al., 1995, 2001, 2005, 2005). To control for market size, researchers may use GDP, per capita GDP, or population. When dealing with innovation diffusion, it is also essential to measure a country's capacity to absorb new technologies; various measures of human capital are used, including years of secondary or tertiary education, or the population employed in high-tech or R&D sectors. Studies also want to account for a nation's economic relationship to the rest of the world, so they might control for membership in a trade bloc or other trade agreements. These studies have also found that controlling for industry can yield better results. For example, researchers have looked at the different effects IPRs can have in traditional manufacturing vs. more high-tech sectors such as chemicals and pharmaceuticals (Javorcik, 2004). Overall, it is important to consider a wide array of factors in addition to patent quality that may affect patent flows.

Finally, it is also useful to discuss the literature specifically related to intellectual property rights protection and green technologies. Namely, do stronger IPR protections engender more environmental innovation? Barton (2007) makes one of the first attempts to examine the relationship between IPR protection and environmentally sound technologies (ESTs). In photovoltaics, he concludes that patents might not present an obstacle to access for developing nations due to the level of competition induced by the high number of businesses in the industry worldwide. Dechezleprêtre, Glachant, Ménière (2010) analyze data from 66 countries between 1990 and 2003 to determine whether higher IPR protection increases the transfer of ESTs. The authors find a statistically significant, positive relationship between the strength of a country's IPR laws and patents filed in wind, solar, hydro, cement, building, and methane. They find no statistically significant relationship in biomass, geothermal, waste, and fuel injection. They find a statistically significant negative relationship in ocean and light. Popp et al.

(2011) examines how technological innovations, represented as increases in a global technology stock, affect the use of renewable energy technologies in four areas: wind, solar photovoltaic, geothermal, and electricity from biomass and waste. They find a small, statistically significant positive effect of increased knowledge on renewable energy investment. When broken down by technology, a statistically significant positive effect is found only for the wind and biomass sectors.

The literature in this area shows that while using patent citations is a tried and tested measure of patent quality, much work remains to be done at disaggregated levels. A review of relevant research also shows that more empirical work remains to be done in determining whether a positive relationship exists between patent quality and patent flows. Finally, although some have explored the relationship between IPR laws and the flow of green technology, it remains a relatively new area of study, and more work can be done to determine whether the solar sector behaves like other industries with respect to citations and IPR laws. In this dissertation, I hope to move the literature forward by exploring answers to these questions.

CHAPTER 4
PATENTS: A RELIABLE MEASURE OF INTERNATIONAL TECHNOLOGY TRANSFER?

For decades, researchers have widely used patent filings to measure technology flows among countries; nonetheless, it is worth exploring how reliable patents are as a measure of international technology transfer. A few key questions emerge: First, what constitutes technology transfer (also referred to as technology diffusion)? Second, what are the most common measures of technology transfer? And finally, which one of these measures best gauges diffusion across borders?

Albors-Garrigos et al. (2009, p. 156) call technology transfer “an active process, during which technology traverses the borders between two entities,” including nations, firms, or people. This definition reflects a process that is broad, and that can be intentional or unintentional. Steiner et al. (2009, p. 18) go further, noting that technology transfer must also include “the capacity to assimilate, implement, and develop a technology, which ultimately leads to its consolidation in the receiving country.” For the purposes of this study, I define technology transfer as the process by which technology moves from one country to another in such a form that it can be assimilated or implemented in that country.

The process of measuring technology transfer, however, has bedeviled researchers for decades. There are no perfect, direct gauges, but several are common: R&D expenditures, FDI flows, trade flows, licensing, and patent counts (Park 2007). I discuss each of these in turn before examining patent counts and the relative advantages they hold over other measurement methods in the case of the research contained in this dissertation.

Expenditures on research and development have often been used to measure innovation and technology transfer. The most basic issue with this measure is the fact that it is by definition an input in the technology-development process, while ITT measures output (Lanjouw et al., 1998). Data availability and accuracy can also be problematic. First, data are unavailable for many firms, nations, and years, particularly in the developing world. Moreover, when they are available, they are not necessarily recorded and collected consistently over time, which further decreases their usefulness (Lanjouw et al., 1998). Finally, they are not disaggregated, so it is not possible to analyze these data sector-by-sector (Dechezleprêtre, 2010), as I do here. Keller (2009) argues that R&D expenditures constitute a very noisy measure since returns to R&D can vary drastically over time and across firms, institutions, and countries.

FDI and trade flows are sometimes used to measure international technology transfer. For the former, FDI, particularly in the R&D sector, can represent the acquisition of new technology in a country. Trade flows of new goods, intermediate or final, can also indicate the adoption of new technology. The central problem with using FDI and trade flows to measure ITT is that the data available are highly aggregated (Dechezleprêtre, 2010). It is difficult to find extensive data that break down FDI into investment in distribution, manufacturing, and R&D. Therefore, while a country may see a spike in investment inflows, if it is due to the construction of a new textile factory that uses existing technology, that does not represent technology transfer. For example, Sawhney and Kahn (2011) find that U.S. FDI in outflows in the wind and solar sectors to both developed and developing countries result in increased exports of solar and wind technologies to the U.S. from those nations. The data were gathered using the North

American Industry Classification System (NAICS), which allows FDI flows to be disaggregated by sector. However, sector disaggregation alone cannot pinpoint the type and amount of FDI dedicated to R&D; therefore, using FDI flows to measure innovation in the solar and other green sectors remains problematic. Moreover, this study seems to indicate a feedback effect between FDI and trade in green sectors, indicating that neither may be appropriate to use to isolate the effect of innovation in environmental technologies.

Second, FDI and trade flows are indirect measures (Dechezleprêtre, 2010). Even if the incoming investment is directly related to R&D, or imports are high-technology inputs or products, it is difficult to measure to what extent these transfers spill over into the larger economy. Will research done within an MNC subsidiary spread to the rest of the country as a whole? Does importing a new high-tech green product result in new technology being made available more widely? It is neither certain nor easily quantifiable. Indeed, Popp (2011, 2012) notes that the effectiveness of both trade flows and FDI as conduits of technology transfer depends largely on a nation's capacity to absorb technology. While this is true of all modes of technology transfer, it is equally applicable to the green-energy sector.

Licensing is probably the best way to measure technology transfer. When a firm pays for a license for a technology, this indicates that the technology is actually being used (transferred), while also attaching an exact monetary value to that technology (Nelson, 2009). Researchers have used royalty and licensing fees to examine whether strengthening IPR laws increases cross-country licensing (see Maskus and Yang, 2005). However, as with other measures of ITT, the problem here is one of data availability. The only licensing data available are aggregated, so researchers have no way of knowing whether the fees are being paid to use new technology or not. Licensing data are truly useful only if they are accessible at the industry or firm level, and these are not available on a wide scale. Gathering industry- or firm-level licensing data requires conducting surveys, which can be costly and difficult, and may yield low responses. As an example, Steiner et al. (2009) conducted a licensing survey of 500 organizations involved in clean-energy technologies and had a response rate of only 30 percent. In addition to the low response rates, survey data also require researchers to identify and correct for any possible selection issues.

So far, we have seen that for the purposes of examining the solar-energy sector, the data available for R&D expenditures, FDI flows, and trade flows are inadequate to describe and quantify flows of international technology transfer accurately. Moreover, these measures of ITT have not been shown to be positively correlated with the quality of innovations, a key part of my research here. While licensing may be the preferred measure, such data are also unavailable in a form that is useful to researchers hoping to track and analyze ITT in green-energy sectors. What is left, then, are patent counts as a way to gauge levels of technology transfer. We can first examine the advantages that patents have over the measures discussed previously; then, we can discuss problems with using patent counts and ways that those issues can be mitigated.

Patents have been used to quantify innovation for more than 50 years.[1] For the purposes of this study, these data have several advantages when compared with the

[1] Schmookler and Brownlee (1962) were one of the first to use patent counts to quantify innovation. They used patents to create an “index of inventive activity employed” to measure capital-goods patents and value-added in selected industries. They noted, even at that early date, the problems with aggregated data, as well as the fact that patent characteristics can differ across industries. In one of the first studies of its kind, Comanor and Scherer later

other technology and innovation measures discussed previously. First, patent data are extensive and easily available (Griliches, 1990). Data can be found for almost every country, sometimes going back to the 19th century. Patent applications contain a plethora of useful information not found elsewhere regarding the nationality of the inventor, where the invention occurred, where the patent was filed, the type of technology represented in the patent, and information on patent and publication citations (Lanjouw, 1998). This means that, unlike licensing or FDI data, patent counts can be disaggregated not only by industry but by sectors within industries, allowing for extremely specific and accurate analyses. This is extremely important in the green-energy industry, which has many sectors and sub-sectors; for example, the solar sector alone contains more than 90 separate International Patent Classification (IPC) codes, according to the World Intellectual Property Organization. No other type of data covering the solar sector offers the same breadth and depth as patent data.

Second, since the patent-application process is expensive and complex, the very act of filing a patent indicates that a technology has value and usefulness (Dechezleprêtre, 2010). Indeed, during the last 200 years, very few major inventions have *not* been patented (Oltra, et al., 2008). In addition, empirical evidence supports the claim that filing patents in other countries "signals a willingness to deploy that technology in the recipient nation," and that worldwide, firms read and use patent applications "to improve their own technologies" (Maskus, 2004, p. 23). Hence, we know that patent data provide information that is both wide and deep, while also revealing the value of the technology contained within patents. Finally, because patents make

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found a positive correlation between patent applications and the introduction of new products (Comanor and Scherer, 1969).

technology public and anyone can copy technology embodied in a patent once it expires, patents were in effect designed as agents of technology transfer; as a result, they are an ideal technology-transfer measure.

Nonetheless, problems do exist with using raw patent counts to measure technology transfer. Most obviously, not all technology is patented, nor is it even patentable (Griliches, 1990). Since patenting requires inventors to make public their technology, they may prefer secrecy to patenting. Other technology, such as know-how and learning-by-doing, is tacit and therefore unable to be patented. While patent data may undercount or miss some technologies, on the whole, researchers agree that most economically valuable patents are filed (Haščič, 2010). Moreover, empirical evidence shows a positive correlation between tacit knowledge and the knowledge contained in patents (Dechezleprêtre, 2010).

Of course, the act of filing a patent does not necessarily mean that technology transfer has occurred. In fact, firms may file a patent for completely different reasons. While imitation prevention is the foremost reason for filing a patent, companies may also seek patent protection to block a rival from developing a similar or related invention, or to use as leverage in negotiations or lawsuits (Cohen et al., 2000). Still, others note that because the application process is costly and cumbersome, inventors are unlikely to patent unless they believe they will produce and/or use the technology where the patent is filed (Dechezleprêtre, 2010). Although other motivations for filing patents exist, because patenting requires making public the technology, inventors must assume that filing a patent will be more economically advantageous than not doing so.

Patent value can also present a problem in patent data. It is widely known that the vast majority of patents are of very low value, and that a small proportion of patents account for most of the total value of patents (Dechezleprêtre, 2010; Keller, 2009; Oltra et al., 2008). This is also true in the solar industry, where on average, only about 25 percent of patented solar technologies worldwide are exported (Dechezleprêtre, 2011), indicating that the majority have a lower value.[2] Therefore, using raw patent counts to quantify technology transfer is highly inadvisable because there is a high probability that the patents being counted have low value, and thus account for very little, if any, actual technology transfer. Lanjouw et al. (1998) propose weighting patent counts by data on patent renewals and the number of countries where a patent is filed to measure the patent's value more accurately. Doing the latter is extremely common. Patents filed in multiple countries can be assumed to be of even greater value, and indeed, this coincides with evidence showing that exported technologies are of the highest value of all technologies (Lanjouw, 1998). Weighting patent counts by citation data can also correct for this problem (Dechezleprêtre, 2010 and Keller, 2009) and is the method I use here. Phalin (2012) confirmed a robust, positive relationship between patent citations and patent quality in the solar sector. Therefore, by using patent citations as a quality measure in my regression on patent counts, I can be relatively confident that I am measuring patents of higher value. In other words, because the quality measure allows me to capture patents whose technology is more likely to be employed, I am more closely capturing a measure of technology transfer.

[2] This is compared with about a 30 percent export rate in the wind sector.

The last problem with patent data is that the propensity to patent varies widely across industries (Dechezleprêtre, 2010). Patents are most likely to be filed in the pharmaceutical, chemical, and car industries (Oltra et al., 2008). Hence, if we examine aggregated patent data and see an increase in patenting over time, this may indicate more innovation, or it could indicate a higher propensity to patent. The simplest way to correct this issue is to use patent data disaggregated by sector or industry (Basberg, 1987), which is one reason I restrict my analysis to the solar-energy sector of the clean-energy-technology industry. Of course, this correction could present a disadvantage because sector-specific results may not be generalizable. However, what may be lost in generalizability may be gained in accuracy, so it seems to be a tradeoff worth making.

Overall, patent data have proved to be a widely used and dependable source of data and information for researchers examining international technology transfer in the clean-energy industry. This is because 1) they allow for specific, disaggregated analysis, unlike FDI and trade flows; 2) they are easily accessible, unlike licensing data; and 3) they are more reliably and consistently collected and maintained than data on R&D expenditures.

After reviewing the most common measures of technology diffusion—R&D expenditures, FDI flows, trade flows, licensing, and patent counts—and their possible use for examining the solar sector, a general conclusion can be reached: Yes, problems exist with using patent data to gauge technology transfer, but they are the best available measure in this case compared with all the others, especially once certain issues are corrected. To rephrase the well-known Churchill quote: It has been said that patent counts are the worst way to measure technology transfer—except for all the others that have been tried. Basberg observed in 1987 that, “We have a choice of using patent data cautiously and learning what we can from them, or not using them and learning nothing about what they can teach us.” This advice still holds true today.

CHAPTER 5
THEORETICAL AND ECONOMETRIC FRAMEWORK

This work is based on the model of Gallini et al. (2001), who base their work on Eaton and Kortum (1994, 1995), Kortum and Lerner (1997), and Rafiquzzaman and Whewell (1998). Gallini et al. analyze aggregate data of patents filed in Canada from Germany, the United Kingdom, and the United States. Eaton and Kortum (1994) model the creation of new inventions and their international diffusion. In their model, the value of a patent depends on its quality, q, a random variable drawn from a cumulative distribution. They derive the following threshold condition:

$$V_{nit}^{pat}(q) - V_{nit}^{not}(q) = c_{nit}$$

$V_{nit}^{pat}(q)$ is the value of filing a patent with quality q from country i in country n; $V_{nit}^{not}(q)$ is the value of not filing a patent with quality q from country i in country n. The patent will be filed as long as $c_{nit} \geq 0$. Three country characteristics directly affect this threshold: the lag time it takes for the technology to be adopted in country n, the strength of patent protection laws in country n, and the cost of patenting in country n. These can be proxied empirically by a measure of human capital, an index of patent rights, and filing fees or the need for translation, respectively.

In a later version of this paper (Eaton and Kortum, 1995), the authors expand the model to include the determinants of technology diffusion, “i.e., the probability that an invention from country i will be adopted in country n. We let diffusion from country i to country n depend on: (1) whether n and i are the same country or not, (2) the distance between n and i, (3) the level of human capital in n (the adopting country), and (4) the level of country n’s imports from I relative to n’s GNP.”

Gallini et al. (2001) follow Eaton and Kortum to derive a model measuring the propensity to patent. Their specification is as follows:

$$E\left(\frac{P_{ij}}{N_{ij}^{*}}\right) = \rho(s_j, x_j, z_{ij}, c_j)$$

Where P_{ij} is the number of patents filed in destination country j by the source country i; N_{ij}^{*} is the innovation effect, or the total number of patentable inventions (which is unobservable); ρ is the probability that an invention from country i will be high quality enough for the patent filing to be profitable in country j; s_j is the strength of patent protection in country j; x_j is a set of indicators controlling for the economic environment in j (i.e., GDP, human capital); z_{ij} is a set of indicators describing the relationship between i and j (i.e., distance, trade flows); and c_j is the cost of filing a patent in country j. Taking logs, their econometric specification is as follows:

$$log\left(\frac{P_{ijt}}{n_{it}}\right) = \alpha_0 + \beta s_{jt} + \gamma x_{jt} + \delta z_{ijt} + \theta c_{jt} + \alpha_t + \alpha_i + \alpha_{it} + \epsilon_{ijt}$$

As above, P_{ijt} is the numbers of patents from the source country, i, filed in the destination country, j (Canada), in year t. n_{it} is the amount spent on R&D in i in year t. s_{jt} is the strength of patent protection in j as measured by the Ginarte and Park Index (Ginarte and Park, 1997). x_{jt} is a set of variables measuring human capital, GDP, and an index measuring the effectiveness of j's antitrust laws. z_{ijt} describes the relationship between i and j, including: distance, distance squared, and log(j's imports from i / real GDP). c_{jt} controls for the cost of patenting in j, including fees and a dummy variable indicating whether translation is required. Finally, the authors include time and country fixed effects.

I add to the Gallini et al. model in several ways. First, in this model—as in those of Eaton and Kortum and Kortum and Lerner—quality is randomly drawn from a distribution. I add a quality variable on the right-hand side: a weighted measure of the total number of patent citations from i in year t. Second, I perform a disaggregated analysis, breaking down the patent data and examining only solar technology. This is important because not all results will be the same across industries and technologies. My specification is as follows:

$$E(P_{ijt}) = \rho(s_j, x_j, z_{ij}, c_j, q_{ij})$$

$$log(P_{ijt}) = \alpha_0 + \beta\log(s_{jt}) + \gamma\log(x_{jt}) + \delta\log(z_{ijt}) + \theta\log(c_{jt}) + \varphi\log(q_{ijt}) + \epsilon_{ijt}$$

In my analysis, the source country, i, is the United States. I use 16 OECD nations as destination countries: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Japan, Netherlands, Norway, Spain, Sweden, Switzerland, and the United Kingdom. In addition, I add a variable controlling for the existence of pro-renewable-energy policies in country j.

CHAPTER 6
VARIABLES AND DATA

The dataset includes the United States as the source country of solar patents and 84 nations as destination countries where the patents may be filed. The dependent variable, P_{ijt}, is the number of solar patents filed in country j from country i (the United States) in year t. Data for this variable were downloaded from Espacenet, the patent database of the European Patent Office. This database contains information on patents, including filings and citations, from more than 100 countries worldwide. To gather the relevant information required for this study, I first assembled all the International Patent Classification (IPC) codes that relate to solar technologies from the World Intellectual Property Organization's (WIPO) "IPC Green Inventory" list, which was created to allow researchers to identify environmentally sound technologies more easily.

Using these IPC codes, a script was written in the computer language C++ that, when executed, downloaded automatically from Espacenet data for each solar-related patent between the years 1952 to October 2011. (Appendix A contains a more detailed description of the computer program and process.) The pieces of data for each patent include: the patent application number, the patent application country, the patent application date, other countries where the patents were filed, and forward patent citations. Using this data, I create the dependent variable, P_{ijt}, which is the total number of solar patents from country i (the U.S.) filed in country j in year t. Thirty-six observations from Canada were dropped from the sample because in the EPO database they had origin/destination years listed as 00000000. Note that due to the model's specification, this is an aggregate measure of the number of solar patents, rather than an examination of individual patents.

My variable of interest, *qual*, is a proxy for the aggregate quality of the patents being filed in country j from the United States in year t. *Qual* is derived from the total number of citations received by all patents from the U.S. filed in country j in year t. However, I cannot use the raw total number of citations received by these patents. This is because the total number of citations reflects both the number of patents filed in a country as well as the quality of these patents; i.e., the more patents filed, the more citations there will be regardless of quality. Therefore, the total number of citations is a proxy for both the number of patents and the average patent quality, and, as such, would be subject to upward bias in these regressions. To deal with this bias, I divide the number of citations of the patents filed from the U.S. in country j in year t by the number of patents filed from the U.S. in country j in year t. This yields a ratio of citations to patents that functions as a proxy for the aggregate quality of patents filed in a particular country in a particular year, which serves the purpose of this analysis much better. Therefore, *qual* can be thought of as a measure of citations per patent.

I also need to be concerned with the fact that it takes patents 20 years to receive 75 percent of the citations they will ever likely receive. Therefore, I run two different sets of analyses: one on the full dataset, which includes solar patents from the years 1952–2011, and another on a trimmed version of the dataset, which includes solar patents from only 1991 and earlier. In the trimmed dataset, we know that these patents will have received the majority of the citations that they are likely to receive. As theory predicts, I expect the coefficient on *qual* to be positive and statistically significant.

Another variable of interest is *ipr*. This is the Ginarte and Park index, which measures “how strongly patent rights will be protected” in a given country (Ginarte and

Park, 1997).[1] Using data from 110 countries between 1960 and 1990, Ginarte and Park created an index that has since become the benchmark measure most economists use for a country's level of patent protection. The G&P Index covers five aspects of a country's patent law: "1) extent of [law's] coverage, 2) membership in international patent agreements, 3) provisions for loss protection, 4) enforcement mechanisms, and 5) duration of protection" (Ginarte and Park, 1997). Scores for each are given between 0 and 1, and a weighted average yields a total score between 0 and 5 for every five years from 1960 to 2005. The expected results for this variable are ambiguous. Most studies examining high-income nations and aggregate patent data find a positive, statistically significant relationship between IPR strength and patents filed. However, when broken down by national income and/or industry, these results do not always hold.

I include *gdp* as an independent variable to control for market size. This variable, taken from the Penn World Tables, is total PPP converted GDP in millions of 2011 dollars (Heston et al., 2011). I hypothesize that larger markets will be more likely to draw patents because there is a higher chance of profitability in more developed economies. Thus, I expect the coefficient on *gdp* to be positive.

A measure of human capital, *humk*, is also included as an independent variable. This variable measures the destination country's ability to absorb new technologies and innovations. A larger stock of human capital will signal that a country is better equipped to deal with new technologies. I expect a higher level of patenting in countries with more human capital, and thus a positive coefficient on the *humk* variable. The data for the variable *humk* are average years of tertiary education every five years beginning in

[1] I thank Dr. Walter Park, who generously provided me the latest edition of the index, which includes rankings up to 2005.

1950 and ending in 2010. These data are found in the Barro and Lee dataset on worldwide educational attainment (Barro and Lee, 2010).

Variables that describe the relationship between the United States and country j are also important when controlling for exogenous factors. I include *dist*, which is simply a measure of direct-line distance between Washington, D.C., and country j's capital, per Gallini et al. These distances can be found in Fitzpatrick and Modlin (1986). Because countries that are nearer to one another tend to have higher trade and closer economic relationships, I expect the coefficient on this variable to be negative; i.e., the farther the distance, the fewer patents filed. Another variable describing the relationship between the U.S. and country j is bilateral trade flows, *imps*. Countries with higher trade flows exchange more products and technology, so I expect the coefficient on this variable to be positive. The data for *imps* comes from the Feenstra and Lipsey NBER–United Nations Trade Data 1962–2000 dataset.

I also need to control for the cost of filing a patent in country j. This is a difficult variable to proxy because so little data exist. I could easily find information on current patent costs in each of the countries in the dataset and assume that costs are constant over time, as did Gallini et al. However, since the 1980s, patent costs have risen in Japan and the United States, while they have fluctuated at the European Patent Office (de Rassenfosse and van Pottelsberghe, 2012). Data for other nations are not readily available.

The first variable I use to control for cost is *cost*. This variable is the cost of filing a patent in constant US 2000 dollars in Japan, the United States, and the European

Patent Office between 1980 and 2007.[2] It is used only in the analysis of OECD nations. Because I do not have data on each of the individual European countries in my dataset, I use the EPO numbers as a proxy to measure filing costs in these nations. This is not ideal, but excluding a cost measure would be worse for the analysis than having no measure, even a blunt one, at all. Another disadvantage of this variable is that I must exclude Canada and Australia when I use it since I have no comparable data for these countries. I expect the coefficient on *cost* to be negative; as the cost of filing a patent rises, fewer will be filed. Note that the *cost* variable includes filing and other fees required by offices, but not translation fees.

Another option is to exploit the fact that the cost of translation fees for patents can range in the thousands of dollars and therefore represent a significant portion of the overall cost of filing patents abroad (European Commission, 2010). There is no way to obtain specific information on translation fees since they are generally done by private companies; however, I can create a dummy variable, *lang*, equal to 1 if the course country (U.S.) and destination country share an official language (i.e., if translation is not required). Information for this variable was found in the CIA World Factbook. This is a blunt measure, but it does have the advantage of bringing more national specificity to the analysis. Although not an ideal gauge of cost, excluding a cost measure would be worse for the analysis than having no measure at all. I expect the coefficient on the variable *lang* to be positive; a variable equal to 1 indicates that translation is not needed, which means overall patent-filing costs will be much lower for those nations.

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[2] I thank Dr. Gaetan de Rassenfosse and Dr. Bruno van Pottelsberghe de la Potterie for generously sharing with me their data on patent fees.

So far, I have included independent variables that control for patent quality, the economic environment in the destination country, the relationship between the source and destination countries, and the cost of filing patents in the destination country. However, since this analysis concerns solar technology, it is also important to consider whether any policies in the destination country regarding renewable energy may also encourage solar-technology inflows. A wide range of policies can be used to encourage alternative-energy R&D and production, including feed-in tariffs, subsidies, and tax incentives. Rather than creating a separate variable for each of these policies, I have created a dummy variable, *renew*, equal to 1 if pro-renewable-energy policies existed in destination country j in year t–1. I lag this variable because these policies often do not begin having effects immediately. I constructed this variable using the International Energy Agency's World Energy Outlook Policy Database. I expect the coefficient on this variable to be positive; pro-renewable-energy policies are likely to encourage inflows of solar technology and attract such innovation to the destination countries.

For the complete dataset of all 84 countries, I also add a meteorological indicator, *sun*, which captures average hours of sunshine per year. This data, from the World Meteorological Organization, was accessed via the United Nations Data Explorer. I expect a positive sign on *sun* since nations with more sunlight on average can be expected to produce more solar technology. However, there may be some ambiguity in this variable, particularly if production is being off-shored to a country with less sunlight. In addition, so many other factors determine production and use of solar technology, such as infrastructure and general economic performance, that meteorological data may capture only a small sliver of the solar-technology decision process. Second, extensive, worldwide solar/cloud-cover data are not as widely available as some other data points; therefore, including the meteorological data causes more than 100 observations to be dropped, reducing the accuracy of the results. In other words, there is a tradeoff between adding a plausible (but not necessarily central) factor in the solar-technology decision and accuracy of the results as a whole. Finally, there is also possible selection bias; i.e., countries that don’t have adequate sun data may lack data because of poor infrastructure or poor reporting standards, which could bias the results.

CHAPTER 7
RESULTS: OECD COUNTRIES

Almost 80 percent of green-energy patents are filed by six nations—Japan, the United States, Germany, France, the United Kingdom, and South Korea (Latif, Maskus, et al., 2011). Thus, it can be seen that technology in this sector is fairly concentrated at a national level. Figure 7-1 shows the top 20 destination countries for U.S. solar patents between 1952 and 2011. Japan, China, Canada, Australia, and Germany comprise the top five.

In this section, I focus on a select group of OECD countries per Gallini et al. This has the advantage of controlling somewhat for cross-country heterogeneity since these nations are similar in market size and economic background. The dataset includes the United States as the source country of solar patents and 16 OCED nations as destination countries where the patents may be filed: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Japan, the Netherlands, Norway, Spain, Sweden, Switzerland, and the United Kingdom.

I first examine my dataset trimmed to include only the years 1991 and earlier. This is to account for the fact that most patents receive 75 percent of all citations they will ever receive within 20 years of being filed. Thus, limiting the years in the analysis helps control for the problem that newer patents have fewer citations not necessarily because of lower quality, but because of their age. Looking at the summary statistics in Table 7-1, we see that in an average year, the U.S. will file about 30 solar patents in country j. However, almost one third of all patents filed in the U.S. will not be filed elsewhere. About 40 percent of patents will be filed in two to 20 countries. The variable *quality* is a raw count of the citations received by the patents in this dataset. Note that it differs from *qual*, which is weighted by the number of patents filed. On average, all the patents filed from the U.S. in j in year t will receive a total of about 282 citations. Almost 36 percent of the p_{ijt} pairs receive no citations. The measure of IPR strength, *ipr*, has a mean of 2.98, above average in the Ginarte and Park index; in this case, an "average" rating would be 2.5 since the index is from 0 to 5.

Next, I need to determine which econometric model works best for the data at hand. Gallini et al. use a log-linear specification to measure the propensity to patent. However, the dependent variable is a count, and a significant portion of them are zeros. It can be argued that OLS specifications are better matched to continuous, as opposed to discrete, data. Moreover, when data on the dependent variable contain a large portion of zeros, as do the data here, it may be better to use a model that takes this into account. The first model to consider using count data is the Poisson model. However, Poisson requires $E(y|x) = Var(y|x)$, i.e., that the mean equals the variance. This is unlikely in the current case; thus, a negative binomial specification, which allows and corrects for differences in the variance, should be better suited to this analysis. Indeed, examining the large χ^2 value in results from Tables 7-3 and 7-4 indicates that the data are not Poisson, that they are overdispersed, and that a negative binomial specification is appropriate.

I now analyze the results of the negative binomial regressions. Looking first at Table 7-3, Column I, the coefficient on *qual*, the weighted measure of quality, which is the variable of interest, is positive and statistically significant. Recall from Section 6 that *qual* is a ratio of citations to patents that serves as a proxy for the aggregate quality of patents filed in a particular country in a particular year. This indicates that the difference in logs of expected counts of p_{ijt} would increase by about .05 units for a one-unit change in the quality ratio, while holding other variables in the model constant. Alternately stated, a one-unit change in the weighted quality ratio would cause p_{ijt} to increase by about 5%. Using the summary statistics found in Table 7-1, we can calculate the effect at the mean: A one-unit change in *qual* will lead to 1.5 more patents being filed in a given year. We can also calculate the effect within one standard deviation, which would be almost 9 patents. (I calculate this effect by multiplying the coefficient on *qual* by the standard deviation of *qual* and multiplying this number by the mean of p_{ijt}.)

The coefficient on the variable that measures patent-law strength, *ipr*, is negative and statistically significant at the 1 percent level. Results show that the difference in logs of expected counts of p_{ijt} would decrease by about .68 units for a one-unit increase in the IPR index. In other words, a one-unit change in the IPR index would cause p_{ijt} to decrease by about 68%. The effect at the mean translates to a fall of almost 24 patents. We can also calculate the effect within one standard deviation, which would be about 12 patents. This is a large and unexpected effect. While others have also found a negative result (Gallini et al.), some have found a positive and statistically significant relationship between IPR strength and patents filed in the solar industry (Dechezleprêtre et al.). The results here could be explained by other factors. For instance, it could be that in the solar industry in developed nations, strengthened IPR laws act as a deterrent to competition by ensuring market share for established firms, which discourages patent flows. Although this hypothesis requires further testing, some analysis has already been done concerning the different effects that strengthened IPR laws could have on an importing country. Using aggregate data, Maskus and Penubarti (1995) found that stronger IPR laws may reduce imitation and encourage firms to increase exports to the country, thus causing a “market-expansion effect”; otherwise, such laws could reduce imitation and encourage firms to raise unit price, thus having a “market-power effect.” The authors found that the market-expansion effect outweighed the market-power effect when examining data on OECD exports to the developing world, but it may be that the effects differ when broken down by industry. In addition, it could be that in highly developed economies, harmonization of laws and enforcement renders the need to file patents less pressing.

Human capital has an unexpected negative, statistically significant, and large effect. Specifically, a one-unit change in the human capital measure would cause p_{ijt} to decrease by about 214%. We can also calculate the effect within one standard deviation, which would be about 13 patents. This may be due to the fact that there is little variation in the number of years of schooling in this set of OECD countries; the summary statistics show that 68% of citizens in the countries included here will have between .11 and .71 years of schooling beyond high school, which is a negligible difference in terms of the real-world effect of accumulation of human capital.

As expected, distance has a negative and statistically significant effect on the number of patents filed, though the magnitude is small: A one-mile increase in distance results in a .0017 percent fall in the number of solar patents filed. However, note that the standard deviation of distance is more than 3300, so the effect within one standard deviation of the mean will be almost 17 patents. *gdp* and *imps* both have statistically significant and positive effects on the number of solar patents filed. The effect of *gdp* within one standard deviation of the mean is almost 22 patents. *imps* is only marginally statistically significant; its effect within one standard deviation of the mean is almost a 17-patent increase.[1]

The dummy variable indicating the existence of pro-renewable-energy policies in the destination country, *renew*, is positive as expected but is not statistically significant. It may be that my current proxy is not adequately picking up the effect that I want to measure. Alternately, there may be a feedback effect whereby higher innovation in renewable energies causes such policies to be created, not the other way around. The coefficient on *cost* has a statistically significant, negative effect on the number of patents filed. Results indicate that a one-unit change in cost would cause p_{ijt} to decrease by about .02%. This translates into a near 12-patent decrease within one standard deviation of the mean.

Column II of Table 7-3 examines the negative binomial specification including the *lang* dummy variable. The coefficient on *qual* is comparable to the previous regressions both in terms of statistical significance and size. Moreover, the results for the other variables are similar as well. The coefficient on *lang*, though positive as expected, is only marginally statistically significant. Finally, Column III of Table 7-3 examines the negative binomial specification including the *lang* dummy variable as the only cost measure. In this case, all variables except *dist* and *renew* are statistically significant, though *humk* is in the wrong direction. As predicted, *lang* has a positive and statistically significant effect. The results in Table 7-3, Column III, indicate that the difference in logs of expected counts of p_{ijt} would increase by a factor of about 1.1 if the dummy equals 1.

[1] Because I was concerned about collinearity between distance and imports, I also ran regressions with each variables separately; results did not change much.

Full Dataset

For comparison, we can also consider the negative binomial results of the full dataset; we see that they are in fact similar to those for the trimmed analysis. Looking first at Table 7-4, Column I, the coefficient on *qual* is positive, statistically significant, and similar to the trimmed results at about .059. Though the coefficient on *ipr* remains negative in this specification, it is no longer statistically significant. Human capital has an unexpected negative effect, while distance is also positive, but statistically insignificant. *Renew* is also statistically insignificant, but the coefficient on *cost* does have a statistically significant, if small, negative effect on the number of patents filed.

Column II of Table 7-4 examines the negative binomial specification including the *lang* dummy variable. The coefficient on *qual* is comparable to the previous regressions both in terms of statistical significance and size. Moreover, the results for the other variables are similar as well. The coefficient on *lang*, though positive as expected, is not statistically significant. Finally, Column III of Table 7-4 examines the negative binomial specification including the *lang* dummy variable as the only cost measure. In this case, all variables are statistically significant, though *humk* and *dist* are in the wrong direction.

Robustness of Results

As a check on the above results, I also run log-linear specifications on both the trimmed and full datasets. The variable of interest, *qual*, is positive and statistically significant across all specifications. The main difference is that the magnitudes are much larger in the linear specifications. For example, Table 7-6 shows log-OLS results from the trimmed dataset. The coefficient on *qual* indicates that a 1 percent increase in the measure of quality causes a .38 percent increase in the number of patents filed. In other words, a 100 percent increase in the quality ratio leads to 38 percent increase in the number of patents filed. Looking again at the summary statistics, we see that the mean of *qual* is about 5.12, while the standard deviation is about 5.85. Thus, we see that a 100 percent increase is likely, and that this is therefore an economically significant coefficient in this specification as well. We also see a larger magnitude effect for *gdp* in comparison with the negative binomial specification. Meanwhile, the effect of *ipr*, which is negative and statistically significant, is smaller. The results suggest that a 1 percent increase in the IPR index causes a 2.47 percent fall in the number of patents filed. Looking at the mean and standard deviation of IPR, we nonetheless see that this is an economically significant result in this specification as well.

Not as many of the control variables are statistically significant in linear specifications. Moreover, the signs of the coefficients on *humk*, *cost*, *renew*, and *gdp* change depending on which variables are used to measure cost. The complete results for these specifications are reported in Tables 7-5–7-7. However, because of the large number of zeros in the dependent variable, the results of the negative binomial regressions are likely to be a more accurate characterization of the relationship between quality, IPR strength, and the propensity to patent.

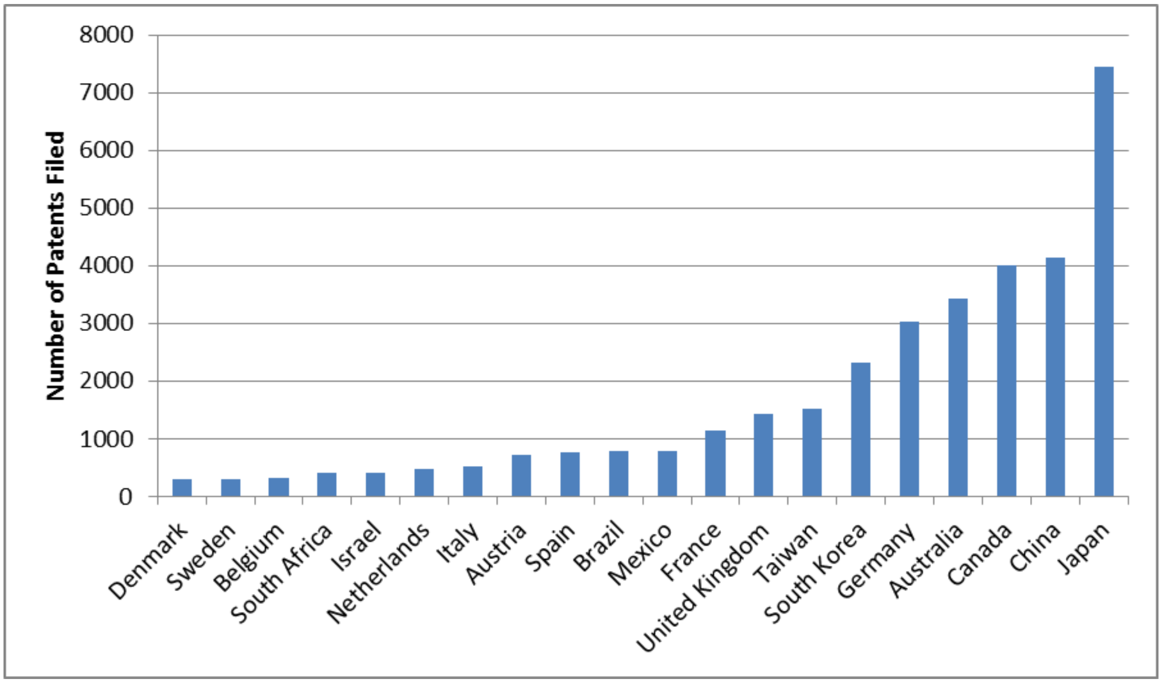

Figure 7-1. Top 20 destination countries for U.S. solar patents, 1952–2011

Table 7-1. OECD summary statistics, trimmed

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
pijt	680	29.64706	77.30466	0	666
quality	680	281.6294	817.1486	0	8100
qual	680	5.12054	5.853727	0	50
ipr	544	2.984651	0.603163	2.008333	4.675
gdp	662	317168.6	688220.7	4513.926	5946800
humk	680	0.27806	0.211903	0.0331	1.303
dist	680	6609.176	3311.276	0	15943
imps	480	5913972	1.11E+07	57469	7.61E+07
cost	180	4166.978	1824.601	246	6824
lang	680	0.235294	0.424495	0	1
renew	374	0.032086	0.176463	0	1

Table 7-2. OECD summary statistics, full

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
pijt	1020	54.27353	190.8957	0	2483
quality	1020	276.4696	780.3543	0	8100
qual	1020	4.390836	5.380992	0	50
ipr	884	3.527008	0.859096	2.008333	4.875
gdp	968	691027.5	1587278	4513.926	1.44E+07
humk	1020	0.40784	0.303943	0.0331	1.5598
dist	1020	6609.176	3310.464	0	15943
imps	624	9593222	1.90E+07	57469	1.56E+08
cost	420	4823.283	1858.418	246	8025
lang	1020	0.235294	0.424391	0	1
renew	714	0.212885	0.409634	0	1

Table 7-3. OECD negative binomial results, trimmed

Variable	I cost	II cost/lang	III lang
constant	6.14048* [0.949836]	5.802057* [0.9553224]	5.358989* [0.4785652]
qual	0.0497978* [0.0140127]	0.0503595* [0.0138216]	0.0501218* [0.0121826]
ipr	-0.6815216* [0.2140033]	-0.7907816* [0.2185659]	-0.9709525* [0.1375253]
humk	-2.135974* [0.6405463]	-1.848331* [0.6530437]	-2.193245* [0.4859487]
gdp	0.00000105** [0.000000436]	0.00000132* [0.000000454]	0.00000132* [0.000000205]
dist	-0.0001739** [0.00008]	-0.0000984 [0.000088]	0.0000183 [0.0000248]
imps	0.0000000509*** [0.000000027]	0.0000000265 [0.0000000294]	0.0000000211* [0.00000000791]
renew	0.396122 [0.3125041]	0.4264614 [0.3081512]	-0.0844464 [0.3072135]
cost	-0.0002106* [0.0000532]	-0.0001846* [0.0000543]	
lang		0.541377*** [0.2865833]	1.096371* [0.1764086]
N	168	168	352
χ^2	849.26	741.97	4087.5

Standard errors in brackets
*= statistically significant at 1% level; **= statistically significant at 5% level; ***= statistically significant at the 10% level
N = 168

Table 7-4. OECD negative binomial results, full

Variable	I cost	II cost/lang	III lang
constant	2.243044* [0.7921048]	1.973077** [0.8095166]	3.795624* [0.3751833]
qual	0.0586222* [0.0169586]	0.057468* [0.0168175]	0.0563394* [0.0129992]
ipr	-0.1221819 [0.1815693]	-0.1870611 [0.185547]	-0.6144548* [0.1059338]
humk	-2.845379* [0.5360646]	-2.566862* [0.5682592]	-2.387045* [0.4133247]
gdp	0.00000138* [0.000000301]	0.00000154* [0.000000321]	0.0000009217* [0.000000118]
dist	0.0001154*** [0.0000698]	0.0001621** [0.0000774]	0.0001015* [0.0000196]
imps	-3.84E-09 [0.0000000158]	-0.0000000152 [0.0000000177]	0.0000000209* [0.00000000408]
renew	0.2745408 [0.182232]	0.3174615*** [0.1841768]	0.505246* [0.1742732]
cost	-0.0000846** [0.0000435]	-0.0000685 [0.0000449]	
lang		0.3927209 [0.2817994]	1.422557* [0.1721787]
N	294	294	496
χ^2	2075.99	2065.7	7308.95

Standard errors in brackets
*= statistically significant at 1% level; **= statistically significant at 5% level; ***= statistically significant at the 10% level

Table 7-5. OECD baseline OLS results

Variable	Trimmed	Full
constant	-7.898576	-30.01547**
	[13.64942]	[12.74285]
qual	0.2543524**	0.2261105**
	[0.1175648]	[0.1172358]
ipr	-10.09929*	-13.65478*
	[2.771582]	[2.769846]
humk	9.99337	25.54223*
	[9.079358]	[8.862276]
gdp	0.0000177**	0.0000184*
	[0.00000854]	[0.00000556]
dist	0.0075039*	0.0109371*
	[0.0015391]	[0.00135]
imps	0.000000771	0.000000659**
	[0.000000519]	[0.000000266]
renew	4.370742	1.913827
	[2.970277]	[2.767707]
cost	-0.0022476*	-0.000647
	[0.0006367]	[0.0006155]
N	168	294
R^2	0.8359	0.8493

Standard errors in brackets
*= statistically significant at 1% level; **= statistically significant at 5% level; ***= statistically significant at the 10% level

Table 7-6. OECD log linear results, trimmed

Variable	I cost	II cost/lang	III lang
constant	3.558483 [7.446854]	-1.304101 [7.953427]	-7.115385* [1.673547]
qual	.3789241* [.1294908]	.3745841* [.127848]	.218637** [.0887525]
ipr	-2.473575* [.5872381]	-2.830319* [.6467856]	-3.481379* [.347222]
humk	.167515 [.1955187]	.1698834 [.19943]	-.3246087** [.1331725]
gdp	.5412406* [.1951259]	.5169336* [.196241]	-.0348758 [.1551628]
dist	-.4538205 [.7010568]	.1143857 [.7832732]	.161428 [.117386]
imps	.1748 [.1732275]	.1709159 [.1744482]	.7921719* [.1406844]
renew	.3796127 [.4239422]	.4143905 [.4257975]	-.0609414 [.3480032]
cost	-.5219366* [.1692918]	-.4449594 ** [.1748984]	
lang		.4315299*** [.2599005]	.1475781 [.1340851]
N	148	148	327
R^2	0.6270	0.6328	0.5964

Standard errors in brackets
*= statistically significant at 1% level; **= statistically significant at 5% level; ***= statistically significant at the 10% level

Table 7-7. OECD log linear results, full

Variable	I cost	II cost/lang	III lang
constant	-14.34548** [5.999005]	-17.85084* [6.27317]	-8.294074* [1.636412]
qual	0.3104596** [0.1269877]	0.3017453** [0.1265791]	0.1858412** [0.0855511]
ipr	-2.52938* [0.6213028]	-2.755392* [0.6486045]	-3.412448* [0.3122358]
humk	0.2706155 [0.1779701]	0.3078322*** [0.1810047]	-0.2052258 [0.1246531]
gdp	0.460278** [0.1966467]	0.4978671** [0.2011078]	-0.0870124 [0.1573013]
dist	1.431803** [0.5694547]	1.865468* [0.6272655]	0.2953518** [0.1190165]
imps	0.2006617 [0.1797459]	0.1365887 [0.1892359]	0.8442886* [0.1446801]
renew	0.3259215 [0.2463205]	0.3750733 [0.2482332]	0.332537 [0.2309321]
cost	-0.2461272*** [0.1429778]	-0.1855691 [0.144494]	
lang		0.3977977*** [0.2143608]	0.1751574 [0.1470642]
N	243	243	440
R^2	0.5262	0.5306	0.5291

Standard errors in brackets
*= statistically significant at 1% level; **= statistically significant at 5% level; ***= statistically significant at the 10% level

CHAPTER 8
RESULTS: ALL COUNTRIES

I first examine the dataset trimmed to include only the years 1991 and earlier. This is to account for the fact that most patents receive 75 percent of all citations they will ever receive within 20 years of being filed. Thus, limiting the years in the analysis helps control for the problem that new patents have fewer citations not necessarily because of lower quality, but because of their age.

Trimmed Dataset: High-Income Group

In the previous section, I analyzed a subset of 16 OECD nations. Here, I expand the dataset to include 84 high-, upper-middle-, and lower-middle-income nations. I begin first by examining the results for all high-income nations in my dataset, which I define as a per capita GDP of at least $20,000. I chose $20,000 because, with the exception of Mexico and Turkey, most OECD nations have per capita incomes no lower than around $20,000. Therefore, this level of GDP is less likely to result in the heterogeneity that would occur if I defined high-income as the World Bank does, at about $12,500 per capita GDP. In my dataset's high-income group, Luxembourg has the maximum per capita GDP, at $80,119; Poland has the lowest, at $20,334 (IMF, 2012). The average per capita GDP of the high-income group is $37,367.

The summary statistics and results can be seen in Tables 8-1 and 8-5 Column I. Looking at Table 8-1, we see that in an average year, the U.S. will file about 15 solar patents in country j. However, about 55 percent of all patents filed in the U.S. will not be filed elsewhere. About 31 percent of patents will be filed in two to 20 countries. The variable *quality* is a raw count of the citations received by the patents in this dataset. Note that it differs from *qual*, which is weighted by the number of patents filed. On average, all the patents filed from the U.S. in country j in year t will receive a total of about 139 citations. Almost 60 percent of the p_{ijt} pairs receive no citations. The measure of IPR strength, *ipr*, has a mean of 2.61, above average in the Ginarte and Park index.

I now analyze the results of the negative binomial regressions, run in the same way as the previous section, which are found in Table 8-5 Column I. As with my earlier results, the sign on *qual* is positive while the sign on *ipr* is negative. The coefficient on *qual* is statistically significant at the 10% level. These results indicate that the difference in logs of expected counts of p_{ijt} would increase by approximately .018 units for a one-unit change in the aggregate quality ratio, while holding other variables in the model constant. In other words, a one-unit change in the aggregate quality ratio would cause p_{ijt} to increase by about 1.8%. Using the summary statistics in Table 8-1, we can calculate the effect at the mean: A one-unit change in *qual* will lead to about 0.27 more patents being filed in a given year. We can also calculate the effect within one standard deviation, which would be 2.07 patents. This is a smaller effect than that found in the subset of OECD nations, where the quality measure caused p_{ijt} to increase by about 5%. The coefficient on *ipr*, while negative as before, is not statistically significant.

We can also compare the other independent variables in Table 8-5 Column I with the OECD trimmed results, seen in Table 7-3 Column III. *Humk*, the measure of human capital, is negative as before but not statistically significant. *gdp* is positive and statistically significant, as before. *dist* is negative but statistically insignificant, whereas it was positive and statistically significant previously. *imps*, *renew*, and *lang* have the same signs as before.

In addition to adding more countries to my dataset, I also add a new variable, *sun*, a meteorological measure of average hours of sunlight per day per country. A scatterplot of *sun* against the dependent variable, p_{ijt}, reveals a nonlinear relationship across both income groups. As a result, it is not surprising that when I add the *sun* variable to the regression by itself, it does not perform well and causes the other variables to perform worse also. (Appendix B contains these results.) Because several important factors affect the propensity to patent solar technology in a country, of which available sunlight is only one, I interact the *sun* variable with *ipr*, *humk*, and *gdp*. The reasoning here is that if a country has abundant sunlight but little legal structure, infrastructure, or income, the solar energy available won't matter much. These results can be seen in Table 8-6 Column I.

The most striking difference here is that the aggregate measure of quality, *qual*, while positive as before, is no longer statistically significant. However, two of the three interaction terms are positive and statistically significant. These results may indicate that when it comes to solar technology, sun availability—in concert with higher levels of human capital and stronger IPR laws—is a more important factor than quality alone. As with the results in the previous section, the coefficient on *ipr* continues to be negative and statistically significant. As expected, the need for translation, represented by the variable *lang*, reduces the number of patents filed by a factor of about 0.7. At the mean, this translates to approximately 10 fewer patents per year. Surprisingly, the variable on *renew*, the dummy indicating whether a country has pro-renewable-energy policies in place, is negative and marginally statistically significant. It may be that my current proxy is not adequately picking up the effect that I want to measure. Alternately, there may be a feedback effect whereby higher innovation in renewable energies causes such policies to be created, not the other way around.

Trimmed Dataset: Lower-Income Group

We can now examine the trimmed results for lower-income nations, those with a per capita GDP below $20,000. Hungary has the highest per capita GDP in this group, at $19,591; Zimbabwe has the lowest, at $487. The average per capita GDP for this group is about $9,346, which the World Bank defines as upper-middle-income.

The summary statistics for these data can be found in Table 8-2. The characteristics of the high-income vs. lower-income group exhibit striking differences. Looking at Table 8-2, we see that in an average year, the U.S. will file about 1.17 solar patents in country j (compared with 15 patents for the high-income group). However, almost 88 percent of all patents filed in the U.S. will not be filed elsewhere (compared with about 55 percent in the high-income group). Just over 7 percent will be filed in two to 20 countries (compared with about 31 percent in the high-income group). On average, all the patents filed from the U.S. in country j in year t will receive a total of about 11 citations (compared with 139 citations in the high-income group). Almost 90 percent of the p_{ijt} pairs receive no citations (compared with 60 percent in the high-income group). The measure of IPR strength, *ipr*, has a mean of 1.43, well below the Ginarte and Park index average of 2.5, and also well below the high-income-group average of 2.61.

Looking at the regression results themselves, found in Table 8-7 Column I, we see that the main variable of interest, *qual*, is positive and statistically significant at the 10% level, indicating that the difference in logs of expected counts of p_{ijt} would increase by about .014 units for a one-unit change in the aggregate quality ratio, while holding other variables in the model constant. In other words, a one-unit change in the aggregate quality ratio would cause p_{ijt} to increase by about 1.4%. Using the summary statistics in Table 8-2, we can calculate the effect at the mean: A one-unit change in *qual* will lead to about 0.016 more patents being filed in a given year. We can also calculate the effect within one standard deviation, which would be about 0.17 patents. While these results are marginally statistically significant, in terms of economic significance, the positive effect of quality on the propensity to file solar-technology patents in lower-income countries is minimal.

The other variable of interest, *ipr*, is positive but not statistically significant. These results may reflect issues of data availability. Of the 48 lower-income nations in my dataset, 12 do not have IPR data available[1]; 10 others, mostly former Soviet or Soviet-allied countries, do not have data available until 1995 and are thus not included in the trimmed results.[2] The other independent variables, also seen in Table 8-7 Column I, perform similarly to those in the high-income regression. *Humk* is negative and statistically significant, while it was also negative but statistically insignificant for the high-income group. *Gdp* and *dist* are positive and negative, respectively, and both are statistically significant, as before. The sign on *imps* changes, indicating that higher trade between countries reduces the propensity to patent by an extremely small amount, an unexpected result. The coefficient on *renew* is negative as it was in the high-income group, but it is not statistically significant. Again as expected, the need for translation, represented by the variable *lang*, reduces the number of patents filed by a factor of

[1] Armenia, Croatia, Cuba, Estonia, Georgia, Kazakhstan, Kyrgyzstan, Macedonia, Moldova, Slovenia, Tajikistan, Montenegro.

[2] Results available from 1985 for China; results available from 1995 for Bulgaria, Czech Republic, Hungary, Lithuania, Poland, Romania, Russia, Slovakia, and Ukraine.

about 1.64, larger than the factor of .48 found for the high-income group. At the mean, this translates to almost 2 fewer patents per year.

Now we can examine the results with the *sun* variable interacted with *gdp*, *humk*, and *ipr*, found in Table 8-8 Column I. *Qual* is again positive and statistically significant, but as before, the economic significance is scant. In this specification, the coefficient on *ipr* remains negative but becomes statistically significant. However, *sun_ipr*, the interaction term, is positive and statistically significant, indicating that a combination of sun and more robust IPR laws may lead to more solar patents being filed. However, because the coefficient on the interaction term is so small, this positive effect, while statistically significant, does not seem to have any tangible economic significance. We see the same type of results for *humk*, which is negative and statistically significant alone but has a positive, statistically significant, but minimal effect when interacted with *sun*. Interestingly, *sun* by itself is negative and statistically significant. It could be that other, more important, factors influence the solar-technology decision and therefore outweigh sun availability alone. The other independent variables perform similarly to those in Table 8-7 Column I, the regression without the *sun* interaction terms.

Full Dataset: High-Income Group

Examining the dataset trimmed to years 1991 and earlier is important to control for the problem that newer patents have fewer citations not necessarily because of low quality but because of young age. However, restricting the dataset also limits data availability, particularly for one of my variables of interest, *ipr*. Therefore, it is worth running the same regressions as above on the full dataset to see if we can discern significant differences.

The summary statistics can be seen in Table 8-3. We see that in average year, the U.S. will file about 28 solar patents in country j (compared with 15 for the trimmed dataset). However, almost 49 percent of all patents filed in the U.S. will not be filed elsewhere (compared with about 55 percent for the trimmed dataset). 28 percent of patents will be filed in two to 20 countries (compared with about 31 percent in the trimmed dataset). On average, all the patents filed from the U.S. in country j in year t will receive a total of about 139 citations (the same as in the trimmed dataset). About 55 percent of the p_{ijt} pairs receive no citations (compared with almost 60 percent in the trimmed dataset). The measure of IPR strength, *ipr*, has a mean of 3.18, well above the trimmed average of 2.61.

I now analyze the results of the negative binomial regressions, found in Table 8-5 Column II. As with my earlier results, the sign on *qual* is positive while the sign on *ipr* is negative. The coefficient on *qual* is statistically significant at the 5% level, indicating that the difference in logs of expected counts of p_{ijt} would increase by about .023 units for a one-unit change in the aggregate quality ratio, while holding other variables in the model constant. In other words, a one-unit change in the aggregate quality ratio would cause p_{ijt} to increase by about 2.3%. Using the summary statistics in Table 8-3, we can calculate the effect at the mean: A one-unit change in *qual* will lead to about 0.65 more patents being filed in a given year. We can also calculate the effect within one standard deviation, which would be about 4.5 patents. This coefficient is again much smaller than both the full and trimmed results from the subset of OECD countries, where the effect for both was around 5%. The coefficient on *ipr*, while negative as before, is again not statistically significant.

We can also compare the other independent variables in Table 8-5 Column II with the previous OECD trimmed results, seen in Table 7-4, Column III. *Humk*, the measure of human capital, is negative and statistically significant. *gdp* is positive and statistically significant, as before. *dist* is positive and statistically significant. *Imps* is positive and statistically significant across all tables; *renew* is positive and statistically significant in Table 7-4 Column III, but negative and statistically insignificant in Table 8-5 Column II. Finally, *lang* exhibits the same sign and significance across all results.

Now we can examine the full high-income results with the *sun* interaction terms, found in Table 8-6 Column II. The most striking difference here is that *ipr*, while negative as before, becomes statistically significant, as it was in Table 7-4, Column III. Meanwhile, the interaction of *sun_ipr* is positive and statistically significant. *Gdp* is positive and statistically significant, while *sun_gdp* is negative and marginally statistically significant. *Humk* is negative and statistically significant, while *sun_humk* is positive and statistically significant. Overall, these results seem to indicate that sun availability in concert with other factors, such as legal systems, infrastructure, and education, may encourage solar-technology transfer rather than any of these factors alone. As expected, the need for translation, represented by the variable *lang*, reduces the number of patents filed by a factor of about 0.5. The variable on *renew*, while negative, is no longer statistically significant.

Full Dataset: Lower-Income Group

We can now examine the full results for lower-income nations. The summary statistics for these data can be found in Table 8-4. In an average year, the U.S. will file about 2.7 patents in country j (compared with 1.17 solar patents in the trimmed data, Table 3). However, similar to the trimmed lower-income group, almost 84 percent of all patents filed in the U.S. will not be filed elsewhere. 9.3 percent will be filed in two to 20 countries (compared with just over 7 percent in the trimmed lower-income group). On average, all the patents filed from the U.S. in country j in year t will receive a total of about 11 citations (the same for the trimmed lower-income group). Almost 87 percent of the p_{ijt} pairs receive no citations (compared with 90 percent in the trimmed lower-income group). The measure of IPR strength, *ipr*, has a mean of 2.05, below the G&P average of 2.5 but above the trimmed lower-income average of 1.43.

Examining the regression results, found in Table 8-7 Column II, we see that the signs on the main variables of interest, *qual* and *ipr*, remain positive and negative, respectively, as before, but that neither is statistically significant. The lack of statistical significance may reflect issues of data availability. Even though the full dataset includes observations from China and former Soviet nations, the 12 missing countries not included could reduce the accuracy of the results.[3] The other independent variables, also seen in Table 8-7 Column II, perform similarly to those in the trimmed lower-income regression. The only difference is that *imps* is not statistically significant.

Now we can examine the results with the *sun* variable interacted with *gdp*, *humk*, and *ipr*, found in Table 8-8 Column II. In this specification, *qual* remains positive and statistically insignificant, but *ipr* keeps its negative sign while gaining statistical significance. As with the trimmed lower-income group, the *sun_ipr* interaction is positive and statistically significant. However, this is the only interaction term that is statistically significant in these results. Interestingly, *sun* by itself is negative and statistically

[3] Armenia, Croatia, Cuba, Estonia, Georgia, Kazakhstan, Kyrgyzstan, Macedonia, Moldova, Slovenia, Tajikistan, Montenegro.

significant. Compared with other specifications, the independent variables in the Table 8-8 Column II results do not yield many statistically significant results.

Overall, the results for higher-income nations perform similarly to the results found in the subset of 16 OECD countries. The results here differ, however, from the only other empirical analysis that I am aware of examining the effect of stronger IPR laws on the patenting of environmental technologies. Dechezleprêtre et al. (2011) conduct sector-specific regressions for several environmental industries in 96 countries between 1995 and 2007. According to their analysis, stronger IPR laws have a positive effect that is statistically significant at the 1% level on solar patenting abroad.

Several factors may account for the differences between my results and those of Dechezleprêtre et al. First, the time frame and national composition of our data differ. I conduct analyses on both high- and middle-income nations from 1952–1991 and 1952–2011 separately, while they analyze all countries together over a shorter time period. In addition, my data analyze only solar technology outgoing from the United States. Second, their analysis does not include the measure of patent quality that mine does. Indeed, when I run the analysis on my data without using the quality measure, the *ipr* variable becomes positive and marginally statistically significant for the high-income countries and negative for the lower-income countries (but only statistically significant using the full data set). Third, Dechezleprêtre et al. use a patent-breadth measure of their own construction, which I do not include. Fourth, they use the Park & Lippoldt IPR index rather than the G&P index. Finally, they did not use interaction terms with the meteorological indicators. With these differences taken together, it is not surprising that my results differ.

Table 8-1. Trimmed, high-income nations summary statistics

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
pijt	1440	14.57917	55.03398	0	666
quality	1440	139.1736	578.1591	0	8100
qual	641	8.230194	7.804564	0	68.5
ipr	928	2.61091	.7387082	0	4.675
humk	1400	.2344377	.1925699	.0281	1.303
gdp	1164	194521.8	538851.2	157.7524	5946800
dist	1400	7843.714	3445.941	0	15943
imps	890	3762704	8631188	2880	76100000
renew	974	.026694	.1612705	0	1
lang	1440	.2222222	.4158841	0	1
sun	1240	1957.592	542.626	1157.1	3353.55

Table 8-2. Trimmed, lower-income nations summary statistics

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
pijt	2120	1.174057	6.427171	0	107
quality	2120	10.98538	65.2599	0	1165
qual	255	9.22992	10.22286	0	83
ipr	967	1.432921	.7254176	0	4.341667
humk	1840	.1299278	.1215751	.0016	.904
gdp	1285	74662.89	176090.9	82.74619	1706318
dist	1960	8362.551	3541.677	1823	16360
imps	1099	990912.5	2442438	1	25300000
renew	1062	.0028249	.0530993	0	1
lang	2120	.1509434	.3580782	0	1
sun	1480	2284.929	442.3077	1317.562	3468.708

Table 8-3. Full, high-income nations summary statistics

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
pijt	2160	28.12454	134.7981	0	2483
quality	2160	138.5278	552.8843	0	8100
qual	1103	6.317243	6.956223	0	68.5
ipr	1544	3.182611	.9967091	0	4.875
humk	2100	.3630812	.2930161	.0281	1.5598
gdp	1794	415509.3	1208561	157.7524	14400000
dist	2100	7843.714	3445.53	0	15943
imps	1183	6231174	14700000	2880	156000000
renew	1614	.1765799	.381431	0	1
lang	2160	.2222222	.415836	0	1
sun	1860	1957.592	542.5531	1157.1	3353.55

Table 8-4. Full, lower-income nations summary statistics

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
pijt	3180	2.705346	23.98405	0	726
quality	3180	10.85975	59.85566	0	1165
qual	512	6.283733	8.560475	0	83
ipr	1653	2.055712	1.114057	0	4.541667
humk	2760	.2021941	.2030974	.0016	1.587
gdp	2146	194938.3	632307.7	82.74619	11300000
dist	2940	8362.551	3541.375	1823	16360
imps	1518	1953428	7348557	1	140000000
renew	1602	.0892634	.2852126	0	1
lang	3180	.1509434	.35805	0	1
sun	2220	2284.929	442.2579	1317.562	3468.708

Table 8-5. High-income nations

Variable	I—Trimmed	II—Full
constant	2.830954*	2.520893*
	[.4477508]	[.3077731]
qual	0.0181586***	.0229523**
	[.0105798]	[.01017]
ipr	-0.1546193	-.1134582
	[.136787]	[.0897001]
humk	-0.5335707	-.8676658*
	[.4366192]	[.3011774]
gdp	0.00000144*	0.000000941*
	[0.00000026]	[0.00000013]
dist	-0.00000747	.0000319**
	[.0000229]	[.000016]
imps	0.0000000209**	0.0000000154*
	[0.00000000839]	[0.00000000411]
renew	-.5076545**	-.035951
	[.2506399]	[.160591]
lang	0.4824089*	.7153815*
	[.1501773]	[.1239607]
N	457	644
χ^2	7767.55	12000

Standard errors in brackets
*= statistically significant at 1% level; **= statistically significant at 5% level; ***= statistically significant at the 10% level

Table 8-6. High-income nations w/sun interaction terms

Variable	I—Trimmed	II—Full
constant	9.385993*	8.117742*
	[1.455864]	[1.075063]
qual	0.0130424	.0208639**
	[.0103745]	[.0097136]
ipr	-1.656895*	-1.696221*
	[.5644635]	[.4494788]
humk	-7.140312*	-4.290176*
	[1.896204]	[1.458858]
gdp	0.00000103	0.00000327*
	[0.00000131]	[0.000000915]
dist	.0000356	.0001097*
	[.0000354]	[.0000263]
imps	-0.000000012	-0.0000000344*
	[0.0000000265]	[0.0000000124]
renew	-.3990825***	-.1183232
	[.2351678]	[.1496096]
lang	.69931*	.5220402*
	[.1803713]	[.1463313]
sun	-.0034245*	-.0030976*
	[.0007041]	[.0005033]
sun_gdp	0.000000000434	-0.000000000814***
	[0.000000000681]	[0.000000000487]
sun_humk	.0028144*	.0015041**
	[.0008204]	[.0006084]
sun_ipr	.0008029*	.0008275*
	[.0002868]	[.0002213]
N	396	557
χ^2	5327.79	7303.04

Table 8-7. Lower-income nations

Variable	I—Trimmed	II—Full
constant	3.958188*	3.264327*
	[.3140219]	[.2173395]
qual	.0138862***	.0073805
	[.0082447]	[.0076096]
ipr	.1000573	-.0965665
	[.1079751]	[.0795142]
humk	-2.424992*	-1.681088*
	[.5809949]	[.3399262]
gdp	0.00000119*	0.000000968*
	[0.000000224]	[0.0000000892]
dist	-.0002782*	-.0001806*
	[.0000254]	[.0000169]
imps	-0.000000072*	-0.00000000107
	[0.0000000188]	[0.00000000316]
renew	-.2100385	-.0133917
	[.7352274]	[.2606343]
lang	1.642622*	1.426293*
	[.1863629]	[.1370179]
N	180	274
χ^2	608.42	1294.72

Standard errors in brackets

*= statistically significant at 1% level; **= statistically significant at 5% level; ***= statistically significant at the 10% level

Table 8-8. Lower-income nations w/sun interaction terms

Variable	I—Trimmed	II—Full
constant	9.117117*	7.547661*
	[1.204876]	[.7837144]
qual	.018779**	.011745
	[.0087269]	[.0078011]
ipr	-1.23887**	-1.500062*
	[.6244091]	[.3439177]
humk	-13.22754**	-1.012846
	[5.407465]	[3.490371]
gdp	0.00000318	-0.000000393
	[0.00000237]	[0.00000105]
dist	-.0002424*	-.0002014*
	[.0000346]	[.0000242]
imps	-0.0000000503**	-0.00000000248
	[0.0000000214]	[0.00000000343]
renew	-.0395182	.2416033
	[.6674709]	[.2485642]
lang	1.875209*	1.741561*
	[.191813]	[.1486871]
sun	-.002239*	-.0018089*
	[.00048]	[.0003371]
sun_gdp	-0.000000000942	0.000000000581
	[0.00000000101]	[0.000000000446]
sun_humk	.0048127***	.0000832
	[.0028049]	[.0017197]
sun_ipr	.0005203**	.0005896*
	[.0002251]	[.0001401]
N	155	233
χ^2	387.04	536.43

CHAPTER 9
CONCLUSION

In this dissertation, I examine the relationship between patent quality and the international transfer of solar technology. I also explore the relationship between IPR laws and ITT. The analysis includes a subset of OECD members, as well as high- and lower-income nations. By examining the countries in these income groupings, I can determine if patent flows behave differently for these nations.

To understand global technology flows in the international solar market, understanding the structure of the international solar market is helpful. First, this analysis noted that there is a chasm between countries that supply solar technology versus nations that manufacture solar technology. Specifically, most solar patents are from Japan and the United States, while most production occurs in China and the rest of Asia. Second, there is a divide between those nations that demand solar energy versus countries that supply it. Producers include Asian countries, while most demand comes from Europe and the United States. However, this is changing, with nations like China and Brazil implementing policies designed to encourage solar-energy consumption.

The literature shows that using patent citations is a proven method of measuring the overall quality of patents. However, accuracy of results is enhanced when the analyses can control for industry; hence, the importance of using disaggregated data, and the reason why this dissertation examines only one sub-sector of the green-energy industry.

When examining ITT, it is important to establish whether the chosen method of measuring technology transfer is the best for the analysis. Via a literature discussing the different measures of technology transfer, I show that patent counts can be a viable measure of technology transfer. While they do present some problems, these can be corrected by examining disaggregated patent flows and using a patent-quality measure. Moreover, other methods of measuring technology transfer, including R&D expenditures and FDI flows, have proven to be even more problematic than patent counts. Therefore, even though the measure used here is not perfect, it is one of the better methods available to track levels of technology diffusion.

The results of this analysis show that, on the whole, patent quality is a factor in the international transfer of solar technology; the variable of interest *qual* was positive and statistically significant in 19 out of 22 regressions. Although results of another study have shown a positive relationship between IPR laws and patent flows in the solar sector, my results show that when an aggregate quality measure is included along with IPR, IPR strength no longer has a positive effect; the variable of interest *ipr* was negative in 21 of 22 regressions, and statistically significant in 16 of those. This may be due to the fact that globally, solar technology, even the newer PV variety, is fully developed and easily available, so IPR rights do not play a large role in this technology (Kirkegaard, 2010). However, this may change on the frontier of solar R&D, which today comprises solar nanotechnology (Kirkegaard, 2010). Results were also fairly consistent between higher-income and lower-income nations.

In addition, I added a meteorological variable to the larger dataset to determine whether nations with more hours of sunlight on average see more incoming transfers of solar technology. My results show that on its own, sunlight is not a statistically significant indicator of solar patent filings. However, when interacted with other variables, such as the IPR measure, GDP, and human capital, sun has a positive, statistically significant relationship with incoming solar technology transfers. This may indicate that solar resources alone are not a deciding factor in producing solar technology; other factors, such as income, infrastructure, and legal systems, may need to be developed first to attract solar technology.

Overall, the results here confirm the importance of disaggregating data when examining international technology transfer. This analysis shows that when it comes to IPR protection, solar technology is not the same as other technologies and sectors. Moreover, I have been able to show for the first time that quality is a factor the international diffusion of solar technology.

APPENDIX A
COMPUTER PROGRAM USED TO GATHER DATA

Below is a step-by-step list of the process used to gather data on the patents and citations used in this study.

1. The program read the list of IPC codes
2. For given year and month range, the program
    a. Accessed web pages using the following templates
       http://worldwide.espacenet.com/searchResults?page=0&IC=[CODE]&DB=EPODOC&PD=[YEAR][MONTH]&locale=en_EP&ST=advanced&compact=false
       http://worldwide.espacenet.com/searchResults?page=0&IC=H01L31/00&DB=EPODOC&PD=197001&locale=en_EP&ST=advanced&compact=false
    b. Downloaded the HTML code and stored it on the local hard disk
    c. If the file did not contain all the results, the search was narrowed and broken down into days. In that case, the program downloaded HTML using the following template
       http://worldwide.espacenet.com/searchResults?page=0&IC=[CODE]&DB=EPODOC&PD=[YEAR][MONTH][DAY]&locale=en_EP&ST=advanced&compact=false
    d. If in one day too many patents were filed for the results to be returned on a single web page, corresponding files were downloaded manually
3. For each search result HTML file, the following actions were performed
    a. Ignored files with more than 15 search results, as these files were broken down into smaller files as described above in 2
    b. Followed each link in the search results and download its HTML content
    c. Analyzed each downloaded file to search for a “more” button, which linked to additional information. If the phrase was present, followed it and download complete data
    d. Followed the link “View list of citing documents” and downloaded its HTML content (This option may no longer be available on the website)
4. For each downloaded citations file, the program then
    a. Checked if the file had a reference to a “next” button (that is it, checked if the citations were listed on more than one page)
    b. If needed, downloaded the file with the next portion of citations
    c. Redid parts a. and b. until all citations were downloaded
5. Then the program created a CSV data file “patents.csv” and

    a. Loaded each stored patent file and read and extracted the data from the file
    b. Appended the data into corresponding columns of the CSV file
6. Then the program created a CSV data file “citations.csv” and
    a. Loaded each stored citation file and read and extracted the data from the file
    b. Appended the data into corresponding columns of the CSV file
7. At each step, the program checked for the integrity of the downloaded data by ensuring that the entire file was downloaded, that it really contained data rather than an error message, etc.

After this procedure, the files were ready to be imported into data-analyzing software (MS Access, Stata). The specific code used in this process is available upon request, as are the downloaded files themselves.

APPENDIX B
RESULTS WITH *SUN* VARIABLE ONLY

Table B-1. High-income nations w/sun only

Variable	I—Trimmed	II—Full
constant	2.427767*	1.946772*
	[.5364347]	[.3902793]
qual	.015032	.0202603**
	[.010917]	[.0101822]
ipr	-.091001	-.0767611
	[.1419479]	[.093954]
humk	-.7740828	-.8743347**
	[.499311]	[.3435773]
gdp	0.00000203*	0.00000184*
	[0.000000456]	[0.000000247]
dist	.0000478	.0001184*
	[.0000338]	[.0000257]
imps	-0.0000000305	-0.0000000411*
	[0.0000000277]	[0.0000000131]
renew	-.4924884**	-.0987498
	[.2443889]	[.1583828]
lang	.691433*	.6826475*
	[.1747335]	[.1447772]
sun	-.0000139	-.0000676
	[.0001197]	[.0001034]
N	396	557
χ^2	5871.91	8766.21

Standard errors in brackets
*= statistically significant at 1% level; **= statistically significant at 5% level; ***= statistically significant at the 10% level

Table B-2. Lower-income nations w/sun only

Variable	I—Trimmed	II—Full
constant	6.604848*	4.13132*
	[.7864616]	[.3201093]
qual	.0165569***	.0077132
	[.0089892]	[.0083272]
ipr	-.048417	-.2546875*
	[.1156631]	[.0937474]
humk	-6.505824*	-1.248246*
	[1.783716]	[.4369271]
gdp	0.000000775*	0.000000838*
	[0.000000226]	[0.000000085]
dist	-.0002605*	-.0001376*
	[.0000344]	[.0000219]
imps	0.0000000379***	0.00000000377
	[0.0000000196]	[0.00000000342]
renew	-.1463312	.2903299
	[.7009319]	[.2808021]
lang	1.675434*	1.503355*
	[.1848643]	[.1601738]
sun	-.0008577*	-.0004201*
	[.0001907]	[.0001108]
N	155	233
χ^2	510.11	1082.48

Standard errors in brackets

*= statistically significant at 1% level; **= statistically significant at 5% level; ***= statistically significant at the 10% level

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