Learning Spillovers in the PV Cell Industry

by

Andrew Flint

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Declaration of Authorship

I, Andrew Flint, declare that this thesis titled, ‘Learning Spillovers in the PV Cell Industry’ is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person nor material which to a substantial extent has been accepted for the award of any other degree or diploma of the university or other institute of higher learning, except for where due acknowledgement has been made in the text.

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A dynamic structural-empirical model is developed in order to estimate the size of the learning spillover within the Photovoltaic (PV) industry. Firms produce a homogeneous good and make capital investment decisions for the next period. The size of the spillover is estimated to be 8.83% indicating that learning is a private good within the PV industry. A simple policy analysis finds that production and productivity both decrease as the size of the spillover is increased.
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Chapter 1

Introduction

The goal of this thesis is to estimate the spillover of learning between firms in the photovoltaic (PV) cell production industry, in the years 2003 to 2008. In order to do so, I develop a dynamic structural-empirical model that includes firms’ capital investment decisions, and the effect of learning on the productivity of a firm. A firm’s production based learning, broadly defined here as reductions in production costs as a function of cumulative output, is dependent on its own output, as well as the output of the entire industry if there is a spillover. The size of the spillover is measured to be 8.83%, indicating that learning is a private good within the PV industry. Learning, as a private good, has the potential to create barriers to entry for firms looking to enter into the market, as well as slowing the rate of industry wide cost reduction. The motivation for estimating the spillover is to provide a starting ground to establish whether market failures are present within the PV industry, so that it can be determined which policies are required by policy makers to support PV.

To estimate the spillover I require a structural-empirical model. The problem is that the spillover of learning is not directly observed from the data. In order to estimate the spillover therefore, I apply economic theory to the way learning and spillovers impact on a firm’s productivity, which can be estimated empirically from the data. I am able to use a structural-empirical model because there is a large body of relevant economic literature to build on. If there was no economic theory to base my model on, I could only use descriptive econometric models to describe a relationship that appears in my data. The advantage of using a structural model is that I can apply economic theory and make statistical assumptions in order to estimate the actual size of the spillover, as I define it within my model.

Renewable energy technologies have the potential to substantially reduce global greenhouse gas emissions. Environmental policies, such as carbon taxes or cap based systems, create dynamic
incentives for the development and adoption of renewable energy technologies by the internalisation of the emissions externality. These policies do not directly address possible market failures within technology innovation and diffusion, and so a portfolio of environmental policies that also target renewable energy technologies may be necessary in order to achieve efficient market outcomes.

The PV industry is a heavily subsidised industry with many different policies currently in place to spur along the innovation and diffusion of PV. Currently, there is no empirical evidence that PV is being supported by the correct portfolio of policies, or whether it should be supported by policies at all. In a paper on the impacts of Germany’s PV promotion, Frondel et al. [2008] estimates that the cost of abating carbon dioxide with PV is as high as 760 Euros per tonne. In comparison, the cost of abating one tonne of carbon dioxide under the European Emissions Trading System (ETS) peaked at 30 Euros per tonne of carbon dioxide during the same period (Frondel et al. [2008]). Despite this, PV in Germany has been guaranteed the largest financial assistance per kilowatt hour out of all renewable energy technologies (Frondel et al. [2008]). Given the high cost of abating with PV, it is questionable whether the current PV policies are the correct ones from a socially efficient point of view. To know this for certain however requires an inspection of the market failures which are present. The size of the spillover is pivotal in this debate about subsidies for PV. Learning has the ability to create market failures, either by the barriers to entry that it creates, or by the public good nature of learning if there is a spillover. It is the intention that the result of this thesis could be used for further research into the issue of market failures in the PV industry. From this, a revision of the current policy approach for PV, as well as other renewable energy technologies, could be required.

Learning impacts on the composition of an industry in a number of different ways. Within an industry with heterogeneous firms, the firms with the greatest level of cumulative production are the firms with the greatest level of learning, and should therefore, ceteris paribus, be able to produce at lower costs than their competitors with less production experience. Learning can therefore create inequality between firms. Furthermore, firms looking to enter the market might face barriers to entry if they cannot produce at the same costs as incumbent firms. A ramification is that there may also be strategic effects: firms could use learning as a means to block entry or to gain a competitive edge; by temporarily producing above the profit maximising level of output a firm could spur along the learning effects and therefore reap the benefits of learning sooner.

The effect of learning within an industry is complicated by the fact that spillovers of learning occur. Learning spillovers occur when firms can benefit from other firm’s production based learning. This is due to the public good nature of knowledge and there is no a priori to suggest that knowledge will be supplied by the market up to a socially efficient level. Nonetheless, an industry as a whole can benefit from learning spillovers. For efficiency reasons, firms should not
have to learn the same production techniques individually, or repeat the same mistakes as firms before them. Furthermore, if the industry as a whole learns together then the industry could potentially approach some low cost industry state at a faster rate. Theoretically then, spillovers could create equality between firms and lower the barriers to entry for firms looking to enter the market, and so the industry could become a more competitive, low cost industry sooner, if spillovers exist. This is only a superficial argument however, and in fact, the economic literature does not give any definite answers to what the effect of learning spillovers will be on a market.

Spillovers also create disincentives for firms to create knowledge if they also benefit their competitors. Furthermore, firms that imitate might prefer to free ride and hence remain as imitators rather than innovators. For every theory about spillovers, there is another theory that contradicts it. Whether or not a spillover is beneficial for an industry is therefore ambiguous, and there may be an optimal point somewhere between a complete spillover and no spillover at all. To truly understand the effect of a spillover on a particular industry, there needs to be an empirical analysis. The first step is to be able to estimate the size of the spillover. This is the aim of this thesis. Once the size of the spillover is known, then some predictions can be made about the effect of the spillover. From this, the next question is whether the nature of the spillover is leading to a technological market failure in some form, in which case government intervention could be warranted. Garnaut [2008] calls for Government support for research in new technologies, and support for early movers in the adoption of new technologies, due to the public good nature of knowledge. The result from this thesis provides insight into whether learning is actually a public good within the PV cell industry, and therefore whether Garnaut [2008]’s approach to supporting emissions abating technologies is valid for the PV cell industry, or, if there should be a different policy approach.

For the sample of firms that did not enter or exit in the period of 2003 to 2008, the spillover is measured to be 8.83%. This is indication that learning is a private good within the market. Firms therefore create production based learning privately. Due to the private good nature of learning, the rate in which the industry approaches a low cost state might be inhibited. If the size of the spillover is the same for firms looking to enter the market, then learning could also be creating barriers to entry, which constitutes a market failure. Supporting early movers in the PV industry might not be required because they can retain most of the first mover learning benefits. Instead, in order to produce efficient market outcomes, policy makers may need to reduce the barriers to entry for firms looking to enter into the market. Industrial forgetting is not found to be a strong effect, since the industry retains 90.3% of its learning stock each year.

This thesis is organised as follows: in section (2) I provide an overview of the PV industry; in section (3) I review some of the relevant economic literature surrounding learning spillovers and dynamic structural-empirical models; in section (4) the empirical model is explained and the
results are discussed; section (5) contains an evaluation of the results and a short policy analysis; finally, the conclusion of the thesis is given in section (6).
Chapter 2

The PV Industry

2.1 Introduction

The PV industry is a growing and vastly changing industry: Output has been growing exponentially for the last four decades; the cost of PV modules has been steadily decreasing; and prior to the financial crisis there was an increasing number of firms entering the market each year (Photon-International [2009]). The growth of the PV industry is due to a number of factors including technology improvements, an increase in consumer demand for green electricity, and Government incentives promoting the uptake of PV. Government support for PV is partly encouraged in order to spur along the learning effects so that PV can become a cost competitive technology at a faster rate. Thus far, there are no conclusive empirical estimates of the rate of learning for the PV industry. Furthermore, there is no understanding of what impact a knowledge spillover is having on the industry’s growth or composition. This section outlines some of the characteristics of the PV cell industry.

2.2 The PV Production Process

I only consider the PV cell production process. In order to produce a silicon PV panel there are a number of steps involved (see figure 2.1).\(^1\) Firstly, metallurgical grade silicon is converted into ultra-pure silicon. These rods of ultra-pure silicon are then sliced into silicon wafers. The demand for silicon wafers comes from a number of semiconductor industries; the main two being the computer-chip industry and the PV industry.

\(^1\)Source: www.suntech-power.com.

\(^2\)Silicon PV cells represent the vast majority of PV production. Although I only consider silicon cell production in this section, the process is similar for most technology types.
A silicon wafer producer is typically not also a cell producer. PV cell producers perform a complex set of tasks on the initial wafer in order to turn it into a PV cell. These cells are then sent away to a PV module producer.

In some vertically integrated firms, the PV module producer is also a PV cell producer. Even if a firm is vertically integrated, both the cell and module production processes are not necessarily performed within the same plant: modules are typically produced closer to the final point of sale to save on shipping costs. In general then, the cell production process is discernible from the module production process. The PV module production process is the final stage where cells are put together in a protective panel as the finished product.

A spillover of learning occurs when one firm benefits from what another firm learns in production. In regards to the PV cell production process this could be achieved via new production techniques, the deployment of new technologies, or other ways in which reductions in production costs occur. This has consequences for the industry wide learning and cost reduction, as well as the composition and growth of an industry.

### 2.3 Growth of the PV Industry

As can be seen in figure (2.2), PV production has been growing exponentially for almost the last three decades.
The sample period being considered is 2003 to 2008. The total capacity and production for each year can be seen in figure (2.3). Annual PV cell production has grown from less than 1GW of production in 2003 to almost 8GW in 2008 (Photon-International [2000-2008]). Similarly, the total production capacity of the industry has increased by 240% over that period (Photon-International [2000-2008]).
2.4 The Composition of the Industry

Referring to table (2.1), the composition of the industry has changed significantly over the sample period. In 2003, the top firms produced almost 60% of the total production; in 2008, this fell to less than 30%. In 2003 and 2004, Sharp had over a quarter of the market share; in 2008, despite increasing its own production by almost 60%, Sharp only had a 6% market share and fell to the number four spot. Ahead of Sharp in 2008 were Q-Cells, First Solar, and Suntech; each of these firms were not in the top five in 2003. The industry appears to be becoming less concentrated and firms that have the most production experience are not necessarily dominating the market.

2.5 The Learning Curve

As production experience accumulates, the learning effect leads to reductions in production costs. Figure (2.4) shows that the cost of PV modules decreased as production accumulated in the years 1976 to 2003. Taking prices as a proxy for PV production costs, it can be seen that costs have decreased as a function of output. To some extent the decrease in the costs can be attributed to the learning effect. A spillover could either expedite or impede the rate of learning. As already mentioned, the effect of a spillover on the PV industry is currently unknown.

![Figure 2.4: PV Module Production Versus Price (Santa-Fe-Institute [2009]).](image-url)
### Table 2.1: The Top Five Cell Producers in the Years 2003 to 2008 (Photon-International [2000-2008]).

<table>
<thead>
<tr>
<th>Year</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>2003</td>
<td>Sharp (26.4%)</td>
<td>Kyocera (9.6%)</td>
<td>BP Solar (9.2%)</td>
<td>Shell Solar (8.3 %)</td>
<td>RWE Schott (5.9%)</td>
<td>59.4%</td>
</tr>
<tr>
<td>2004</td>
<td>Sharp (25.8%)</td>
<td>Kyocera (8.3%)</td>
<td>BP Solar (6.8%)</td>
<td>Mitsibishi Elec. (6.0%)</td>
<td>Q-Cells (6.0%)</td>
<td>52.9%</td>
</tr>
<tr>
<td>2005</td>
<td>Sharp (23.5%)</td>
<td>Q-Cells (9.1%)</td>
<td>Kyocera (7.8%)</td>
<td>Sanyo (6.9 %)</td>
<td>Mitsibishi Elec. (5.5%)</td>
<td>52.8%</td>
</tr>
<tr>
<td>2006</td>
<td>Sharp (17.1%)</td>
<td>Q-Cells (10.0%)</td>
<td>Kyocera (7.1%)</td>
<td>Suntech (6.3%)</td>
<td>Sanyo (6.1%)</td>
<td>46.6%</td>
</tr>
<tr>
<td>2007</td>
<td>Q-Cells (9.1%)</td>
<td>Sharp (8.5%)</td>
<td>Suntech (7.9%)</td>
<td>Kyocera (4.8%)</td>
<td>First Solar (4.7%)</td>
<td>35.0 %</td>
</tr>
<tr>
<td>2008</td>
<td>Q-Cells (7.4%)</td>
<td>First Solar (6.4%)</td>
<td>Suntech (6.3%)</td>
<td>Sharp (6.0%)</td>
<td>JA Solar (3.8%)</td>
<td>28.2%</td>
</tr>
</tbody>
</table>
Chapter 3

Literature Review

3.1 Introduction

There are three relevant streams of literature pertaining to this thesis. The first stream is the economic literature surrounding learning and knowledge spillovers. The second stream is the economic literature on dynamic structural-empirical models, and the development of these models. The third stream is the current economic literature that uses elements of dynamic structural-empirical models to investigate characteristics of industrial organisation. The relevance of these three streams to my thesis is as follows: I use the economic literature on learning and spillovers as the motivation for investigating learning spillovers empirically; in order to estimate the spillover, I combine elements and results of past structural-empirical models; the third stream uses the first two streams in a similar manner to mine.

The first stream is concerned with a firm’s decision to invest in knowledge in the form of research and development (R&D) or production based learning. Production based learning is first formally documented in the production of airplanes and in the Swedish iron works. This partly led on to endogenous theories of macroeconomic growth. On the microeconomic side of learning, the ability of learning to reduce production costs is predicted to create barriers to entry. Furthermore, strategic effects between firms might also arise due to learning. To complicate matters, the idea of a knowledge spillover is introduced, which predicts that due the public good nature of knowledge, it would be under supplied by the market compared to a socially efficient level of knowledge production. The theoretical literature does not give any definite predictions as to what the effect of a spillover will be on the market, as the end result may depend on a variety of factors. In order to address this issue, there has been empirical research into the effect of spillovers on individual markets.
The second stream is the evolution of dynamic models to include firm heterogeneity and the estimation techniques that have developed to solve these models. The need for such models arises out of economic policy debates, which are concerned with dynamic decisions, such as entry, exit, and investment decisions. Solving these models is a major challenge due to both the complexity and computational capability. New estimation techniques, that reduce the computational burden make up a growing body of literature relevant to the second stream.

Similarly to mine, the third stream combines theory and empirics to investigate characteristics of industrial organisation. One advantage of these models is that they can be used for policy analysis.

The literature review is organised as follows: in section (3.2) I discuss the first stream of literature; in section (3.3) I discuss the second stream; in section (3.4) I outline some of the current economic papers relevant to the third stream.

### 3.2 Knowledge Spillovers

The economic literature surrounding knowledge production is mainly concerned with either production based learning or R&D, but sometimes there is no distinction between the two. Production based learning is a positive by-product of production that results in gaining knowledge.\(^1\) R&D on the other hand, is a direct investment into knowledge. The literature contains economic theories about the effects of knowledge production on the composition and efficiency of markets. The idea that knowledge production can be shared, in the form of a knowledge spillover, leads to further theories about what the effect of spillovers is on the composition of the market and also the production of knowledge. Spillovers are shown empirically to exist, but the effect of a spillover on a market cannot be determined only from the literature, as the end result may depend on many other industry factors.

Cost reductions resulting from production is first documented by Wright [1936], where he notices that the number of labour hours required in airframe production reduce as a function of the number of airframes of the same type being produced. The reason being, as workers gain experience in airframe production, and other similar repetitive tasks, they learn how to become more efficient. A similar effect is noticed by Lundberg [1961] in the iron works in Sweden: over a fifteen year period there was no new investment in the Horndal steel mill, but productivity still managed to rise by two percent per annum. The fact that there is no new investment implies that the production processes remain the same, and so the increase in productivity results from production based learning. This effect is sometimes referred to as the “Horndal Effect.”

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\(^1\)By production based learning I am referring to either learning by doing, learning by interacting, or learning by searching. See Bruce [2008] for a comprehensive explanation of the different types of production based learning.
Production based learning brings about improvements in productivity and efficiency, and so Arrow [1962] extends the idea of learning to endogenous theories of macroeconomic growth. In his paper, Arrow [1962] formalises a model to include production based learning as a determinant of economic growth, rather than treating technological change as exogenous.

Benkard [2000] develops this idea of cost reducing production based learning to include organisational forgetting and spillovers of learning between production lines. The reason being, while cost reducing learning is well documented, firms may also learn from other production processes if they produce different products. Furthermore, firms may also forget previous learning, and so forgetting is a depreciation on the stock of learning. Using production data for the Lockheed L-1011 between 1970 and 1984, Benkard [2000] identifies both the learning effect and the forgetting effect, concluding that both are observable by-products in organisations.

Knowledge production may also have effects on the composition of markets if spillovers exist. Spence [1981] develops the theory that production based learning potentially creates barriers to entry and protection from competition for early entrant firms, and firms that achieve large market shares. Policy makers can try to impose competition on the market, but this can have the effect on slowing the technical efficiency in the market for industries with moderate learning curves. Spence [1981] finds that for industries with either fast or slow learning curves, imposing competition does not have an effect on the technical efficiency of the industry, but these results are preliminary and are only intended as a starting ground. Although he is referring to production based learning, as opposed to knowledge resulting from R&D, he does not explicitly differentiate between the effects of the two in this paper.

In a later paper, Spence [1984] begins to make this differentiation between R&D learning and production based learning. He notes three possible problems associated with R&D investment. The first two are not unique to R&D, and are also applicable to markets with product differentiation and fixed costs. The first problem is that the success of R&D is determined by its private benefits, rather than its public benefits, and so there is no \textit{a priori} to suggest the market will supply “optimal” amounts of R&D. The second problem arises if R&D is being invested in non-competitive markets: there are likely to be consequences for prices, margins and allocative efficiency. The third problem is unique to R&D: the appropriability of R&D by competitors. On the one hand, if R&D can be appropriated then a disincentive to invest into R&D is created. On the other hand, if R&D can be easily appropriated then the industry will develop technical efficiency at a faster rate. By using a theoretical model, he finds that reasonably concentrated markets with a high level of spillover will produce the best market performance results. However, this neglects the problem of the disincentive to invest into knowledge production. By factoring this in, and applying appropriate subsidies to counteract the disincentive, he finds that high market performance can be achieved with high spillovers of knowledge.
Ghemawat and Spence [1985] apply this notion of appropriability, or spillovers, to learning curves and market performance. In agreement with Spence [1981] and Spence [1984], they presuppose that spillovers will increase the rate of cost reduction in an industry, but that spillovers will produce a disincentive to create knowledge in both production based learning and R&D. They find that for production based learning, the efficiency effect dominates the disincentive effect. For R&D however, the disincentive effect dominates the efficiency effect. And so spillovers can have differing effects in the ways that knowledge is created. Where spillovers have the same effect on both is in the lowering of market barriers, which potentially increases the efficiency of an industry.

Jaffe [1986] outlines the difficulties in identifying spillovers anecdotally but finds empirical support for the existence of spillovers. He finds that firms within R&D intensive industries are likely to be more R&D intensive themselves, and to receive higher returns for their investment. If however, the firm is not R&D intensive itself, then it is likely to be less profitable compared to their R&D intensive neighbours. While these results are completely circumstantial, he takes them to substantiate the spillover phenomenon.

Eeckhout and Jovanovic [2002] challenge the idea that spillovers lead to industry convergence to some efficiency level. Similar to Spence [1981] and Spence [1984], and Ghemawat and Spence [1985], there is a trade-off between the disincentive effect of spillovers and the rate of industry cost reduction. Industry cost reduction, in this instance, is actually leading towards convergence of firms towards the technological frontier. They argue that the free riding effect from spillovers counteracts convergence because imitators have a disincentive to invest into knowledge production because this decreases the knowledge stock available to imitators. The result is that firms remain in their same technologically relative position by settling for technologies that are within the frontier. They conclude that free-riding, resulting from spillovers, promotes inequality between firms.

Jaffe et al. [2005] extends the theories about market failures resulting from knowledge spillovers, to renewable energy technologies markets. Market failures resulting from the negative externality of pollution, potentially coincide with market failures resulting in the technological market (possibly from knowledge spillovers), so that renewable energy technologies are doubly under supplied by the market. He calls for a portfolio of policies that address both the environmental externality and the technological spillover, in order to have an efficient supply of pollution reducing technologies.

There is a rich body of literature that discusses learning and spillovers in some detail, but there is no conclusive theories that can be applied directly to an industry to determine what the effect of learning and spillovers will be. In order to understand the effect of learning and spillovers on a specific market, I believe that the analysis will first of all need to be empirical to find out what
the level of learning and spillovers are for a certain set of market factors. Once these empirical results are determined, then it can be deduced what the effect of learning and spillovers are on the market in question, and this could be done by either theoretical or empirical means, or a combination of the two.

3.3 Dynamic Structural Equilibrium Models of Imperfect Competition

According to Lucas [1978], for many years it was Viner [1932]'s theory of firm size that dominated economists’ thoughts and policy debates about the size distribution of firms. Viner [1932]'s theory relies on the assumption that firms produce at the minimum point of their U-shaped long-run average cost functions. Production should be allocated amongst firms so that total industry costs are minimised. While this provided a good foundation to understanding efficient firm production and firm size, there is growing evidence against Viner [1932]'s theory. This includes: firms often sell products in different markets and so the Marshaillian demand curve is difficult to apply; most changes in the demand for products are not met by firm entry and exit, but instead are met by changes in firm size; and finally, the rate of firm growth appears to be independent of its size. To explain some of these anomalies in firm size that are not explained by Viner [1932], Lucas [1978] and Kihlstrom and Laffont [1979] develop static models of industry equilibrium that contain heterogeneity amongst firms. The hypothesis behind these static models is that, following Simon and Bonini [1958], researchers can make inferences about random processes that govern firm growth. A natural extension is obviously to take these static models and turn them into dynamic models, and this led on to a whole field of research into industrial organisation.

Jovanovic [1982] and Lippman and Rummelt [1982] introduce the first equilibrium models that include firm specific stochastic elements to explain observed firm dynamics. Jovanovic [1982] provides a theory to explain recent findings that small firms grow faster than large firms and are more likely to fail. He produces a model of a small industry that produces a homogeneous product with a known demand. Firm heterogeneity comes from different cost functions being given to firms randomly. Dynamics in the model come from firm entry, growth, and exit behaviour. His model subjects firms to productivity shocks with unknown firm-specific means and known variance. Efficient firms grow and survive while inefficient firms reduce size and then drop out of the market. According to Jovanovic [1982], this behaviour agrees “broadly” with the observed evidence that small firms grow faster but are more likely to fail. Lippman and Rummelt [1982] produce a similar model of heterogeneous firms supplying a homogeneous product with a deterministic demand, where cost functions are assigned to entrants from a known
probability distribution. This random allocation of cost functions to entrants is used to explain the differences in efficiencies observed across firms. They find that above normal industry rates of return, differences in profitability, and a lack of entry are all possible equilibria even when firms are price takers.

Pakes and McGuire [1994] extend these dynamic models with firm entry and exit, to include firm investment decisions. The main aim of their paper is to provide an algorithm to compute the Markov-perfect Nash equilibrium responses, that were introduced in Maskin and Tirole [1988]. Their framework is intended to be general enough to be applied to many empirical settings, where researchers need to move back and forth between economic theory and empirical analysis. The model includes firm heterogeneity, which comes from uncertain outcomes of capital investments creating idiosyncratic uncertainty amongst firms. The algorithm that they put forward is computationally demanding (not only for 1992 computer standards) despite being analytically simple, and so they discuss the problem of applying their algorithm to industries with many firms. Berry and Pakes [1993] apply the algorithm of Pakes and McGuire [1994] to a superficial analysis of mergers, but mention that any empirical application is limited by computational methods and computer speed. Nonetheless, in order to draw more accurate conclusions on industries with heterogeneous firms, they stress the need for these dynamic models.

At this stage of the development of the literature, the need for dynamic models, that could be applied to empirical analysis in order to explain firm heterogeneity within industries, had been made clear. The next step was to lay down a framework in which this could be applied. While Pakes and McGuire [1994] develop the algorithm to compute Markov-Perfect Nash equilibrium responses, it is Ericson and Pakes [1995] that provide an entire framework that can be applied to empirical studies. Their dynamic model of firm and industry behaviour, which allows for heterogeneity and idiosyncratic shocks, includes firm entry, exit and investment decisions. The framework of their model is intended to be general enough to allow for empirical work, so that it can evaluate the effects of policy on the distribution of responses of firms and industries. While this is a big step in dynamic models and provides the framework that is apparently needed, the largest drawback is the computational burden, even for computers of today’s standards. Necessarily, finding simpler techniques to solve these Ericson and Pakes [1995] models creates a field of research in itself.

One of the first dynamic structural-empirical models to be applied empirically to include firm entry, exit, and investment behaviour is by Olley and Pakes [1996]. They combine elements of Ericson and Pakes [1995], and other papers, to estimate a dynamic model with heterogeneous firms producing a homogeneous good. Empirically, their goal is to estimate productivity dynamics in the US telecommunications industry. They show that these models could be used for

\[ \text{Markov-perfect Nash equilibriums are the equilibriums that result when a strategy depends only on an opponent’s current set of actions, and not on the entire history of actions of all players.} \]
policy analysis and to explain observed differences in productivity. Furthermore, they provide a two-step estimation technique to estimate unobserved firm level productivity, even when the estimating equation is inhibited by the simultaneity problem between a firm’s productivity and level of inputs (first noted in Marschak and Andrews [1988]).

Olley and Pakes [1996] show how these Ericson and Pakes [1995] type models can be applied, but the problem of computational complexity is still a limitation for most empirical analyses. Hopenhayn [1992] addresses this problem of computational complexity by proposing a concept of stationary equilibrium. Stationary equilibrium extends the standard long run industry equilibrium to include firm dynamics, entry, and exit. Tractability in his model comes from assuming the industry state is constant over time; with a continuum of firms each possessing only minute fractions of the market share, he assumes the law of large number holds. Similarly to the concept of stationary equilibrium, Weintraub et al. [2008] introduce the idea of Oblivious Equilibrium to ease the computational burden involved in solving Ericson and Pakes [1995] type models. Oblivious Equilibrium is the notion that firms can make nearly optimal decisions by simply knowing their own state and the long-run industry state. In other words, under certain circumstances a near equilibrium outcome can arise in an industry, even without firms considering their competitor’s states. The advantage of Oblivious Equilibrium is that computational complexity is on the scale of a single firm’s state, rather than all possible state combinations across firms. In their paper, they prove that as the market size grows, Oblivious Equilibrium outcomes closely approximate Markov Perfect Equilibria. Another technique to ease the computational burden is developed by Bajari et al. [2007], where they introduce a two-step algorithm to estimate dynamic games under the assumption that the outcomes are consistent with Markov perfect equilibria. These simplifying computational techniques have made it possible to apply dynamic models to empirical studies of heterogeneous firm behaviour.

3.4 Spillovers in Dynamic Structural Empirical Models

For the most part, the relevant literature on knowledge spillovers is restricted to static analyses. With the benefit of new computation techniques and increased computer power, research into spillovers has been able to develop into empirical studies of dynamic industries with firm heterogeneity. This is an active field of research in industrial organisation. In this section I will give a brief overview of some of the research currently being conducted into this area.

Xu [2008] applies Weintraub et al. [2008]’s concept of Oblivious Equilibrium to solve a dynamic model with heterogeneous firms and monopolistic competition in an empirical paper investigating Korea’s Electric Motor Industry. He develops and estimates the parameters of a dynamic industry equilibrium model of R&D, R&D spillovers, and the productivity of firms that face
dynamic decisions of investment, entry, and exit. He estimates the productivity of firms and the spillover of R&D. By running counterfactuals, he finds that by increasing the substitution between products, plants have a greater incentive to innovate, but also plant turnover is increased. Furthermore, by reducing product mark-ups (a control parameter in the model), the industry will become slightly more productive. On the other hand, by reducing the cost of entry, the industry does not become any more productive.

Finger [2008] applies the two-step estimation technique of Bajari et al. [2007] to investigate the effect of research-inducing policies on the US chemicals industry. He creates a dynamic oligopoly model to find that increased investment into R&D by larger firms due to a subsidy was offset by reductions in innovations by smaller firms. The net effect being that the effectiveness of the subsidy and the greater benefits to society were limited.

Bloom et al. [2008] investigate two competing effects of spillovers in R&D: the competitor’s ability to steal one firm’s R&D investment, and the positive effects of spillovers to an industry. By looking at a panel of data for US firms over two decades, they find that the benefits resulting from spillovers outweigh the negative effects. Finally, Cai [2008] conducts an empirical analysis to show how knowledge spillovers can explain firm size heterogeneity. Her model provides an environment where firms can invest in imitation, rather than only innovation, and she finds that imitation contributes greatly to firm growth rates. This leads to firm size distributions to become homogeneous in the long run.
Chapter 4

Empirical Model

4.1 The Equilibrium Framework

The goal is to measure the spillover from the industry-wide learning pool that enters into a firm’s productivity. A firm’s productivity is its ability to create output by utilising the factors of production. The entry and exit decisions of firms are not considered due to a data limitation. The only decision that a firm makes is to choose the level of inputs.

A firm’s productivity is not directly observable from the data. A firm on the other hand knows their level of productivity and sets their level of inputs accordingly. This poses the simultaneity problem first raised in Marschak and Andrews [1988]. In order to account for the simultaneity problem, I adapt the model of Olley and Pakes [1996] to include learning but not firm entry and exit decisions. Olley and Pakes [1996] show that the simultaneity problem can be overcome by employing a two stage regression technique; this is outlined in section (4.3.2). I assume that productivity is the only unobserved state variable that causes differences in firm behaviour and that a firm’s profit in any given period is a function of its state, where a firm’s state is given by its productivity $\omega_{i,t}$, and its capital stock $K_{i,t}$. A firm only faces one decision: the level of capital investment for the next period.

The two state variables, capital and productivity, evolve in different ways. Capital is directly set by a firm and accumulates according to $K_{i,t+1} = (1 - \delta)k_t - I_{K_{i,t}}$, where $\delta$ is the depreciation of capital and $I_{K_{i,t}}$ is firm $i$’s investment into capital at time $t$. The productivity of a firm on the other hand cannot be directly set, and it is assumed to evolve due to both exogenous and endogenous factors. Productivity evolves partly exogenously according to the evolution of the industry productivity frontier $X_t$. Xu [2008] includes $X_t$ in the productivity function.

\footnote{The simultaneity problem is a form of endogeneity where the explanatory variables are determined jointly with the independent variable. It occurs here because the unobserved error is correlated with production.}
of a firm and ranks firms below the frontier according to their level of productivity, so that the most productive firm takes on the industry frontier level of productivity. In my model, I simply allow for exogenous improvements to productivity to occur over time, which is intended to proxy for exogenous productivity improvements resulting from improvements in the industry technological frontier. Endogenous improvements in productivity occur due to production based learning, which was first formally documented by Wright [1936]. Production based learning results from past output, and so a firm can indirectly impact on its own level of productivity based upon past levels of output. Furthermore, if there is a spillover from the industry wide stock of learning to individual firms then industry wide production can affect a firm’s productivity.

4.2 Data

The price level in each period is taken to be the average yearly PV cell price reported by the US Energy Information Association. The capital and production data comes from Photon International market surveys for the years 2000 to 2008, which are released in March of every year. Photon International is a global PV industry trade magazine, released monthly, that provides information on market and technology developments. Photon International’s yearly market survey gives the previous year’s production and capacity for every firm in the industry. The time period of the data is a year. The dataset taken from Photon International is considered to be accurate but is incomplete; it has the following characteristics:

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs.</th>
<th>Missing Vbls</th>
<th>Mean (MW)</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Production</td>
<td>647</td>
<td>136</td>
<td>28.089</td>
<td>68.899</td>
<td>0</td>
<td>584.6</td>
</tr>
<tr>
<td>Capacity</td>
<td>551</td>
<td>232</td>
<td>51.083</td>
<td>116.248</td>
<td>0</td>
<td>1000</td>
</tr>
</tbody>
</table>

To complete the dataset I impute the missing values using the Multiple Imputation Using ICE method (Schafer [1999] and Rubin [1996]). I discard the observations for firms that enter or exit within the period 2003 to 2008 because I am not modelling entry or exit. The characteristics of the final imputed datasets can be seen in table (4.2).

The imputed data has higher averages and larger spreads. This is expected because the original dataset has some zero production and zero capacity values. The range of data is approximately equal except for the imputed data does not have a zero-minimum observation since all zero observations are discarded.

\(^2\)Out of the top ten firms in 2008, only one firm entered after 2003. The observations for this firm had to be discarded. Apart from this, the majority of production came from firms that were already in the market in 2003 and who still remained in the market in 2008.
Table 4.2: Characteristics of the Imputed Datasets.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs.</th>
<th>Mean (MW)</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dataset One</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Production</td>
<td>366</td>
<td>46.112</td>
<td>85.933</td>
<td>0.002</td>
<td>584.6</td>
</tr>
<tr>
<td>Capacity</td>
<td>366</td>
<td>74.508</td>
<td>135.485</td>
<td>0.008</td>
<td>1000</td>
</tr>
<tr>
<td>Dataset Two</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Production</td>
<td>366</td>
<td>46.465</td>
<td>86.293</td>
<td>0.0001</td>
<td>584.6</td>
</tr>
<tr>
<td>Capacity</td>
<td>366</td>
<td>72.774</td>
<td>132.149</td>
<td>0.001</td>
<td>1000</td>
</tr>
<tr>
<td>Dataset Three</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Production</td>
<td>366</td>
<td>47.052</td>
<td>86.343</td>
<td>0.001</td>
<td>584.6</td>
</tr>
<tr>
<td>Capacity</td>
<td>366</td>
<td>73.257</td>
<td>132.735</td>
<td>0.001</td>
<td>1000</td>
</tr>
</tbody>
</table>

The results are constrained by a lack of labour data. Not enough labour data could be collected to do a reasonable imputation. Given the time constraint of this thesis, I had to run my model without labour data. Excluding labour data could be reasonable if labour does not add any information to the firm’s input decision; if there is a constant labour to capital ratio throughout the industry then including labour data would not provide any more information in my model. Unfortunately, this is not a realistic assumption to make within the PV industry as it is a global industry with different labour rates, different levels of automation, and thus firms make different labour decisions. The consequences of not including labour data are further discussed in section (4.5).

4.3 The Equilibrium Model

The model treats PV cells as a homogeneous good. The price of cells is the same for all manufacturers and it is taken to be the average cell price during the sample period. A firm’s learning is given by its own cumulative past output, as well as the total learning of the industry if there is a spillover.

4.3.1 Learning

Similarly to Benkard [2000], learning for a firm takes the following form

\[ d_{i,t} = \theta(\Omega_{t-1} - \sum_{t} q_{i,t-1}) + \sum_{t} q_{i,t-1} \]  (4.1)

where \( d_{i,t} \) is the effect of learning on productivity for firm \( i \) in period \( t \), \( \Omega_{t} \) is the industry stock of learning, \( \theta \) is the spillover of learning from the industry to an individual firm, and \( \sum_{t} q_{i,t-1} \) is...
the sum of the firm’s cumulative past output. R&D is not included in the model due to a data limitation. The industry stock of learning is given by

$$\Omega_t = \rho \Omega_{t-1} + Q_t$$

where $Q_t$ is the total industry production in period $t$, and $\rho$ is the depreciation of knowledge, or organisational forgetting first documented in Benkard [2000].

### 4.3.2 Estimating Equation

The production function is assumed to take the following Cobb-Douglas form

$$Q_{i,t} = A_{i,t} L^{\alpha_L}_{i,t} K^{\alpha_K}_{i,t} e^{(\alpha_0 + \omega_{i,t} + u_{i,t})} L^{\alpha_L}_{i,t} K^{\alpha_K}_{i,t}$$

where $\omega_{i,t}$ is the productivity of a firm and $u_{i,t}$ is an independently and identically distributed error term with zero mean and standard deviation $\sigma^2$. From a firm’s point of view, they know their total factor productivity at the start of each period. From the econometrician’s point of view, the total factor productivity of a firm is made up of two parts: a non-random productivity element $\omega_{i,t}$ and a random productivity shock $u_{i,t}$ that impacts on firm $i$ in period $t$.\(^3\)

To see how learning affects the productivity of a firm, I assume that the non-random productivity element $\omega_{i,t}$ is observable to the econometrician at the start of period $t$. It takes the form $\omega_{i,t} = h(d_{i,t}, X_t, K_{i,t})$, where $h$ is a function to be specified later, of the learning entering the firm’s productivity $d_{i,t}$, the exogenously improving industry technological frontier $X_t$, and the firm’s current level of capital $K_{i,t}$.

Rewriting equation (4.3) in log terms and denoting lower-case variables as representing the log of a variable:

$$q_{i,t} = \alpha_0 + \alpha_L l_{i,t} + \alpha_K k_{i,t} + \omega_{i,t} + u_{i,t}.$$  (4.4)

From my perspective as the econometrician, productivity has unobservable components and therefore it enters into the error term equal to $\omega_{i,t} + u_{i,t}$. Due to the no labour data limitation, the $l_{i,t}$ term also enters into the error term so that the error term becomes $\omega_{i,t} + u_{i,t} + l_{i,t}$.

A firm knows its productivity $\omega_{i,t} + u_{i,t}$ for period $t$ at the start of the period. It then chooses the level of inputs for that period based upon its productivity. This poses an endogeneity problem

\(^3\)It is feasible that $u_{i,t}$ is also unobservable to the firm and so at the beginning of period $t$ they set their level of inputs according to the foreseeable productivity element $\omega_{i,t}$. However, this would require extending the model to include dynamic uncertainty, which is more computationally demanding.
between the unobserved error term \((\alpha_{l,i_t} + \omega_{i,t} + u_{i,t})\) and the level of capital \(k_{i,t}\). Equation (4.4) cannot therefore be estimated using simple OLS because the estimates would be biased. To correct for this bias, I employ the Olley and Pakes [1996] two-step procedure, which is developed to handle this issue.

Substituting \(\omega_{i,t} = h(d_{i,t}, X_t, K_{i,t})\) into equation (4.4) gives the first estimating equation:

\[
q_{i,t} = \beta_0 + \phi(d_{i,t}, X_t, k_{i,t}) + \tilde{u}_{i,t} \tag{4.5}
\]

where \(\tilde{u}_{i,t} = u_{i,t} + \beta \alpha_{l,i_t} + \gamma k_{i,t} + h(d_{i,t}, X_t, K_{i,t});\) and \(h(d_{i,t}, X_t, K_{i,t}) = g(k_{i,t}) + \gamma T T\).

The second stage regression is then

\[
q_{i,t} - \beta_0 = \beta \gamma k_{i,t} + \varphi(d_{i,t-1}, X_{t-1}, k_{i,t-1}) - \gamma k_{i,t-1} + \epsilon_{i,t} \tag{4.6}
\]

where \(\epsilon_{i,t}\) is i.i.d, and \(\varphi(\cdot)\) is a polynomial in last period’s productivity. Olley and Pakes [1996] show that equation (4.6) will produce a consistent estimate of \(\beta_k\). The intuition is that a firm’s capital investment decision for one period is only dependent upon the previous period’s productivity, and not on the productivity for the period that the investment is being made for.

### 4.3.3 Optimal Capital Investment

Firm dynamics comes from a firm’s capital investment decision. A firm’s value in time \(t\) is the total value of the firm over the current and future periods. Following Xu [2008], a firm’s value function \(V(K_{i,t})\) at time \(t\) is given by

\[
V(K_{i,t}) = \max_{K_{i,t+1}} \pi(K_{i,t}) - c_k(K_{i,t+1} - (1 - \delta)K_{i,t}) + \beta V(K_{i,t+1}) \tag{4.7}
\]

where \(K_{i,t}\) is the capital stock of firm \(i\) at time \(t\), \(c_k\) is the marginal cost of capital, \(\delta\) is the depreciation of capital, and \(\beta\) is the discount rate.

Taking the first order condition with respect to \(K_{i,t+1}\) and maximising gives

\[
\frac{\partial V(K_{i,t})}{\partial K_{i,t+1}} = -c_k + \beta \frac{\partial V(K_{i,t+1})}{\partial K_{i,t+1}} = 0. \tag{4.8}
\]
Similarly, taking the derivative of equation (4.7) with respect to $K_{i,t}$ gives

$$\frac{\partial V(K_{i,t})}{\partial K_{i,t}} = \frac{\partial \pi(K_{i,t})}{\partial K_{i,t}} + c_k(1 - \delta). \tag{4.9}$$

In period $t+1$, equation (4.9) becomes

$$\frac{\partial V(K_{i,t+1})}{\partial K_{i,t+1}} = \frac{\partial \pi(K_{i,t+1})}{\partial K_{i,t+1}} + c_k(1 - \delta). \tag{4.10}$$

Using the profit function

$$\pi(K_{i,t}) = P_tQ_{i,t} - r_{i,t}K_{i,t} = P_tA_{i,t}K_{i,t}^{\alpha_k} - r_{i,t}K_{i,t}$$

where $A_{i,t} = e^{(\alpha_0 + \omega_{i,t} + u_{i,t})}$ is the total factor productivity, $P_t$ is the average cell price, and $r_{i,t}$ is the rent on capital. Taking the derivative of $\pi(K_{i,t+1})$ with respect to $K_{i,t+1}$ in period $t+1$ gives

$$\frac{\partial \pi(K_{i,t+1})}{\partial K_{i,t+1}} = \alpha_kP_{t+1}A_{i,t+1}K_{i,t+1}^{\alpha_k-1} - r_{i,t+1}. \tag{4.11}$$

Substituting this expression into equation (4.10), and combining equations (4.8) and (4.10) gives

$$0 = -c_k + \beta \frac{\partial V(K_{i,t+1})}{\partial K_{i,t+1}}$$

$$= -c_k + \beta \left( \frac{\partial \pi(K_{i,t+1})}{\partial K_{i,t+1}} + c_k(1 - \delta) \right)$$

$$= -c_k + \beta \left( \alpha_kP_{t+1}A_{i,t+1}K_{i,t+1}^{\alpha_k-1} - r_{i,t+1} + c_k(1 - \delta) \right).$$

Rearranging and solving for the optimal capital stock $K_{i,t}^*$ for any firm $i$ in any period $t$ gives

$$K_{i,t}^* = \left( \frac{c_k \left( \frac{1 - \beta(1 - \delta)}{\beta} \right) + r_{i,t}}{\alpha_kP_tA_{i,t}} \right)^\frac{1}{\alpha_k-1}. \tag{4.12}$$
4.3.4 Moments

The moments to be used are the differences between capital and quantity estimates and the actual realisations of capital and quantity, respectively. The theoretical moments are:

\[
\begin{align*}
\mu_1^t &= E(q_t) - \bar{q}_t = 0 \\
\mu_2^t &= V(q_t) - s_{q_t}^2 = 0 \\
\mu_3^t &= E(k_t) - \bar{k}_t = 0 \\
\mu_4^t &= V(k_t) - s_{k_t}^2 = 0
\end{align*}
\]

where \( \bar{q}_t \) and \( \bar{k}_t \) are the average observed production and capital in period \( t \); \( s_{q_t}^2 \) and \( s_{k_t}^2 \) are the observed variances of production and capital; and, \( E(\cdot) \) and \( V(\cdot) \) are the means and variances of the predicted values.

The empirical moments to be used are:

\[
\begin{align*}
m_1^t &= \frac{1}{N} \sum_{i=1}^{N} \hat{q}_{i,t} - \bar{q}_t \\
m_2^t &= \frac{1}{N} \sum_{i=1}^{N} \hat{q}_{i,t}^2 - \left( \frac{1}{N} \sum_{i=1}^{N} q_{i,t} \right)^2 - s_{q_t}^2 \\
m_3^t &= \frac{1}{N} \sum_{i=1}^{N} \hat{k}_{i,t} - \bar{k}_t \\
m_4^t &= \frac{1}{N} \sum_{i=1}^{N} \hat{k}_{i,t}^2 - \left( \frac{1}{N} \sum_{i=1}^{N} k_{i,t} \right)^2 - s_{k_t}^2
\end{align*}
\]

Denoting the vector of moments by \( \bar{m} \) and letting \( \Pi \) be the weighting matrix, the Generalised Method of Moments (GMM) problem is then

\[
\min_{\rho, \theta, r} \bar{m}^T \Pi^{-1} \bar{m} \tag{4.13}
\]

where \( \Pi \) is a diagonal matrix containing the empirical standard deviations for: production, the standard deviation of production, capital, and the standard deviation of capital in each time period.
4.3.5 Computation Method

Using Matlab, I apply the following computation technique to obtain my estimates of the parameter values.

For particular values of $\rho, \theta,$ and $r$:

1. Compute $\{\Omega_t, d_{i,t}\}_{t=1, i=1}^{T,N}$ using equations (4.1) and (4.2).
2. Run first regression (equation (4.5)) to obtain estimates for $\hat{\beta}_0$ and $\phi(\cdot)$.
3. Run second regression (equation (4.6)) to obtain estimates for $\hat{\beta}_k$.
4. Predict $\hat{q}_{i,t}$ using equation (4.4) in order to compute $m^1_t$ and $m^2_t$.
5. Predict $\hat{k}_{i,t}$ using equation (4.12) in order to compute $m^3_t$ and $m^4_t$.
6. Solve minimisation problem over all values of $\rho, \theta,$ and $r$ (equation (4.13)).

To obtain the standard error of the estimates, I use the following method (Greene [2000]). Let $M_t(\tau)$ be a $(4T \times 1)$ matrix of the form

$$M_t(\tau) = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ m^1_t \\ m^2_t \\ m^3_t \\ m^4_t \\ \vdots \\ 0 \\ 0 \end{bmatrix}$$

where $\tau$ represents the estimated parameter, $T$ is the total number of time periods, and 4 is the number of moments per time period. Then let $\hat{\Phi}$ be a $(4T \times 4T)$ matrix such that

$$\hat{\Phi} = \frac{1}{T-1} \left[ \sum_{t=1}^{T} M_t(\tau)M_t(\tau)^T \right].$$

Finally, let $\hat{G}$ be a $(4T \times 3)$ derivative matrix of the form
\[ \hat{G} = \begin{bmatrix} \frac{\partial \hat{M}}{\partial \theta} & \frac{\partial \hat{M}}{\partial \rho} & \frac{\partial \hat{M}}{\partial r} \\ \vdots & \vdots & \vdots \end{bmatrix} \]

where \( \hat{M}(\tau) = \frac{1}{T} \sum_{t=1}^{T} M_t(\tau) \), and \( \theta, \rho, \) and \( r \) are the estimated parameters.

The covariance matrix is then given by

\[ Var = (\hat{G}^T \Pi \hat{G})^{-1} \hat{G}^T \Pi \left(\frac{1}{T} \Phi\right) \Pi \hat{G} (\hat{G}^T \Pi \hat{G})^{-1} \tag{4.14} \]

where \( \Pi \) is the optimisation matrix defined in section (4.3.4).

### 4.4 Model Estimation

#### 4.4.1 Preliminary Estimates

In order to estimate the parameters, I set the depreciation of capital \( \delta \) equal to zero and the discount rate \( \beta \) equal to one. Referring to equation (4.12) for the optimal capital investment decision, the cost of capital \( c_k \) drops out by setting \( \beta = 1 \) and \( \delta = 0 \), so that the cost of capital \( c_k \) does not need to be optimised over or normalised. The estimated parameters using the computation technique outlined in section (4.3.5) are shown in table (4.3), where \( \theta \) is the spillover, \( \rho \) is the forgetting effect, \( r \) is the rent on capital, and \( \Sigma = \hat{m}^T \Pi^{-1} \hat{m} \) is the sum of the squared moments (equation (4.13)). The standard errors are given in the parentheses.

**Table 4.3: Estimated Parameters for Model One.**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Imputed Data Set Number</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
<td>2</td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>( \theta )</td>
<td>0.122</td>
<td>0.041</td>
<td>0.102</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0575)</td>
<td>(0.00369)</td>
<td>(0.0161)</td>
<td></td>
</tr>
<tr>
<td>( \rho )</td>
<td>0.878</td>
<td>1.000</td>
<td>0.918</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.120)</td>
<td>(0.0794)</td>
<td>(0.0539)</td>
<td></td>
</tr>
<tr>
<td>( r )</td>
<td>1.076</td>
<td>1.100</td>
<td>1.100</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.696)</td>
<td>(0.0207)</td>
<td>(0.234)</td>
<td></td>
</tr>
<tr>
<td>( \Sigma \ (\times 10^4) )</td>
<td>1.173</td>
<td>1.224</td>
<td>1.542</td>
<td></td>
</tr>
</tbody>
</table>
All estimates of the parameters are significant at the 10% level. Following Rubin [1987], I take the overall estimate for the parameters to be the average of the estimates. The variance of the parameters is

\[ T = \bar{U} + \left( 1 + \frac{1}{3} \right) B \]

(4.15)

where \( B \) is the variance of the estimates \( \left( \frac{1}{4} \sum_{j=1}^{4} (\hat{Q}_j - \bar{Q})^2 \right) \), \( \bar{U} \) is the average of the estimated variance \( \left( \frac{1}{4} \sum_{j=1}^{4} (U_j)^2 \right) \), \( \hat{Q}_j \) is the estimate of the parameter, and \( U_j \) is the standard error of the parameter.

The estimated parameters and standard errors are reported in table (4.4). All estimates of the parameters are significant at the 10% level.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Std. Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \theta )</td>
<td>0.0883</td>
<td>0.0597</td>
</tr>
<tr>
<td>( \rho )</td>
<td>0.903</td>
<td>0.115</td>
</tr>
<tr>
<td>( r )</td>
<td>1.019</td>
<td>0.1868</td>
</tr>
</tbody>
</table>

Most of the variation in the moments comes from the capital estimates. Figure (4.1) shows each of the moments generated for data set one; the capital moments (m3 and m4) have values of the order of 10^4. This suggests that the capital estimate is controlling the optimisation.
A possible reason why capital is controlling the optimisation process can be seen in equation (4.12). By setting $\delta = 0$ and $\beta = 1$, equation (4.12) becomes

$$K^*_i,t = \left( \frac{r_{i,t}}{\alpha_k P_t A_{i,t}} \right)^{\frac{1}{\alpha_k - 1}}$$  \hspace{1cm} (4.16)

where $r_{i,t}$ is the rent on capital, $P_t$ is the average industry cell price, $A_{i,t}$ is the total factor productivity, and $\alpha_k$ is the coefficient of capital estimate in equation (4.4). In all of the regressions, the estimates of $\alpha_k$ are found to be slightly greater than one. Referring to equation (4.16), $\frac{1}{\alpha_k - 1}$ approaches infinity as $\alpha_k$ approaches one. The estimate for the optimal capital investment then grows large very quickly as $\alpha_k$ approaches one. Because of this problem, I require a different specification for the optimal capital investment.
4.4.2 Secondary Estimates

4.4.2.1 Revised Optimal Capital Investment Decision

Following Xu [2008], I include a capital adjustment cost in the optimal capital investment decision equation:

\[ c(K_{i,t}, K_{i,t+1}) = c_a \left( \frac{I_{i,t}}{K_{i,t}} \right)^2 K_{i,t} \]  

(4.17)

where \( I_{i,t} = K_{i,t+1} - (1 - \delta)K_{i,t} \), and \( c_a \) is a parameter to be optimised over that ensures a convex cost of adjustment.

Substituting equation (4.17) into the original value function for a firm (equation (4.7)) produces the revised value function for a firm:

\[ V(K_{i,t}) = \max_{K_{i,t+1}} \pi(K_{i,t}) - c_k I_{i,t} - c_a \left( \frac{I_{i,t}}{K_{i,t}} \right)^2 K_{i,t} + \beta V(K_{i,t+1}) \]  

(4.18)

where \( K_{i,t} \) is the capital stock of firm \( i \) at time \( t \), \( c_k \) is the marginal cost of capital, \( \delta \) is the depreciation of capital, \( \beta \) is the discount rate, and \( c_a \) is the adjustment cost of capital.

Substituting in the profit function gives:

\[ V(K_{i,t}) = \max_{K_{i,t+1}} P_t A_{i,t} K_{i,t}^{\alpha_k} - r_t K_{i,t} - c_k (I_{i,t}) \]

\[ -c_a \left( \frac{I_{i,t}}{K_{i,t}} \right)^2 K_{i,t} + \beta V(K_{i,t+1}) \]  

(4.19)

Taking the first order condition with respect to \( K_{i,t+1} \) and maximising gives

\[ \frac{\partial V(K_{i,t})}{\partial K_{i,t+1}} = -c_k - \frac{2c_a I_{i,t}}{K_{i,t}} + \beta \frac{\partial V(K_{i,t+1})}{\partial K_{i,t+1}} \]  

(4.20)

Using the envelope theorem, the derivative of equation (4.19) with respect to \( K_{i,t} \) is

\[ \frac{\partial V(K_{i,t})}{\partial K_{i,t}} = \alpha_k P_t A_{i,t} K_{i,t}^{\alpha_k-1} - r_t - c_k (1 - \delta) \]

\[ -c_a \left( (1 - \delta)^2 - \left( \frac{K_{i,t+1}}{K_{i,t}} \right)^2 \right). \]  

(4.21)

In period \( t + 1 \) equation (4.21) becomes
\[
\frac{\partial V(K_{i,t+1})}{\partial K_{i,t+1}} = \alpha_k P_{t+1} A_{i,t+1} K_{i,t+1}^{\alpha_k-1} - r_{t+1} - c_a (1 - \delta) - c_a \left( 1 - \delta \right)^2 - \left( \frac{K_{i,t+2}}{K_{i,t+1}} \right)^2.
\] (4.22)

Substituting equation (4.22) into equation (4.20) and setting equal to zero gives

\[
\alpha_k P_{t+1} A_{i,t+1} K_{i,t+1}^{\alpha_k-1} - r_{t+1} - c_a \left[ 1 - \left( \frac{K_{i,t+2}}{K_{i,t+1}} \right)^2 \right] + 2 \left( \frac{K_{i,t+1} - K_i}{K_{i,t}} \right) = 0
\] (4.23)

The policy function \( K_{i,t+1} = f(K_{i,t}) \) no longer has a closed form solution. To solve equation (4.23) for \( K_{t+1} \), I use the following function approximation method.

Let \( G(K_{i,t}, K_{i,t+1}, K_{i,t+2}) \) represent equation (4.23) and let the optimal level of capital for the next period be of the form

\[
f(K_{i,t}) = a + bK_{i,t} + cK_{i,t}^2
\] (4.24)

where \( a, b \) and \( c \) are parameters to be estimated. To solve this approximation I pick three values for capital: \( K1 = \hat{K}_{i,t} \), \( K2 = 0.95 \times \hat{K}_{i,t} \), and \( K3 = 1.05 \times \hat{K}_{i,t} \), where \( \hat{K}_{i,t} \) is the estimated optimal capital level for period \( t \) made in period \( t - 1 \). I use the 5% values to be confidence intervals either side of the predicted capital level. The three unknowns \( (a, b, c) \) are then solved by the system of equations:

\[
G(K1, f(K1), f(f(K1))) = 0
\]
\[
G(K2, f(K2), f(f(K2))) = 0
\]
\[
G(K3, f(K3), f(f(K3))) = 0.
\]

The predicted optimal capital investment for firm \( i \) made in period \( t \) is then

\[
K_{i,t+1}^* = a + b\hat{K}_{i,t} + c\hat{K}_{i,t}^2.
\] (4.25)

### 4.4.2.2 Results

The best results were obtained for low values of \( c_a \). The problem is, by including the revised optimal capital investment decision I also increase the computation burden significantly.\(^4\) By

\(^4\)For example, in the original specification of capital, 1000 iterations could be completed within one hour. In one instance of the revised optimal capital specification, 10 000 iterations (because I am estimating an extra parameter) took over 29 hours.
increasing the accuracy of the capital estimate, I increase the computational burden. There is therefore a trade-off between increasing the accuracy of the estimates and being able to estimate enough values of the parameters to be confident that all parameter combinations are exhausted.

The best results obtained are reported in table (4.5). It can be seen that the estimates are not significant at the 10% level, which they were in the previous estimate. I therefore accept the first estimates (table (4.4)) to be the final estimates. Due to time and computational constraints, I restricted the values that the parameters can be optimised over. If these restrictions do not have to be made, then this estimation technique should produce more accurate results than the original optimal capital estimation.

Table 4.5: Estimated Parameters and Standard Errors Using the Revised Capital Estimate.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Std. Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\theta$</td>
<td>0.15</td>
<td>0.5</td>
</tr>
<tr>
<td>$\rho$</td>
<td>0.9</td>
<td>2.8</td>
</tr>
<tr>
<td>$r$</td>
<td>1</td>
<td>2.8</td>
</tr>
<tr>
<td>$c_a$</td>
<td>0.1</td>
<td>0.3</td>
</tr>
</tbody>
</table>

4.5 The Consequence of Omitting Labour on the Spillover

At the beginning of every period, a firm knows its productivity level for that period. Based upon the level of productivity and capital stock, a firm chooses its level of labour. If labour is included, then there would once again be the endogeneity problem where the level of labour is correlated with the productivity level, which is unobserved to me as the econometrician but observed by the firm.

Due to a data limitation and time constraints, I omit labour from my estimating equations. This would be valid if either: labour does not enter into a firm’s production function, or the correlation between labour and capital, and labour and productivity is zero within the sample (Wooldridge [2006]). Neither of these cases are valid for the sample. The consequence of not including labour is therefore that my estimates for the estimating equation suffer from omitted variable bias. It is most likely that they are positively biased since they overstate the importance of capital and productivity on production.

The main focus of my results is on the estimated parameters, and in particular, the estimate of the spillover, and not on the results from the estimated production function. The effect of not including labour in the estimation of the spillover is complicated and the overall effect is ambiguous. To see this, first of all consider the estimate of learning on productivity; due to the
omitted variable bias, the estimate of the effect of learning on productivity is over estimated. Referring to equation (4.1), learning is comprised of a firm’s own learning and also the spillover from the industry stock of learning. The estimate of the spillover is found by minimising the sum of the square of the moments. If learning is over estimated, then the spillover must correct for this by reducing the effect of learning on productivity. If everything else is held constant, by omitting labour from the estimating equation, the spillover is underestimated. The difficulty in making this prediction is that the other estimated parameters \((c_a, \rho, r)\) also correct for the omitted variable bias. It is difficult to ascertain therefore whether the spillover is actually underestimated, since there could be the case where some parameters are overvalued and others are undervalued in order to correct for the omitted variable bias. The consequence of omitting labour on the spillover is therefore ambiguous.
Chapter 5

Interpretation of Results and Policy Analysis

5.1 The Spillover

The spillover is measured to be 0.083. In any period then, only 8.83% of the total stock of learning enters into a firm’s productivity. For small firms without much production experience, the benefit of the spillover is the greatest. For larger firms with a greater level of production experience, most of their productivity comes from their own production based learning and exogenous improvements in productivity.

There is no definite guideline as to what level of spillover constitutes a public good as opposed to a private good. However, from this estimate of the spillover it appears that firms are more reliant on their own production based learning than the industry’s stock of learning. For a spillover of only 8.83%, learning is mainly a private good.

Learning as a private good has implications for the industry since it refers to cost reductions that come from production experience. The private good nature of learning in the PV industry could therefore be inhibiting the rate at which the industry becomes a low-cost technology as predicted in Ghemawat and Spence [1985]. The private good nature of learning could also create barriers to entry for firms looking to enter the market (Spence [1981]): entrants must produce at greater costs than incumbent firms until they have gained production experience. Furthermore, because there is not industry-wide learning, firms may be keeping their relative ranks within the industry, and therefore not be converging to a more competitive market state. Given that these results only investigate incumbent firms that did not exit over the sample period, it is not possible to cast assertions on market entry and exit, or industry convergence. In any case, these are not the outcomes that are expected from an initial inspection of the data.
Interpretation of Results

As discussed in section (2), within the PV industry there is rapid growth in production and capacity, and the industry is moving towards being a less concentrated industry. Over short periods of time, firms can move into the market and claim significant market shares. It is expected therefore, that there should be a significant level of knowledge spillover; this is contrary to the results. The sample only contains incumbent firms from 2003 to 2008 however, and it might therefore be the case that for incumbent firms learning is mostly private, but for firms entering the market there is an initial pool of learning available, that reduces the barriers to entry for firms entering the market. Alternatively, if there is no initial pool and the spillover were larger, the industry could see greater rates of entry and a more rapid move towards becoming a less concentrated industry. It is impossible to determine what effect the spillover is having on the industry from my model however, and I therefore leave this as an area of future research.

5.2 Policy Analysis

I consider the effect of increasing the spillover on the industry. This is a hypothetical policy where firms are encouraged to share their production based learning with the rest of industry. Such a policy might be difficulty to apply in practice because firms are unwilling to share their production techniques with competitors, and it is difficult to estimate the social benefit of increasing the spillover. This policy is therefore left as a hypothetical policy used to evaluate the effect of increasing the spillover, and not an actual policy recommendation.

By increasing the spillover to 50% as opposed to 8.83%, I find that production decreases by 6.5% and productivity decreases by 2% over the sample period. By increasing the spillover to 100% so that learning is a pure private good, production decreases by 7.7% and productivity decreases by 1.6%. The effect of a spillover, within this model and dataset, is that it decreases production and productivity in each period.

There are a number of reasons why firms might produce more when they retain their production experience without having to share their learning. Firms could strategically over produce in order to spur along learning effects. Conversely, for greater levels of spillover there might be a disincentive for a firm to produce because their production based benefits their competitors.

It appears that higher levels of spillover would have adverse effects on the market. This does not take into account the market barriers to entry that private learning is potentially creating, or the possibility that the rate of industry wide cost reductions is being slowed down. This model is limited because it does not consider firm entry and exit, and does not explicitly model the learning curve. In order to determine whether there are barriers to entry or the rate of industry wide cost reduction is being slowed down, the model necessarily needs to be extended. This could be another area of further research.
Chapter 6

Conclusion

A dynamic structural-empirical model is developed in order to estimate the size of the spillover of learning within the PV industry. The sample contains incumbent firms that remained in the industry in the years 2003 to 2008. The spillover is estimated to be 8.83%. Learning is therefore determined to be a private good. A simple policy analysis finds that when the size of the spillover is increased, the industry output and average productivity over the sample period falls.

The PV industry is supported by Governments in a number of ways. There is currently no indication that these policies are the most effective or deserving means of supporting PV. The result of this thesis is the first step towards economic evidence of a possible market failure within the industry: the private good nature of learning could be creating barriers to entry for firms looking to enter the market. Furthermore, the rate of industry wide cost reductions is possibly being impeded because there is only a minimal amount of industry wide learning. Both of these problems within the market could be possible areas to be addressed by policy makers, and perhaps a revision of the current policies supporting PV is required. To be certain of the effects of the spillover on the PV industry however, further research is needed.

There are a number of areas of research which will naturally follow on from this thesis. First of all, the model could be extended to include firm entry and exit. Estimating the size of the spillover for all firms that produce during the sample period, would give some insight into whether learning is creating barriers to entry for firms looking to enter the market. A further extension would be to model the benefits of R&D on a firm’s productivity in order to estimate the spillover of R&D knowledge on the industry. Possible implications of the outcome would be whether R&D is efficiently supplied by the market or whether R&D, as opposed to learning, is indicative of a public good. Another area of possible further research would be to investigate the effect that a small spillover is having on the rate of industry wide cost reduction for the PV
industry. Each of these extensions would hopefully provide more insight into possible market failures in the PV industry, and therefore how the PV industry should be supported by policy makers.
Bibliography


