Innovation in Solar Panels: An Analysis of Research and Development Expenditures and Induced Innovation on Solar Module Prices

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Abstract

In this paper, I examine the effect of innovation on solar module prices in Canada, the USA, France, Germany, Italy, Japan, and Korea. Using instrumental variables to estimate the demand for solar modules, I estimate the impact of research and development (R&D) expenditures and induced innovation on the price of solar modules. My results indicate that both induced innovation and R&D expenses reduce solar module prices.

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Contents

1 Introduction

Macroeconomic models often assume that economic growth is driven through technological improvements and innovation, though there is still considerable debate with regards to the impact of innovation. Most models posit that there are important spill-over effects or externalities that a firm generates when it develops new knowledge. This results in all firms improving their productivity, due to the breakthrough created by a pioneering firm. The pioneering firm, however, does not realize the full economic profits associated with their discovery since they do not benefit from the increased productivity of other firms. Thus, such models recommend that the government enact policies to stimulate additional research up to a socially optimal level. From a practical perspective, however, the optimal level of investment in innovation is incredibly difficult to quantify since it requires economists to determine the number of ideas in an economy at a given time, and how they ripple throughout society. This creates enormous challenges for policy makers striving to create the ideal conditions for long-run prosperity, along with providing accountability for their economic development programs. Nonetheless, economists have developed various frameworks for measuring the returns associated with R&D expenditures.

In reality, governments do not always provide R&D funds to areas with direct impacts on economic growth, but often allocate it towards areas with little commercial application such as the military, pure science, and climate change. The financial value of these investments is difficult to assess since their results may not immediately lead to commercial applications. Proponents of these policies, however, argue that there are still spillover effects associated with these investments, which will eventually yield considerable benefits to the rest of the economy in order to justify their associated costs. This introduces a substantial amount of uncertainty for policy makers when they are calculating cost-benefit analyses in order to determine whether to spend on certain R&D areas. To deal with this difficulty, economists used case studies to understand the rate of return of a specific investment, which can be used to understand the long-run benefits of these research breakthroughs. Many of these case studies, however, focus on successful investments which generated large economic returns. This can mislead researchers into thinking that the estimated rate of return from a case study is considerably higher than what it truly is. As a result, it is important for policy makers to understand the likely rate of return when they make an investment in R&D in a field that does not have an available market.

Renewable energies are an area that may yield insight into these issues, since R&D expenditures were justified in developing technologies that reduce greenhouse gas emissions along with the goal of creating a sustainable energy market. The bulk of these R&D programs also go to reducing the cost of products that are are now adopted in different markets such as windmill turbines, solar panels, and biofuels, indicating that there is price data associated with these items. As well, R&D plays a significant role in these markets since they are relatively new technologies that are more likely benefit from the new knowledge produced by research. Thus, it may be able to quantify a rate of return to R&D expenditures in an area that also has social benefits. This also provides an opportunity to see if there are other methods of increasing knowledge other than R&D, since it has been argued that public policies such as tax credits or subsidies can "induce innovation" in these areas. In this paper, I analyze the impacts of R&D expenditures in Canada, France, Germany, Italy, Japan, Korea, and the United States on the price of solar panels in their respective markets while controlling for induced innovation through instrumental regression. My results indicate that reduced solar module prices are due to R&D expenditures and induced innovation.

2 Literature Review

2.1 Productivity and Research and Development Expenditures

There is a substantial amount of literature on the impact of R&D expenditures on productivity, along with different empirical estimates at the country, industry, and firm level. The bulk of the following discussion is from a literature review by Hall et al (2009) on measuring the rates of return to R&D, unless cited otherwise. R&D returns are measured from the firm's production function. Hall et al (2009) describe two different approaches to measuring the returns from research and development expenditures. The Primal Approach presents an augmented Cobb-Douglas production function shown below:

$$Y = C^{\alpha} L^{\beta} K^{\gamma} (K^0)^{\delta} e^{\mu}$$

Where Y is the firm's output, C refers to the firm's capital, L is the firm's labour, K refers to the firm's level of knowledge, K^0 is the knowledge of other firms, and e^{μ} refers to a disturbance. It is easy to adapt this model to estimate the returns to new knowledge at the firm or industry level by taking logs of the previous equation:

$$y_{i,t} = \lambda_{i,t} + \eta_{i,t} + \alpha c_{i,t} + \beta l_{i,t} + \gamma k_{i,t} + \delta k^0_{i,t} + \mu_{i,t}$$

In this equation, the rate of technical progress is decomposed into two variables: $\lambda_{i,t}$ is the firm or industry-specific effect of technological progress and $\eta_{i,t}$ is a time effect. Taking first differences, we can eliminate $\eta_{i,t}$ and measure the growth in productivity as a function of the growth in the other variables. Ignoring external knowledge, firm-specific knowledge can be estimated as:

$$\gamma \Delta k_{i,t} = \frac{\rho(R\&D - \tau K_{i,t-1})}{Y_{i,t}}$$

Where $R\&D_{i,t}$ is the gross expenditures allocated towards R&D, $\tau K_{i,t-1}$ is the depreciation of knowledge from the previous period, and ρ measures the marginal productivity of R&D capital. This can be substituted into the previous first-differences equation to measures the gross rate of return to R&D directly, but this requires information on the depreciation of knowledge in the economy. Normally, the depreciation rate of knowledge is assumed to be zero, although subsequent studies have disputed this hypothesis [1]. An alternative specification of the model, assuming constant returns to scale, competitive behaviour, and profit-maximizing levels of factors of production provides the following equation for total factor productivity growth:

$$\Delta TFP_{i,t} = \lambda t + \frac{\rho(R\&D - \tau K_{i,t-1})}{Y_{i,t}} + \delta \mu_{i,t}$$

The dual approach assumes firms are cost minimizers and profit maximizers, then uses the duality theorem to represent technology as a cost function, profit function, or a value function. This represents a distinct advantage of the dual approach over the primal in terms of its ability to create a mathematical function for technology. In addition, the dual approach can be expanded to model financial decisions, multiple choices, and multiple outputs. This methodology provides a richer set of equations to estimate, but also requires proper model specification in order for the results to be meaningful.

There are also substantial measurement issues when attempting to understand the relationship between R&D expenditures and productivity. Normally, productivity is measured as the ratio of an output index to an input index, but there is no consensus on which index to use. This creates a number of problems since output can be measured as the gross output, value-added, or sales of a firm or industry. Any analysis of productivity requires

[1] Readers are encouraged to read Bernstein and Mamuneas (2006) along with Hall (2005). Please consult the bibliography for the full reference

the researcher to determine which variable to measure, and ensure that it is uniform across the industries that they are researching. As well, output measures normally do not reflect quality changes in the price deflators. This generates considerable complications since R&D may lead to the creation of new products or improved products, which may not be captured by the chosen output index. Thus, it becomes important to incorporate this factor into industries that are defined through improved quality such as computers, pharmaceuticals, and semiconductors. Otherwise, the returns to R&D are underestimated.

Measurement of inputs also has considerable problems due to the double-counting of R&D, correcting labour and capital differences for their capital, and the sensitivity of inputs due to the use of different forms of capital. Firms that report the expenditures allocated towards labour and capital do not normally differentiate between those who work in the production of goods and those who focus on R&D. As a result, R&D is double-counted when placed into the inputs. As well, many econometric studies report lower R&D elasticities when accounting for the educational qualifications of the workforce, which may be due to the high degree of correlation between R&D activities and an educated workforce. This raises an extremely important issue in that there are other factors that affect productivity growth other than new knowledge. These variables are not easily observed since they can refer to sectoral or firm differences such as management quality or appropriability conditions for R&D. Appropriability conditions refer to the suitability of new knowledge for a given industry and help determine the appropriateness of certain R&D investments for their industry. Typically, these factors are controlled through dummy variables in panel data.

An additional difficulty that econometricians face in quantifying the return to R&D is the measurement of the level of knowledge, which also requires the selection of a depreciation (or obsolescence) rate for knowledge. This rate is difficult to ascertain since it changes over time in response to the level of public research and advancements in scientific theory. It also requires the researcher to determine the lag structure of R&D in generating returns, which continues to be incredibly complex. Past researchers have experimented with different approaches to determine how quickly knowledge becomes obsolete. One methodology involves the use of patent renewal data, which arrived at a rate of obsolescence of 10%. Another approach was to vary the rate of depreciation in estimating the knowledge stock and its impact on rate of return to R&D. Different authors found small differences in the estimated R&D effects when the rate of knowledge depreciation varied from 8% to 25%, which suggests that the selection of the depreciation rate should be in this range.

A major source of complication with regards to R&D is to determine the lag effects associated with research breakthroughs and its eventual relationship to productivity growth. This is especially relevant to my study since solar R&D was initiated in the 1970s, and some of their original ideas are still adopted with regards to current solar technology. Moreover, spillover effects are also difficult to measure since they require more time to take effect as firms capitalize on new production processes and products. Studies have employed different methodologies to determine an appropriate lag, although there is no consensus on this issue. Estimates vary from as little as a year to 10 to 30 years for research in pure science.

Econometric issues also emerge when quantifying the benefits of R&D. One particular problem deals with the simultaneity bias that arises due to the possibility that firms which observe productivity growth are more likely to invest in R&D. This can be addressed through instrumental variables or the dual approach. Despite all of these issues, econometric studies indicate that there is a positive return associated with R&D expenditures and the estimates range from 20-30%. The dual and primal approach yield similar rates of return to R&D.

R&D also produces two spillover effects: knowledge and rent. Knowledge spillovers occur when consumers and firms pay prices that do not reflect the value to them due to information asymmetries and imperfect competition. Increasingly competitive markets, then, lead to reduced prices as firms cannot profit as much as they once did. Knowledge spillovers refer to firms producing ideas that can improve the productivity of other firms. This has led economists to estimate the social return to R&D in order to capture externalities in the marketplace. Social returns to technology have been measured using two methodologies: case studies and econometric approaches. Case studies involved analyzing a particular breakthrough that led to considerable spillover effects, such as Grilliches (1958) analysis of the social rate of return to research on hybrid corn. However, it is difficult to extrapolate the rates of returns from these studies to the overall social rate of return since many case studies analyze successful R&D projects. Econometric approaches include an aggregate economy-wide R&D stock in the TFP equation, although this creates further difficulties since TFP may be driven by other factors not associated with R&D. Other methods used to measure international spillovers include measuring the amount of trade between countries and the number of migrating research personnel (scientists, engineers, educated individuals). Other studies included spatial effects in order to account for the number of spillovers that may arise due to R&D.

There is considerable uncertainty surrounding R&D investment due to the low probability of a payoff, especially if it is research into a field or technology that may not be properly understood (Popp et al., 2009). Hence, a socially optimal investment may not be undertaken by the private sector if they perceive the investment as too risky. Moreover, a new, profitable and useful technology may not be adopted if an insufficient number of users have not adopted it previously. This may be due to asymmetric information, where investors and consumers are unsure of the long-run survival of the technology and delay their purchase of it. As well, the adoption of new technologies may be hindered due to a principal-agent problem. This refers to one party receiving the benefit of the new technology, but the investment costs are borne by the other party. The other party is unable to properly anticipate the intended benefits and also lacks a proper incentive to introduce or use the new technology.

In recent years, the ”induced innovation hypothesis” has gained considerable popularity from environmental economists for arguing that environmental regulations provide firms and consumers with an incentive to find new technologies and methods for minimizing costs. Two frameworks have emerged to analyze the implications of this hypothesis: the neoclassical and the evolutionary approach (Jaffe et al., 2010). The neoclassical approach proposes a production function whose parameters change with R&D investments. The evolutionary approach, on the other hand, assumes that firms are not necessarily profit-maximizing and miss technological opportunities until an environmental shock induces new opportunities for profit. This creates the potential for firms to earn even larger profits than they did earlier, thus creating a so-called ”win-win”view of environmental regulations. Proponents of this view argue that a win-win scenario is more common than most people believe because regulation increases the spread of information, reduces uncertainty about environmental investments, develops technologies that lead to a long-run competitive advantage, and exerts pressure on firms to adapt to a new system. It is easy to argue against many of these reasons, primarily due to the assumption that firms are not profit-maximizing in the evolutionary approach and require external pressure to change.

Empirical evidence on induced innovation does not yield a consensus on its supposed impact. Some studies indicate that the effects of induced innovation are small and are far less than the costs of regulations. As a result, it is difficult to justify them if their benefits do not outweigh their cost. However, a significant number of studies give considerable weight to the induced innovation hypothesis. Newell et al (2000) find that home appliances increased their energy efficiency in response to energy prices between 1958 and 1993. Popp (2002) shows that the number of energy-related patents increase in response to higher energy prices. Moreover, he finds that sulphur and nitrogen emission regulations in the United States, Japan, and Germany increased the number of patents associated with air pollution. Since a variety of environmental policies can be implemented, economists have attempted to quantify which policy is the most effective towards inducing innovation. However, the ranking of different policies depends considerably on the innovator's ability to benefit from the externality to other firms, the costs of innovation, environmental benefits, and the number of firms that produce the targeted emission.

Economists also adapted the induced innovation framework to understand the market dynamics occurring in the renewable energy industry. Johnstone et al. (2010) analyze the impacts of renewable energy policies on renewable energy patents. Patents are considered a good proxy for the level of technological innovation in an economy since it is a measure of output, whereas other variables such as R&D expenditures or the number of scientific personnel are input measures. This can also indicate the effectiveness of R&D expenditures by quantifying the number of patents that exist based on the prior R&D expenditures. However, patents are still considered an imperfect indicator of innovative activity since they do not reflect the financial value of a discovery or research breakthrough. In addition, there is still considerable dispute over the classification of patents by different countries, indicating that there is a substantial amount of subjective error. Thus, the number of patents for one technology in a country may differ from the number of patents for the same technology in a different country. Nonetheless, patent counts are a strong indicator of the underlying innovative activity that occurs in an economy, especially since they represent a type of discovery. The authors model renewable energy patents as a function of policies, R&D expenditures, electricity growth consumption, electricity prices, and the total number of filings at the European Patent Office using a negative binomial regression . The authors find that policy instruments play a key role in inducing innovation, but that different policies are helpful for some industries whereas others are shown to have no effect. For example, they find guaranteed prices and feed-in tariffs to be particular effective for inducing solar patents, whereas renewable energy certificates favour technologies that are closer to market distribution such as wind energy. The model proposed by Johnstone et al. (2010) indicates that policies are effective at inducing innovations in certain markets, but alternative models have been used to model the prices of specific renewable energy technologies.

There is a considerable literature that uses experience curves in order to model the cost decreases that have occurred in different renewable energy markets. Experience curves are also known as learning-by-doing, and refer to firms that reduce their total costs as they become accustomed to a certain technology that produces their desired product. Normally, it models the costs of a good as a function of the amount of experience in production that occurs. This is done by specifying the costs of production as a function of the cumulative capacity, although this creates significant problems for estimation since there are other factors that may influence the cost of a good. Nemet (2006) applies the learning-by-doing model to solar module prices, and also uses the plant size, yield, module efficiency, poly-cristalline share, silicon cost, silicon consumption, and the wafer size. Nemet finds that plant size, cell efficiency, and the cost of silicon were the three most important factors in explaining the cost declines, although the overall model only explained 60% of the cost reduction in solar module prices. However, when the model is estimated for the period 1980-2001 rather than 1976-2001, only a small portion of cost reductions are unexplained by the model. Nemet concludes that there are other factors that need to be considered when analysing module prices, such as expected future demand, R&D, and knowledge spillovers.

As evidenced by the preceding discussion, there has been considerable work done with regards to understanding the link between R&D and productivity, along with understanding the roots of technological innovation in environmental technologies. This paper is able to contribute to the extensive literautre in this area by applying the R&D productivity framework to solar energy, in order to provide other economic models to explain the decrease in solar module prices. Before proceeding to the proposed model, it is important to understand the major policy issues surrounding renewable energies and the operation of solar panels.

2.2 Policies Involved in the Implementation of Renewable Energies

Governments have provided considerable funds for R&D activities in renewable energies since the 1970s. Research projects can take on a variety of forms, although it is becoming more common for the solar industry, academics, and the government to pool their resources for different research projects. Nonetheless, as evidenced by data from the International Energy Agency's World Data Service, governments still account for the bulk of research and development activities in renewable energies and solar panels. As of 2010, the five countries with the largest public R&D budgets were the United States, Germany, Australia, Japan, and Korea (IEA PVPS, 2010). Recently, governments implemented other policies in order to create a long-term market for renewable and solar energy.

Couture and Gagnon (2010) indicate that feed-in tariffs recently emerged as one of the most effective policies in increasing the consumption of renewable energies, and as of 2010, they have been implemented in 63 jurisdictions.They provide guaranteed prices for electricity from renewable energy sources for a fixed period of time. As well, they can be adapted to increase the number of participants in the renewable energy market, such as farmers, landowners, and homeowners. This ensures that a variety of individuals get involved in power production as they sell electricity to others. It also reduces the uncertainty surrounding renewable energy investment since firms properly anticipate the price of electricity, although it shifts the risk to the government. Policy makers will then need to be able to create a feed-in tariff rate that covers the cost of installation and provides the investor with a proper return. Feed-in tariffs are implemented without regards to a specific renewable energy technology, although some jurisdictions tend to favor one energy source over another through differential tariff rates. Johnstone et al. (2010) found that feed-in tariffs were significant in increasing the number of solar patents, but are not significant for other technologies.

Other public policies that governments have implemented include general tax credits and subsidies. Government programs, such as the Residential Renewable Energy Tax Credit in the United States, target households that install solar photovoltaic panels. Other programs, such as the New Purchase System for Solar Power-Generated Electricity in Japan, oblige electric utilities to purchase excess electricity produced by different households at certain rates. In essence, these programs could be considered traditional tax or subsidy-incentive programs that differ from the feed-in tariff and R&D policies to foster the renewable energy industry. As well, some governments have implemented market mandates, in which they require electricity companies to produce a certain amount of renewable electricity. Other policies include Sustainable Building Requirements, in which buildings are mandated to reduce their carbon footprint through generating their own electricity. It should be evident that there are a variety of policies that have governments adopted in order to develop their production of solar and renewable energy. However, there are other aspects of solar modules that policy makers should be cognizant of, specifically in how they operate.

2.3 Solar Photovoltaic Cells

Photovoltaic (PV) cells convert sunlight into electricity through the use of crystalline silicon wafers, which remain the dominant material in the industry (Chiras, 2010). They can be further categorized into three types: monocrystalline, polycrystalline, and multicrystalline silicone ribbons. For all of these components, the necessary primary input is silicon. PV cells are then combined with other cells to form a module. Each of the previously described materials is used to create their respective solar module. Monocrystalline cells boast the highest electrical efficiency, followed by polycrystalline and multicrystalline ribbons. After any of the preceeding PV cells are produced, the wafers are exposed to phosphorous gas in a heated diffusion furnace, which then creates a thin layer on top of the silicon. Metal contacts are applied in a grid pattern in order to collect the electrons released from the silicon.

Recently, solar panel manufacturers started using thin-film technology to provide less-costly cells. Silicon is placed on a metal backing glass, which creates a thin film of photo-reactive material. A laser is then used to draw out cells and create connections similar to the ones in the previously mentioned PV cells. Thin-film technology's primary advantage stems from the fact that it does not require ingot production, which is used in traditional

PV cell production and is quite expensive. However, thin-film cells are less efficient than other PV cells, which can lead to larger modules. Thin-film technology accounted for 12% of module production in 2010. The bulk of R&D activity around the world is devoted to optimizing solar panel production in order to reduce overall costs, although some companies are researching high efficiency modules known as the Hetero-Junction with Intrinsic Thin-Layer. These modules show considerable promise as they demonstrate higher efficiencies than previously reported solar modules.

PV modules are implemented by consumers in four different ways: off-grid domestic, off-grid non-domestic, grid-connected distributed, and grid-connected centralized (IEA PVPS, 2010). Off-grid PV systems are not connected to the main electrical grid, but are used for things like remote communications or water pumping. Centralized PV modules are used by electricity companies to provide electricity to different users whereas distributed PV modules are used by households or buildings to generate their own power. The bulk of solar energy growth in the last 10 years occurred in the grid-connected PV modules, which is likely due to feed-in tariffs.

The preceding discussion has covered a variety of topics that are especially relevant to solar modules, R&D, and public policies. With this information, I will present my econometric model.

3 Proposed Empirical Model

A model that explains the movement in solar panel prices needs to incorporate R&D expenditures, along with public policies. To start with, we expand the supply framework that was introduced earlier:

$$Y_{i,t} = L_{i,t}^{\alpha} C_{i,t}^{\beta} N_{i,t}^{\gamma} G_{i,t}^{\eta} K_{i,t}^{\delta} (K^0)_{i,t}^{\zeta} e_{i,t}^{\mu}$$

Here Y is the output of solar modules in country i at time t, G is the amount of government involved in the solar energy industry, L is the amount of labour, C is the amount of capital, N is the amount of materials, K is the amount of knowledge the solar industry has, and K^0 is the amount of knowledge that other countries have about the solar industry. Assuming cost minimization and profit maximization, the firm produces solar panels through the following equation:

$$Y_{i,t} = f(w_t, r_t, b_t, K_{i,t}, K_t^0, P_{i,t}^{solar}, G_{i,t}, \mu)$$

Here w is the wage, r is the rental rate of capital, b is the cost of materials, μ is a random shock, and $P_{solar,i,t}$ is the price/watt of electricity that is produced from a solar panel. It is assumed that there is no economic cost associated with acquiring industry and outside knowledge. It is also assumed that firms are wage, rent, and material cost takers as they are too small to affect each of those variables. As well, it should be noted that all functions from here onwards are log-log.

Demand for solar electricity is assumed to be given by:

$$P_{i,t}^{solar} = f(Y_{i,t}, P_{i,t}^{electricity}, G, M_{i,t}^{total})$$

where Y is solar electricity consumption in a country, P_{solar} is the price/watt of solar panels, $P_{electricity}$ is the price of electricity substitutes, and M_{total} represents the total income accruing to electricity consumers. Government is added to the demand-side since its effects through policies can affect both supply and demand. Currently, the bulk of electricity is produced by natural gas, oil, and coal. It is also assumed that consumers are indifferent towards the environmental effects of alternative electricity producers, and are only concerned with the amount of electricity they can consume. Thus, we can estimate the supply-side equation while instrumenting solar energy production with demand side variables. Our estimated equation is:

$$P_{i,t}^{solar} = f(b_{i,t}, w_{i,t}, r_{i,t}, Y_{i,t}, G_{i,t}, K_{i,t}, (K^0)_{i,t}, \mu)$$

This model presents econometric problems due to data constraints, but also due to the non-stationarity of the price of solar modules. By taking first differences, we arrive at:

$$\Delta P_{i,t}^{solar} = f(\Delta b_{i,t}, \Delta w_{i,t}, \Delta r_{i,t}, \Delta Y_{i,t}, \Delta G_{i,t}, \Delta K_{i,t}, \Delta(K^0)_{i,t}, \Delta\mu)$$

And our instrumented equation becomes:

$$\Delta Y_{i,t} = f(\Delta P_{i,t}^{electricity}, \Delta M_{i,t}^{total} \Delta b_{i,t}, \Delta w_{i,t}, \Delta r_{i,t}, \Delta Y_{i,t}, \Delta G_{i,t}, \Delta K_{i,t}, \Delta(K^0)_{i,t}, \Delta\mu)$$

In this model, I assume that the real rental rate of capital and the real price of silicon is constant, thus $\Delta r = \Delta b = 0$. The final empirical model is presented below:

$$\Delta P_{i,t}^{solar} = f(\Delta K_{i,t}, \Delta(K^0)_{i,t}, \Delta w_{i,t}, \Delta Y_{i,t}, \Delta G_{i,t})$$

This model expands the framework that was presented by Hall et al (2009) in calculating the effect of knowledge on total factor productivity growth. The primary difference is through the assumption of constant cost of real materials and the rental rate of capital. This was done due to data limitations since it is difficult to obtain data on capital productivity improvements and on the price of silicon.

To estimate this model, I will use a two-stage regression where the first-stage involves modelling the change in the solar energy market with the instruments of electricity prices and household incomes. The second stage then determines the returns to R&D and its spillovers by modelling solar module prices as a function of the change in knowledge, government policies, and the results of the first-stage regressions.

The change in knowledge variables refer to a vector of R&D variables that include lagged solar R&D expenditures, total in-country R&D expenditures, and international R&D expenditures on solar panels. Total in-country R&D expenditures are meant to capture the effect of knowledge spillovers from other industries. International solar R&D expenditures are used to examine the role of international knowledge spillovers that occur. It is difficult to follow the approach by Hall et al. in constructing a knowledge variable based on past R&D expenditures since it requires a depreciation rate that has not been quantified. Moreover, knowledge needs to incorporate spillover effects that may result from technological breakthroughs in other industries or markets. This is particularly relevant to solar panels since improvements may be observed in the production of their materials or components that direct PV research may not touch upon. As well, the change in knowledge is best represented by R&D expenditures, not the change in R&D expenditures since they are used to discover new knowledge and thus, represent the change in knowledge, which is what we are interested in.

For this model, I assume that in-country solar R&D expenditures require seven years to have an effect on the price of solar modules, whereas international solar R&D expenditures and other R&D expenditures affect solar module prices after eight years. This is due to the limited amount of data on solar module prices and R&D expenditures that is available, and also to provide structure to the lag effects that may be observed. Solar energy is a relatively new industry, and so it would be quicker than other sectors in incorporating technological breakthroughs. Thus, it would be unrealistic to assume that productivity advances require 10 years to have an effect on solar energy producers. However, I do not think that solar module manufacturers are as nimble as adopting the most recent technological breakthrough into their production, hence why there are still lags placed on the R&D variables. Also, I assume that in-country solar R&D expenditures are likely to affect their country's solar module prices faster than other R&D expenses since firms need to spend more time to understand breakthroughs in other markets.

An additional assumption that is made in this model is not to differentiate between private and public R&D expenditures, but to consider them equally effective in developing productivity improvements. This has strong implications in that this empirical model is unable to determine which group is the better researcher. This was done because the bulk of solar energy research expenditures were, until relatively recently, doled out by the government. As well, a separate model is needed to compare the effects of public R&D with private.

The policies variable is a vector of different policies that governments adopt to develop their solar energy industry. In the theoretical model proposed here, they correspond to continuous variables that quantify the government expenditures associated with each policy. This becomes difficult to measure, due to the nature of policies such as tax credits and subsidies. As a result, in the empirical model, these policies are represented as binary variables. This may cause bias in that it will not capture the differing effectiveness of government programs due to its relative size. This also creates further problems since we are taking differenced binary variables, which does not offer that much variation in the government vector. To address this, the government policy variables refer to that time frame and not the differenced variable. Although this is different than what the model suggests, it can indicate the effect that government policies may have on inducing innovation in PV cells.

The change in the overall production of solar energy also represents the effect of induced innovation on solar module prices. Induced innovation, as reviewed earlier, referred to the impact of government policies other than R&D expenses on innovation. Renewable energy policies are normally aimed at increasing renewable energy consumption, which in our model is measured by the change in the overall size of the market.

4 Data

Data for PV modules price was obtained from the International Energy Agency (IEA) Photovoltaic Power Systems Program (PVPS). Price data was typically recorded as the cost of producing a watt of electricity, or the price/W. PVPS is responsible for collecting and disseminating information on PV systems from the 26 reporting countries of the OECD. Each of the participating countries submits an annual report that details pertinent R&D activities, market trends, and the average price/W for a PV module. There are, however, differences between each of the countries in how they obtain the average price/W of a solar module. For example, the Canada trend report completes a voluntary survey of PV companies in order to obtain the average price/W of a solar module. The United States, however, uses information from the Energy Information Administration, US Department of Energy, Solar Energy Industries Association, the Prometheus Institute, GTM Research, and PV Energy Systems. In addition, not all countries report solar module prices, creating considerable data constraints. To address this, I recorded PV module prices from Canada, the United States, France, Japan, Germany, Italy, and South Korea since they were available. As well, these countries were among the top ten producers and consumers of solar electricity in 2010 (the other three, which were omitted, were Australia, Spain, and China). The resulting panel data was also not balanced due to the lack of price data in certain years. Nonetheless, the resulting statistics are still useful since it incorporates market information, and can be considered a reasonable estimate of the average price of PV modules. All prices were converted to US dollars and adjusted for each countrys inflation using information from the Organization for Economic Cooperation and Development (OECD).

Data for the change in the size of the overall market was obtained from the Energy

Information Administration (EIA) of the United States. The EIA compiles information from a variety of international sources and reports the net generation of solar, tidal, and wave generation. The latter two energy sources are still in the early stages of development, so this data is largely representative of solar electrical production.

R&D expenditures were obtained from the IEA World Data Service (WDS). The WDS collects data from OECD member countries that relate to energy policy. Although the WDS normally requires a paid subscription, all R&D data related to energy was free. Thus, total R&D expenditures on solar energy were collected from each of the previously mentioned countries for their pertinent years. It should be noted, however, that this data is the R&D budget of each country, so it does not capture the amount of money spent on R&D. As well, it measures R&D activities combined with demonstration projects. The WDS did contain gaps in R&D information on certain countries, resulting in those module price data points being omitted. The data was provided in US 2010 dollars, but has been converted to 2005 dollars to make meaningful comparisons between module prices and R&D expenditures. Spillover effects from other industries are measured as the total R&D expenditures in a country, as reported from the OECD Statistical Database. International spillover effects from other solar R&D activities were recorded as the sum of other country's total solar R&D expenditures. A better proxy would be international trade data on solar modules, but this is currently unavailable.

Information on international policies was obtained from the Policies Database at the IEA and the PVPS reports. Policies I included are feed-in tariffs, tax credits, and subsidies. As mentioned earlier, they were recorded as binary variables based on their presence in a country. As well, the policies are further categorized based on the implementing jurisdiction in order to compare provincial policies with national ones. This created, however, multicollinearity problems in the estimation, so I categorized the information as though the entire country adopted that policy. Loan guarantees were classified as subsidies.

I was unable to find data on electricity prices, so I used price data on the three primary fossil fuels involved in electrical production: oil, natural gas, and coal. All prices were normalized to 2005 dollars, and I was only able to find information on the international price of these fuels rather than the domestic price. The price of oil was recorded as dollars per barrel, the price of natural gas was recorded as dollars per million BTU, and the price of coal was the dollar per ton. Oil prices were obtained from the Federal Reserve of St. Louis West Texas Intermediate, whereas natural gas and coal prices were obtained from the EIA. In the final model, however, only one fuel was used in order to avoid multicollinearity problems.

Data on labour productivity was obtained from the OECD. This change in labour productivity comes from the whole economy, since there is no widely available data that measures labour productivity in the solar market. Data was presented as the percentage change in labour productivity, and was not altered in the empirical model.

5 Instrumental Variable Regression Results and Analysis

Table 1: Estimation results : Second Stage Regression with Differenced Modules Prices as the Dependent Variable

Variable	Coefficient	(Std. Err.)
Differenced Log Solar Energy Production	-0.269*	(0.136)
In-Country Solar R&D Expenditures (t-7)	-0.151*	(0.060)
World Solar R&D Expenditures (t-8)	-0.008	(0.009)
In-Country Total R&D Expenditures (t-8)	-0.386	(0.242)
Feed-in Tariff	0.151†	(0.078)
Tax Credits	0.128	(0.132)
Subsidies	0.085	(0.059)
Labour Productivity	0.014	(0.018)
Intercept	4.664†	(2.561)

N	88
Log-likelihood	.
R^2(within)	0.1395
R^2(between)	0.8954
R^2(overall)	0.018
$F_{(15,73)}$	3.133

Significance levels : $\dagger$: 10% $*$: 5% $**$: 1%

Table 2: Estimation results : First Stage Regression with Differenced Solar Energy Production as the Dependent Variable

Variable	Coefficient	(Std. Err.)
In-Country Solar R&D Expenditures (t-7)	0.032	(0.107)
World Solar R&D Expenditures (t-8)	0.039*	(0.017)
In-Country Total R&D Expenditures (t-8)	-1.123**	(0.421)
Feed-in Tariff	0.346**	(0.114)
Tax Credits	-0.232	(0.232)
Subsidies	0.015	(0.106)
Labour Productivity	0.073†	(0.037)
Differenced Log Coal Prices	0.170	(0.729)
Differenced Log GDP	-9.363**	(2.249)
Intercept	12.130**	(4.454)

N	88
R^2(within)	0.3077
R^2(between)	0.1843
R^2(overall)	0.0561
$F_{(15,72)}$	3.555

Significance levels : † : 10% ∗ : 5% ∗∗ : 1%

The results, presented in Tables 1 and 2 above, confirm the idea that all types of R&D expenditures negatively impact solar energy prices, with the exception of World Solar R&D Expenditures, since it does not appear to be significant in the second-stage regression at the 10% level. However, World Solar R&D Expenditures are significant in the first-stage regression, which indicates an indirect impact on solar energy prices. This result makes intuitive sense, since World Solar R&D leads to better solar modules on the international market. Households may decide to invest in solar modules produced in other countries as they may be of better quality than the domestic ones. This eventually leads to negative pressure on domestic solar module prices because of the competition from outside solar module manufacturers, and also due to the knowledge spillovers that result from reverse engineering foreign solar modules.

Another interesting result emerges from this model, in that In-Country Total R&D Expenditures are also significant in the second stage regression (p-value of 0.112 indicates that the estimate may lack precision) and in the first-stage regression (p-value of 0.009). However, they exert a negative effect in the first-stage regression on Differenced Log Solar Energy Production. This may be due to Total R&D Expenditures also incorporating research into competitive substititutes for solar energy that include fossil fuels, wind, and biofuels. Thus, Total R&D Expenditures help reduce the price of these alternative fuels and increase uptake of these other fuels rather than increasing solar energy production. Nonetheless, the advances made by Total R&D Expenditures also help reduce solar module prices, as indicated by the second-stage regression results. One improvement to better account for this spillover may be to consider spillovers from industries with a high chance of spillover such as superconductors, silicone processing, and information technologies related to production processes. This ensures we do not incorporate competitive R&D that places downward pressure on solar module prices and solar energy production.

It may be also important to consider the price/W of other renewable energies as they are the most direct competitors for solar module manufacturers. Firms involved in wind or biofuel energy are similar to solar energy with regards to consumer preferences as they emit little to no greenhouse gases compared to fossil fuels. Each of these industries are affected by the market price of electricity, but they are also likely to exert competitive pressure on each other that differs from fossil fuel prices since they are relatively new forms of energy. They also compete with each other to demonstrate their relative effectiveness, despite that there may be other conditions asides from their relative effectiveness that determines their applicability to a certain location.

Labour Productivity is also found to indirectly affect solar module prices by increasing solar energy production. This likely emerges from the importance of new technologies towards solar module production processes, which requires highly trained employees to administer. As well, this may also reflect the importance of spillovers as they make labour generally more productive, which helps to further reduce solar module prices.

Induced innovation is also shown to have a strong impact on solar module prices as it has a p-value of 0.048, but this result is clouded by the weak instruments that were meant to model the Differenced Log Solar Energy Production. The F-value of 3.555 from this model is small, and indicates that the instruments are not particularly effective towards removing the endogeneity of Differenced Log Energy Production. However, the Anderson-Rubin Wald Chi-Square test for weak instruments provided a p-value of 0.0557, which suggests that the instrumentation results are still significant for modelling solar energy production.

The instrument of Differenced Log Coal Prices was found to be insignificant in the first-stage regression, and alternative fuels such as natural gas or oil prices yielded similar results. This may be due to coal prices being a poor proxy for the price of electricity. As well, the coal price that was used was the international price of coal, and not the domestic price of coal in each country. Thus, there are likely market conditions in each of the countries, such as taxes or environmental regulations, that affect the price of coal and are not incorporated into our model. The Differenced Log GDP variable, which was the other instrument in our model to account for household incomes, was found to be significant but also negative. This implies that solar modules are inferior goods, or that increasing incomes decrease the demand for solar modules. This is a surprising result, but may also be true as prosperous households may not be concerned about the possible benefits of adopting solar energy. Other less prosperous households, especially in countries where policies and technology have combined to make solar modules a clear net benefit, may adopt solar modules in order to reduce their long-run costs and create income for themselves if a feed-in tariff is in place. This appears to contradict the labour productivity result, especially since the two variables are positively correlated with one another. To confirm this result, it is necessary to gather further information on the incomes of households that choose to install solar modules.

Feed-in tariffs were the only policy found to be significant at increasing solar energy production with a p-value of 0.003 and, indirectly affect solar module prices. Tax credits and subsidies were ineffective at both stages, indicating that there may be problems with their construction as dummy variables. Nonetheless, the first-stage regression confirms previous ideas in that feed-in tariffs are considered the most effective policy towards increasing renewable energy consumption. Surprisingly, feed-in tariffs were found to also be significant in the second-stage regression with a p-value of 0.052, but also increasing the price of solar modules. This may reflect suppliers not anticipating the increased demand for solar modules that stems from the introduction of feed-in tariffs.

The difference in log modules prices was found to be stationary at the 10% level according to the Dickey-Fuller test (chi-square of 21.3568 and p-value of 0.0928) and at the 1% level with the Phillips-Perron test (chi-square value of 37.9077 and p-value of 0.0007). Both tests were conducted with one lag. The regression results are indicated above with Tables 2 and 3. Fixed effects were found to be insignificant with the Hausman test (p-value of 0.7931), although they were kept in the final model since there are likely differences between each of the countries that are not accounted for.

This model was chosen based on maximizing the significance of each of the variables, so it may not represent the true effect of R&D if the model is mis-specified. Other model results are presented in the appendix which change the years of the lag structure, along with testing the assumption that In-Country Solar R&D Expenditures affected solar module prices faster than other types of R&D. Nonetheless, based on the regression output, this model presents the best results and indicates the likely mechanism which R&D Expenditures affect solar module prices. As well, this model is not completely unrealistic since Hall et al. (2009) indicated that R&D lag effects can take between 10-30 years to affect productivity. Thus, without information from the solar energy industry, it may be that it does take an average of seven years for in-country R&D expenditures to affect solar module prices by affecting the production process.

6 Conclusion

This model has some key results that have strong implications for policy makers. Governments that are striving to increase their renewable energy production should consider the ideas and results from this paper into their cost-benefit analysis. Feed-in tariffs are shown to be the most effective government policy at increasing solar energy consumption. Although there were issues with the instrumental variables, induced innovation is still shown to reduce solar module prices. Thus, feed-in tariffs are an effective policy instrument that increase solar energy production while also making the technology more affordable for all participants. It increases competition in the solar energy market as households increase their demand for solar modules and, the number of solar energy manufacturers increase due to the new opportunities to make economic profit. These new firms will then introduce new technologies in order to offer the most affordable solar modules. This may also reduce the lag between a new innovation and its incorporation into the production process as firms are under further competitive pressures to offer solar modules at reduced prices. Countries that do not adopt feed-in tariffs are likely to observe their renewable energy production increase slightly, which depending on their mix of current energy production, can have considerable negative effects in terms of continued greenhouse gas emissions and other environmental externalities. These factors will need to be considered in a proper cost-benefit analysis on feed-in tariffs.

The model also indicates that R&D expenditures affect solar module prices, both directly and indirectly through solar energy production. A major consideration for policy makers will be to determine what type of renewable energy is most appropriate for their economy and how they can best support it. Research spillovers from other industries are shown to reduce solar module prices, but they also reduce solar energy production by making alternative fuels more affordable as well. This may influence how provincial and municipal governments, who are likely to be more attuned to the geographic advantages of their respective areas, target R&D activities in order to ensure their technology is affordable for the market. National governments, on the other hand, may need to continue to provide R&D for all forms of energy in order to ensure equal opportunities for renewable energies inside their borders. Nonetheless, governments are still encouraged to provide R&D grants to foster the solar energy industry since it leads to more affordable solar modules. One area that should be considered is to foster knowledge sharing opportunities between solar industries around the world and with other industries. This may reduce the lag effects in this model, such that R&D may have a more immediate effect on solar modules rather than taking seven years.

Another major result from this model stems from the importance of international solar R&D expenses towards increasing solar energy production. This suggests that countries should resist creating trade barriers in order to foster international competition amongst solar energy manufacturuers. To confirm this, it will be necessary to obtain data on trade between countries regarding solar modules in order to ascertain the correct level of international knowledge spillovers. This policy proposal, however, is difficult to implement considering the amount of subsidies and grants that solar energy companies receive from the different levels of their governments. Governments will need to coordinate with each other to ensure there is an appropriate amount of support for solar energy while balancing the need for international competition.

There are other concerns with this model, namely in that it does not indicate which R&D activites actually reduced solar module prices. This may reflect a general problem with these types of models, since R&D does not always yield direct results. It will generate new knowledge, but that information may not have a direct financial value associated with it. R&D is, in essence, an input whereas we may be more interested into the outputs of R&D activity in order to compare different programs across the world. One way to address this concern is to replace R&D activities with solar energy patents in order to match output knowledge activities with their associated financial returns. This model may not be able to indicate which specific patents assisted in reducing solar module prices, but it may be a more direct measure of the effect of productive knowledge rather than all knowledge.

Another concern with this model is that it does not quantify the economic impact of induced innovation or targeted solar R&D expenditures. This is of incredible importance to policy makers as they attempt to help develop the solar energy industry with the hope that it will lead to long-run economic benefits. This, however, may be too early to estimate since the solar energy industry is still relatively new. As well, this will need to adopt a different approach that accounts for the amount of firms and labour that are associated with solar energy.

Ultimately, this model concludes that feed-in tariffs are the most effective policy towards increasing solar energy consumption, induced innovation plays a key role in reducing solar module prices, and R&D expenses help improve the quality of solar modules. However, more work needs to be completed in order to weigh the costs and benefits of these policies, along with finding better models to calculate the rate of return to public R&D.

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7 Appendix

7.1 Solar Module Prices from 1990 in Selected Countries

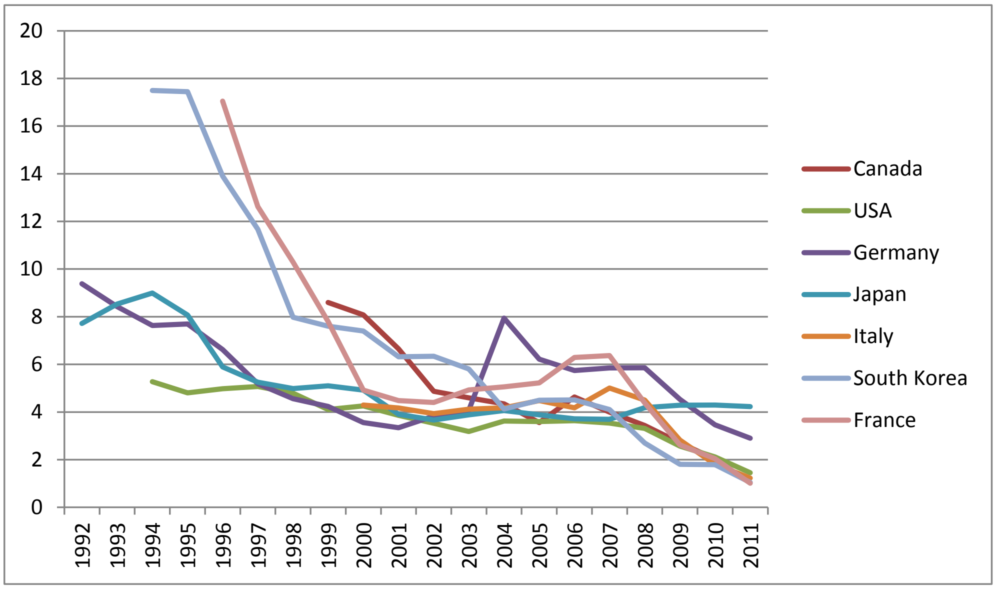

Figure 1: Solar Module Prices over the years in US Dollars

7.2 Summary Statistics

Table 3: Summary statistics

Variable	**Mean**	**Std. Dev.**	**N**
Log Solar Module Prices	1.535	0.512	118
Log Solar R&D Expenditures	4.167	2.929	213
Log Total R&D Expenditures	10.672	1.011	191
World Solar R&D Expenditures	8.233	4.75	223
Feed-in Tariff	0.496	0.501	230
Tax Credit	0.513	0.501	230
Subsidy	0.704	0.457	230
Log Oil Prices	3.541	0.536	147
Log Coal Prices	3.248	0.211	143
Log Gas Prices	1.437	0.471	131
Log Solar Energy Production	18.444	2.129	143
Labour Productivity	1.855	1.667	149

7.3 Altering the lag length

The following tables are a subset of the regression results from other lags and are meant to represent results from other tested models. Tables 4 and 5 correspond to regression results on the second lag of in-country solar R&D and the third lag of world solar and total R&D expenditures.

Table 4: Estimation results : Second Stage Results on Differenced Log Solar Module Prices

Variable	**Coefficient**	**(Std. Err.)**
Differenced Log Solar Energy Production	-0.356*	(0.159)
In-Country Solar R&D Expenditures (t-2)	0.007	(0.030)
World Solar R&D Expenditures (t-3)	-0.013†	(0.007)
In-Country Total R&D Expenditures (t-3)	0.166	(0.252)
Feed-in Tariff	0.128	(0.087)
Tax Credits	0.032	(0.137)
Subsidies	0.055	(0.064)
Labour Productivity	0.013	(0.019)
Intercept	-1.820	(2.708)
N	93	
Log-likelihood	.	
R^2(within)	.	
R^2(between)	0.2367	
R^2(overall)	0.0887	
$\chi^2_{(15)}$	26.759	

Significance levels : † : 10% $*$: 5% $**$: 1%

Table 5: Estimation results : First-Stage Regression on Differenced Log Energy Production

Variable	**Coefficient**	**(Std. Err.)**
In-Country Solar R&D Expenditures (t-2)	0.044	(0.047)
World Solar R&D Expenditures (t-3)	0.002	(0.013)
In-Country Total R&D Expenditures (t-3)	-0.178	(0.424)
Feed-in Tariff	0.274^{*}	(0.126)
Tax Credits	-0.123	(0.222)
Subsidies	-0.052	(0.108)
Labour Productivity	0.105^{**}	(0.039)
Differenced Log Coal Prices	-0.343	(0.787)
Differenced Log GDP	-8.698^{**}	(2.280)
Intercept	1.988	(4.567)
N	93	
R^2(within)	0.2207	
R^2(between)	0.6671	
R^2(overall)	0.3004	
$F_{(15,77)}$	2.424	

Significance levels : † : 10% $*$: 5% $**$: 1%

Tables 6 and 7 correspond to the regression results on the sixth lag of in-country solar R&D and the seventh lag of world solar and total R&D expenditures.

Table 6: Estimation results : Second Stage Results on Differenced Log Solar Module Prices

Variable	Coefficient	(Std. Err.)
Differenced Log Solar Energy Production	-0.128	(0.152)
In-Country Solar R&D Expenditures (t-6)	-0.027	(0.063)
World Solar R&D Expenditures (t-7)	-0.020**	(0.008)
In-Country Total R&D Expenditures (t-7)	-0.170	(0.277)
Feed-in Tariff	0.083	(0.081)
Tax Credits	0.038	(0.155)
Subsidies	0.091	(0.057)
Labour Productivity	0.008	(0.016)
Intercept	1.940	(2.903)
N	89	
Log-likelihood	.	
R^2(within)	0.2234	
R^2(between)	0.1228	
R^2(overall)	0.0035	
$F_{(15,74)}$	2.821	

Significance levels : † : 10% ∗ : 5% ∗∗ : 1%

Table 7: Estimation results : First-Stage Regression on Differenced Log Energy Production

Variable	**Coefficient**	**(Std. Err.)**
In-Country Solar R&D Expenditures (t-6)	0.111	(0.113)
World Solar R&D Expenditures (t-7)	0.009	(0.013)
In-Country Total R&D Expenditures (t-7)	-1.133*	(0.451)
Feed-in Tariff	0.395**	(0.117)
Tax Credits	-0.375	(0.274)
Subsidies	-0.022	(0.111)
Labour Productivity	0.086*	(0.040)
Differenced Log Coal Prices	0.792	(0.750)
Differenced Log GDP	-7.931**	(2.386)
Intercept	12.126*	(4.750)

N	89
R^2(within)	0.3015
R^2(between)	0.4235
R^2(overall)	0.1122
$F_{(15,73)}$	3.5

Significance levels : † : 10% $*$: 5% $**$: 1%

Tables 8 and 9 correspond to the regression results on the ninth lag of in-country solar R&D and the tenth lag of world solar and total R&D expenditures.

Table 8: Estimation results : Second Stage Results on Differenced Log Solar Module Prices

Variable	**Coefficient**	**(Std. Err.)**
Differenced Log Solar Energy Production	-0.293†	(0.172)
In-Country Solar R&D Expenditures (t-9)	-0.149*	(0.066)
World Solar R&D Expenditures (t-10)	0.123	(0.117)
In-Country Total R&D Expenditures (t-10)	-0.530*	(0.227)
Feed-in Tariff	0.086	(0.082)
Tax Credits	-0.006	(0.111)
Subsidies	0.155*	(0.068)
Labour Productivity	0.001	(0.018)
Intercept	5.463*	(2.391)
N	85	
Log-likelihood	.	
R^2(within)	0.1246	
R^2(between)	0.3675	
R^2(overall)	0.0131	
$\chi^2_{(14)}$	36.101	

Significance levels : $\dagger$: 10% $*$: 5% $**$: 1%

Table 9: Estimation results : First-Stage Regression on Differenced Log Energy Production

Variable	**Coefficient**	**(Std. Err.)**
In-Country Solar R&D Expenditures (t-9)	0.090	(0.097)
World Solar R&D Expenditures (t-10)	0.367*	(0.152)
In-Country Total R&D Expenditures (t-10)	-0.673*	(0.331)
Feed-in Tariff	0.324**	(0.098)
Tax Credits	-0.119	(0.171)
Subsidies	0.104	(0.101)
Labour Productivity	0.093**	(0.034)
Differenced Log Coal Prices	-0.295	(0.653)
Differenced Log GDP	-7.125**	(1.952)
Intercept	5.053	(3.897)

N	85
R^2(within)	0.3593
R^2(between)	0.0622
R^2(overall)	0.0683
$F_{(14,70)}$	4.362

Significance levels : † : 10% $*$: 5% $**$: 1%

7.4 Altering the Different Year Assumption

The following tables are representative of the results from other regressions that placed all R&D lags into the same year. Tables 10 and 11 correspond to the third lag of all types of R&D expenditures.

Table 10: Estimation results : Second Stage Results on Differenced Log Solar Module Prices

Variable	**Coefficient**	**(Std. Err.)**
Differenced Log Solar Energy Production	-0.373*	(0.162)
In-Country Solar R&D Expenditures (t-3)	0.039	(0.041)
World Solar R&D Expenditures (t-3)	-0.010	(0.007)
In-Country Total R&D Expenditures (t-3)	-0.020	(0.269)
Feed-in Tariff	0.128	(0.088)
Tax Credits	-0.043	(0.147)
Subsidies	0.076	(0.064)
Labour Productivity	0.017	(0.020)
Intercept	0.063	(2.873)
N	92	
Log-likelihood	.	
R^2(within)	.	
R^2(between)	0.4593	
R^2(overall)	0.0618	
$\chi^2_{(15)}$	25.87	

Significance levels : † : 10% ∗ : 5% ∗∗ : 1%

Table 11: Estimation results : First-Stage Regression on Differenced Log Energy Production

Variable	**Coefficient**	**(Std. Err.)**
In-Country Solar R&D Expenditures (t-3)	0.025	(0.066)
World Solar R&D Expenditures (t-3)	0.003	(0.013)
In-Country Total R&D Expenditures (t-3)	-0.362	(0.450)
Feed-in Tariff	0.289*	(0.126)
Tax Credits	-0.115	(0.238)
Subsidies	-0.030	(0.109)
Labour Productivity	0.102*	(0.040)
Differenced Log Coal Prices	-0.274	(0.789)
Differenced Log GDP	-8.532**	(2.280)
Intercept	4.080	(4.826)

N	92
R^2(within)	0.215
R^2(between)	0.3623
R^2(overall)	0.1711
$F_{(15,76)}$	2.316

Significance levels : † : 10% $*$: 5% $**$: 1%

Tables 12 and 13 correspond to the seventh lag for all R&D expenditures.

Table 12: Estimation results : Second Stage Results on Differenced Log Solar Module Prices

Variable	**Coefficient**	**(Std. Err.)**
Differenced Log Solar Energy Production	-0.095	(0.164)
In-Country Solar R&D Expenditures (t-7)	-0.151**	(0.054)
World Solar R&D Expenditures (t-7)	-0.018*	(0.007)
In-Country Total R&D Expenditures (t-7)	-0.093	(0.255)
Feed-in Tariff	0.102	(0.080)
Tax Credits	0.170	(0.119)
Subsidies	0.062	(0.052)
Labour Productivity	0.009	(0.014)
Intercept	1.534	(2.718)
N	88	
Log-likelihood	.	
R^2(within)	0.3154	
R^2(between)	0.7097	
R^2(overall)	0.0019	
$\chi^2_{(15)}$	59.919	

Significance levels : † : 10% $*$: 5% $**$: 1%

Table 13: Estimation results : First-Stage Regression on Differenced Log Energy Production

Variable	**Coefficient**	**(Std. Err.)**
In-Country Solar R&D Expenditures (t-7)	0.054	(0.111)
World Solar R&D Expenditures (t-7)	0.011	(0.014)
In-Country Total R&D Expenditures (t-7)	-0.904*	(0.451)
Feed-in Tariff	0.364**	(0.119)
Tax Credits	-0.218	(0.239)
Subsidies	-0.001	(0.108)
Labour Productivity	0.078†	(0.039)
Differenced Log Coal Prices	0.217	(0.777)
Differenced Log GDP	-7.180**	(2.429)
Intercept	9.806*	(4.794)

N	88
R^2(within)	0.263
R^2(between)	0.2651
R^2(overall)	0.0705
$F_{(15,72)}$	2.856

Significance levels : † : 10% $*$: 5% $**$: 1%

Tables 14 and 15 correspond to the ninth lag of all R&D.

Table 14: Estimation results : Second Stage Results on Differenced Log Solar Module Prices

Variable	**Coefficient**	**(Std. Err.)**
Differenced Log Solar Energy Production	-0.341	(0.213)
In-Country Solar R&D Expenditures (t-9)	-0.131†	(0.071)
World Solar R&D Expenditures (t-9)	0.157	(0.151)
In-Country Total R&D Expenditures (t-9)	-0.633**	(0.231)
Feed-in Tariff	0.109	(0.087)
Tax Credits	-0.021	(0.112)
Subsidies	0.158*	(0.067)
Labour Productivity	0.000	(0.019)
Intercept	6.366**	(2.277)

N	85
R^2(within)	0.1009
R^2(between)	0.3193
R^2(overall)	0.0117
Log-likelihood	.
$\chi^2_{(14)}$	36.972

Significance levels : $\dagger$: 10% $*$: 5% $**$: 1%

Table 15: Estimation results : First-Stage Regression on Differenced Log Energy Production

Variable	**Coefficient**	**(Std. Err.)**
In-Country Solar R&D Expenditures (t-9)	0.109	(0.097)
World Solar R&D Expenditures (t-9)	0.431^{**}	(0.154)
In-Country Total R&D Expenditures (t-9)	$-0.593^{\dagger}$	(0.323)
Feed-in Tariff	0.293^{**}	(0.099)
Tax Credits	-0.085	(0.172)
Subsidies	0.088	(0.099)
Labour Productivity	0.080^{*}	(0.034)
Differenced Log Coal Prices	-0.397	(0.641)
Differenced Log GDP	-5.941^{**}	(2.049)
Intercept	3.807	(3.753)

N	85
R^2(within)	0.36
R^2(between)	0.0739
R^2(overall)	0.0841
$F_{(14,70)}$	4.37

Significance levels : † : 10% $*$: 5% $**$: 1%