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Learning and Forgetting in the PV Cell Industry

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Abstract

A dynamic structural-empirical model is developed in order to estimate the size of the learning spillover within the world photovoltaic (PV) cell industry. We extend the approach of Benkard (American Economic Review 2000) on industry level, so that the spillover appears across firms within the 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. Industrial forgetting is not found to be a strong effect. A simple policy analysis shows that production and productivity both decrease as the size of the spillover is increased.

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1 Introduction

This paper estimates the spillover of learning between firms in the world photovoltaic (PV) cell production industry in the years 2003 to 2008, based on a dynamic structural-empirical model. The model includes firms' capital investment decisions and the effect of learning on a firm's productivity. Production-based learning of a firm can be, broadly, defined as reductions in production costs as a function of cumulative output. Learning impacts on the composition of an industry in a number of ways: it can deepen inequality within a heterogeneous industry, as firms with high output should, *ceteris paribus*, be able to produce at lower costs than their competitors with less production experience; learning, as a private good, has the potential to create barriers to entry for firms looking to enter into the market. A ramification concerns 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 output level a firm could spur along the learning effects and reap the benefits of its relative advantage sooner.

The effect of learning within an industry is complicated by the fact that *spillovers* of learning occur. This is due to the public-good nature of knowledge. Because firms can benefit from other firms' production-based learning, spillovers provide a disincentive for firms to create knowledge. Firms that imitate might prefer to free ride and, hence, remain imitators rather than become innovators. 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 others' mistakes. Spillovers could thus also enhance 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. As a consequence, there is no *a priori* to suggest that knowledge will be supplied by the market up to a socially efficient level.

While these theoretical arguments are well developed, and have often, though losely, been referred to to favour technology policies, such as support policies for the deployment of renewable energy technologies, empirical research has by far been lacking behind. The problem related to an empirical assessment is that the spillover of learning is not directly observed from the data. To date, estimation of the learning curve in the PV industry relies mainly on the reduced-form log-linear approach (Nemet 2006). This method uses ratios of cumulative output

over time and a learning coefficient estimator to estimate cost ratios.[1] The estimate for the learning coefficient is then used to estimate the learning effect. Among the problems with this approach is that it does not control for factors that may lead to cost reductions other than cumulative output, including plant size, efficiency, and the cost of silicon. Furthermore, as cost data is difficult to obtain, price has been used as a, rather crude, proxy for cost (e.g., Nemet 2006). In general then, the reduced-form approach is not able to accurately isolate and identify the learning effect. Even more doubtful would be an attempt to assess spillovers of learning within an industry using this methodology.

Only recently, structural-empirical models have been used to measure learning curves and spillovers. The strategy there to estimate the spillover is to apply economic theory to the way learning and spillovers impact on a firm's productivity, where productivity can be estimated empirically from the data. For example, Benkard (2000) develops a structural-empirical model for estimating the spillover of learning between production lines for an airplane. He finds that these within-firm learning spillovers and organizational forgetting are both discernible effects in the cost reduction process. Xu (2008) measures R&D spillovers among manufacturing plants for the Korean electric motor industry. Applying the concept of Oblivious Equilibrium (Weintraub et al. 2008), he estimates a dynamic industry equilibrium model of R&D, R&D spillovers, and the productivity of heterogeneous firms that face dynamic decisions of investment, entry, and exit.[2] Due to a data limitation, we focus in this paper on production-based learning spillovers and industrial forgetting for price-taking firms that face only a capital investment decision.

We model learning similar to Benkard (2000), including both learning spillovers and organisational forgetting. The stock of learning is treated as a function of a firm's cumulative output, the spillover of learning from the industry's cumulative output, and industrial forgetting. By focusing on a firm's output instead of its internal production lines, we extend Benkard's approach to the entire industry, so that the spillover appears across firms within the industry. We include industrial forgetting in order to obtain a better indication of the learning process and to produce a more accurate estimate of the spillover. Forgetting reflects the notion that firms may also forget what they have previously learned, in this sense forgetting is a depreciation on the stock of learning. A firm's output in any period is a function of labour, capital, the firm's

[1] Specifically, the form referred to here is: $C_t = C_0(\frac{q_t}{q_0})^{-b}$, where C is unit costs, q is cumulative output, t is time, and b is the learning coefficient.

[2] In subsection 2.2, we cite some further recent contributions in this vein.

total factor productivity, and unobservable productivity shocks. Learning directly impacts on a firm's total factor productivity. We estimate a firm's production function using the two-stage estimation technique developed in Olley and Pakes (1996). This allows us to estimate the total factor productivity and therefore the size of the spillover. The spillover derives as a moment in the Generalised Method of Moments (GMM). To estimate the model, we use data from Photon International Magazine for the PV industry, which includes incumbent firms (that did not enter or exit) over the period 2003 to 2008. We assume firms are price takers, differing only in the size of their output in each period and their capital investment decision.

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%. That is, these firms only have 8.83% of the total industry stock of learning impacting on their productivity in each period. Firms, hence, predominantly utilise their own stock of learning, rather than the industry's. This is indication that learning is a private good within the market. Industrial forgetting is not found to be a strong effect, the industry retains 90.3% of its learning stock each year. That firms create production-based learning privately could imply that the rate of industry-wide cost reductions is inhibited since firms are not learning together; moreover, it may create barriers to entry (Ghemawat and Spence 1985). From our model we cannot predict the effect of the spillover on the industry, however, since we do not include entry and exit. This is left as further research.

The PV industry is a heavily subsidised industry.[3] The two most common subsidy-generating mechanisms in place are feed-in tariffs for renewable electricity and quota-obligation schemes based on tradable green certificates. These policies do not directly address possible market failures within technology innovation and diffusion, however. In order to achieve efficient market outcomes, rather a portfolio of policies will be necessary, with environmental polices (such as carbon taxes or cap-based systems) determining optimal renewable technology deployment by internalising the emissions externality, and policies that directly target technology-related market failures (Jaffe et al. 2005).[4] Currently, there is no evidence that, from a social-efficiency point of view, PV is being supported by the correct portfolio of policies. To inspect the market failures which are present, and in particular whether the nature of the spillover is leading to

[3]For example, Frondel et al. (2008) calculate that the subsidies from the German feed-in tariff scheme for renewable electricity cumulated for photovoltaics (PV) alone to about €26.5bn between introduction of the scheme in 2000 and 2007, to which by 2010 another €27bn may add.

[4]In particular, by construction of a cap-and-trade scheme, such as the EU-ETS, the application of more renewable technologies cannot achieve additional emissions reductions below the levels specified under the ETS.

market failure in some form, as well as the sizing of the spillovers are pivotal to decide whether and what kind of government intervention could be warranted.

The paper is organised as follows. Section 2 reviews some of the relevant contributions surrounding learning spillovers and dynamic structural-empirical models. In section 3, the empirical model is explained. Section 4 sets out the data. Section 5 contains the estimation and states the results. Section 6 evaluates the results and provides a short policy analysis. Section 7 concludes. In appendix, we provide an overview of the PV industry.

2 Related Literature

There are two relevant streams of economic literature pertaining to this paper, the theoretical literature surrounding learning and knowledge spillovers, and contributions dealing with dynamic structural-empirical models. The latter only recently also started to investigate investment behaviour in industries and has tried to size spillover effects.

2.1 Knowledge Spillovers

The economic literature surrounding knowledge production is mainly concerned with a firm's decision to invest in knowledge in the form of either production-based learning or research and development (R&D), but sometimes no distinction is made between the two. While production-based learning is a positive by-product of production that results in gaining knowledge, R&D constitutes a direct investment into knowledge.[5] Arrow (1962) formalised the idea of production-based learning bringing about improvements in productivity and efficiency in a model that includes learning as a determinant of economic growth, rather than treating technological change as exogenous.[6] Spence (1981) developed 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. Thus, if spillovers exist, knowledge production may have effects on the composition of markets. At the same time, imposing competition

[5]By production-based learning we are 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.

[6]Wright (1936) provided an early documentation of cost reductions resulting from production, noting 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. Lundberg (1961) observed over a fifteen-year period no new investment in the Horndal iron works in Sweden, but productivity still rose by two percent per annum.

on an industry with moderate learning curves can result in slowing the enhancement of technical efficiency.

Spence (1984) begins to differentiate between R&D learning and production-based learning. He notes three possible problems associated with R&D investment. First, the success of R&D is determined by its private benefits, rather than its public benefits, so that there is no *a priori* to suggest the market will supply "optimal" amounts of R&D. Second, R&D investments in non-competitive markets are likely to have consequences for prices, margins and allocative efficiency. Third, R&D can be appropriated by competitors, providing, on the one hand, a disincentive to invest into R&D. On the other hand, with R&D appropriation the industry will *ceteris paribus* develop technical efficiency at a faster rate. Ghemawat and Spence (1985) apply the notion of appropriability, or spillovers, to learning curves and market performance. They find that for production-based learning, the increasing effect on the rate of cost reduction in an industry dominates the disincentive effect to create knowledge, while for R&D the disincentive effect dominates the efficiency effect. Spillovers have the same effect independent of the way knowledge is created 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 the firm is not R&D-intensive itself, it is likely to be less profitable compared to their R&D-intensive neighbours. Eeckhout and Jovanovic (2002) challenge the idea that spillovers lead to industry convergence to some efficiency level. They argue that the free-riding effect from spillovers counteracts convergence due to imitators having a disincentive to invest into knowledge production because this decreases the knowledge stock available to imitators. As a result, firms remain in their same technologically relative position by settling for technologies that are within the technological frontier. They conclude that free-riding, resulting from spillovers, promotes inequality between firms.

2.2 Dynamic Structural Equilibrium Models of Imperfect Competition

The second stream are dynamic models that include firm heterogeneity, and estimation techniques to solve these models. Such models are motivated out of economic policy debates, 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. Jovanovic (1982) and Lippman and Rumelt (1982) introduce the first equilibrium models that include firm specific stochastic elements to explain observed firm dynamics. Pakes and McGuire (1994) extend these dynamic models with firm entry and exit, to include firm investment decisions and introduce an algorithm to compute the Markov-perfect Nash equilibrium responses, defined in Maskin and Tirole (1988).[7] Berry and Pakes (1993) apply the Pakes-McGuire algorithm to an analysis of mergers noting the high computational burden.

Ericson and Pakes (1995) are the first to provide an entire framework that can be applied to empirical studies. 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. One of the first dynamic structural-empirical models empirically applied to firm entry, exit, and investment behaviour is Olley and Pakes (1996). They estimate a dynamic model with heterogeneous firms producing a homogeneous good to determine the productivity dynamics in the US telecommunications industry. They show that such models can be used for policy analysis and to explain observed differences in productivity. They provide a two-step estimation technique to estimate unobserved firm level productivity.

Weintraub et al. (2008) recently introduced the idea of Oblivious Equilibrium to ease the computational burden involved in solving Ericson-Pakes-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. As the market size grows, Oblivious Equilibrium outcomes closely approximate Markov Perfect Equilibria. Bajari

[7] Markov-perfect Nash equilibria are the equilibria that result when a strategy depends only on the opponents' *current* set of actions, and not on the entire history of actions of all players.

et al. (2007) develop another technique to ease the computational burden, in form of 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.

The empirical literature on knowledge spillovers has mostly been restricted to static analyses. With the benefit of new computation techniques and increased computer power, research into spillovers has only recently been able to develop into dynamic studies. 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. In a dynamic oligopoly model, he finds 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. 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. Imitation contributes greatly to firm growth rates. This leads to firm size distributions to become homogeneous in the long run.

3 Model

The model treats PV cells as a homogeneous good. The price of cells is the same for all manufacturers, 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. The goal is to measure the spillover from the industry-wide learning pool that enters into a firm's productivity. 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. But a firm knows its level of productivity and sets its level of inputs accordingly. This poses the simultaneity problem, first

raised in Marschak and Andrews (1944).[8] In order to account for the simultaneity problem, we adapt the model of Olley and Pakes (1996) to include learning but not firm entry and exit decisions. Olley and Pakes show that the simultaneity problem can be overcome by employing a two-stage regression technique, outlined in subsection 3.2. We 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 δ 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, moreover, 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 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 our model, we 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. Production-based learning results from past output, and so a firm can indirectly impact on its own level of productivity based on 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.

3.1 Learning

Similarly to Benkard (2000), learning for a firm takes the following form

[8]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.

$$d_{i,t} = \theta(\Omega_{t-1} - \sum_t q_{i,t-1}) + \sum_t q_{i,t-1} \tag{1}$$

where $d_{i,t}$ is the effect of learning on productivity for firm i in period t, Ω_t is the industry stock of learning, θ 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

$$\Omega_t = \rho\Omega_{t-1} + Q_t \tag{2}$$

where Q_t is the total industry production in period t, and ρ is the depreciation of knowledge, or organisational forgetting first documented in Benkard (2000).

3.2 Estimating Equation

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

$$Q_{i,t} = A_{i,t}L_{i,t}^{\alpha_{l,i}}K_{i,t}^{\alpha_k} = e^{(\alpha_0+\omega_{i,t}+u_{i,t})}L_{i,t}^{\alpha_{l,i}}K_{i,t}^{\alpha_k} \tag{3}$$

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 σ^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.[9]

To see how learning affects the productivity of a firm, we 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 (3) in log terms and denoting lower-case variables as representing the

[9]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.

log of a variable:

$$q_{i,t} = \alpha_0 + \alpha_{l,i} l_{i,t} + \alpha_k k_{i,t} + \omega_{i,t} + u_{i,t}. \tag{4}$$

From our 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 between the unobserved error term $(\alpha_{l,i} l_{i,t} + \omega_{i,t} + u_{i,t})$ and the level of capital $k_{i,t}$. Equation (4) cannot therefore be estimated using simple OLS because the estimates would be biased. To correct for this bias, we 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) gives the first estimating equation:

$$q_{i,t} = \beta_0 + \phi(d_{i,t}, X_t, k_{i,t}) + \tilde{u}_{i,t} \tag{5}$$

where $\tilde{u}_{i,t} = u_{i,t} + \beta_l l_{i,t}$; $\phi(d_{i,t}, X_t, k_{i,t}) = \gamma_k k_{i,t} + h(d_{i,t}, X_t, K_{i,t})$; and $h(d_{i,t}, X_t, K_{i,t}) = \gamma_d d_{i,t} + g(k_{i,t}) + \gamma_T T$.

The second stage regression is then

$$q_{i,t} - \beta_0 = \beta_k k_{i,t} + \varphi(\phi(d_{i,t-1}, X_{t-1}, k_{i,t-1}) - \gamma_k k_{i,t-1}) + \epsilon_{i,t} \tag{6}$$

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 (6) will produce a consistent estimate of β_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.

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

$$V(K_{i,t}) = \max_{K_{i,t+1}} \pi(K_{i,t}) - c_k(K_{i,t+1} - (1-\delta)K_{i,t}) + \beta V(K_{i,t+1}) \tag{7}$$

where $K_{i,t}$ is the capital stock of firm i at time t, c_k is the marginal cost of capital, δ is the depreciation of capital, and β is the discount rate.

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

$$\frac{\partial V(K_{i,t})}{\partial K_{i,t+1}} = -c_k + \beta \frac{\partial V(K_{i,t+1})}{\partial K_{i,t+1}} = 0. \tag{8}$$

Similarly, taking the derivative of equation (7) with respect to $K_{i,t}$ gives

$$\frac{\partial V(K_{i,t})}{\partial K_{i,t}} = \frac{\partial \pi(K_{i,t})}{\partial K_{i,t}} + c_k(1-\delta). \tag{9}$$

In period $t+1$, equation (9) becomes

$$\frac{\partial V(K_{i,t+1})}{\partial K_{i,t+1}} = \frac{\partial \pi(K_{i,t+1})}{\partial K_{i,t+1}} + c_k(1-\delta). \tag{10}$$

Using the profit function

$$\pi(K_{i,t}) = P_t Q_{i,t} - r_{i,t} K_{i,t} = P_t A_{i,t} K_{i,t}^{\alpha_k} - r_{i,t} K_{i,t}$$

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

$$\frac{\partial \pi(K_{i,t+1})}{\partial K_{i,t+1}} = \alpha_k P_{t+1} A_{i,t+1} K_{i,t+1}^{\alpha_k - 1} - r_{i,t+1}. \tag{11}$$

Substituting this expression into equation (10), and combining equations (8) and (10) gives

$$\begin{aligned}
0 &= -c_k + \beta \frac{\partial V(K_{i,t+1})}{\partial K_{i,t+1}} \\
&= -c_k + \beta \left(\frac{\partial \pi(K_{i,t+1})}{\partial K_{i,t+1}} + c_k(1-\delta) \right) \\
&= -c_k + \beta \left(\alpha_k P_{t+1} A_{i,t+1} K_{i,t+1}^{\alpha_k - 1} - r_{i,t+1} + c_k(1-\delta) \right).
\end{aligned}$$

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

gives the optimal capital stock for firm i in period t

$$K^*_{i,t} = \left(\frac{c_k \left(\frac{1-\beta(1-\delta)}{\beta} \right) + r_{i,t}}{\alpha_k P_t A_{i,t}} \right)^{\frac{1}{\alpha_k - 1}} \tag{12}$$

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:

$$\mu^1_t = E(q_t) - \bar{q}_t = 0$$
$$\mu^2_t = V(q_t) - s^2_{q_t} = 0$$
$$\mu^3_t = E(k_t) - \bar{k}_t = 0$$
$$\mu^4_t = V(k_t) - s^2_{k_t} = 0$$

where $\bar{q}_t$ and $\bar{k}_t$ are the average observed production and capital in period t; $s^2_{q_t}$ and $s^2_{k_t}$ 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:

$$m^1_t = \frac{1}{N} \sum_{i=1}^{N} \hat{q_{i,t}} - \bar{q}_t$$
$$m^2_t = \frac{1}{N} \sum_{i=1}^{N} \hat{q_{i,t}}^2 - (\frac{1}{N} \sum_{i=1}^{N} q_{i,t})^2 - s^2_{q_t}$$
$$m^3_t = \frac{1}{N} \sum_{i=1}^{N} \hat{k_{i,t}} - \bar{k}_t$$
$$m^4_t = \frac{1}{N} \sum_{i=1}^{N} \hat{k_{i,t}}^2 - (\frac{1}{N} \sum_{i=1}^{N} k_{i,t})^2 - s^2_{k_t}$$

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

$$\min_{\rho,\theta,r} \bar{m}^T \Pi^{-1} \bar{m} \tag{13}$$

where Π 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.

3.5 Computation Method

Using Matlab, we apply the following computation technique to obtain our estimates of the parameter values.

For particular values of ρ, θ, and r:

1. Compute $\{\Omega_t, d_{i,t}\}_{t=1,i=1}^{T,N}$ using equations (1) and (2).
2. Run first regression (equation (5)) to obtain estimates for $\hat{\beta}_0$ and $\phi(\cdot)$.
3. Run second regression (equation (6)) to obtain estimates for $\hat{\beta}_k$.
4. Predict $\hat{q}_{i,t}$ using equation (4) in order to compute m_t^1 and m_t^2.
5. Predict $\hat{k}_{i,t}$ using equation (12) in order to compute m_t^3 and m_t^4.
6. Solve minimisation problem over all values of ρ, θ, and r (equation (13)).

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

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

where τ 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

$$\hat{G} = \begin{bmatrix} \frac{\partial \bar{M}}{\partial \theta} & \frac{\partial \bar{M}}{\partial \rho} & \frac{\partial \bar{M}}{\partial r} \\ \vdots & & \vdots \end{bmatrix}$$

where $\bar{M}(\tau) = \frac{1}{T} \sum_{t=1}^{T} M_t(\tau)$, and θ, ρ, and r are the estimated parameters.

The covariance matrix is then given by

$$Var = (\hat{G}^T \Pi \hat{G})^{-1} \hat{G}^T \Pi (\frac{1}{T} \Phi) \Pi \hat{G} (\hat{G}^T \Pi \hat{G})^{-1} \tag{14}$$

where Π is the optimisation matrix defined in section 3.4.

4 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 1: Total Observations and Missing Variables for Market Survey Data.

Variable	**Obs.**	**Missing Vbls**	**Mean (MW)**	**Std. Dev.**	**Min**	**Max**
Production	647	136	28.089	68.899	0	584.6
Capacity	551	232	51.083	116.248	0	1000

To complete the dataset we impute the missing values using the *Multiple Imputation Using ICE* method (Schafer (1999) and Rubin (1996)). We discard the observations for firms that enter or exit within the period 2003 to 2008 because we are not modelling entry or exit.[10] The characteristics of the final imputed datasets can be seen in table (2).

Table 2: Characteristics of the Imputed Datasets.

Variable	**Obs.**	**Mean (MW)**	**Std. Dev.**	**Min**	**Max**
Dataset One					
Production	366	46.112	85.933	0.002	584.6
Capacity	366	74.508	135.485	0.008	1000
Dataset Two					
Production	366	46.465	86.293	0.0001	584.6
Capacity	366	72.774	132.149	0.001	1000
Dataset Three					
Production	366	47.052	86.343	0.001	584.6
Capacity	366	73.257	132.735	0.001	1000

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.

The results are constrained by a lack of labour data. Not enough labour data could be collected in time to do a reasonable imputation. Therefore, the model has been run without labour data. Excluding labour data could be defensible, 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 our 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 subsection 5.4.

[10] 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.

5 Estimation

5.1 Preliminary Estimates

In order to estimate the parameters, we set the depreciation of capital δ equal to zero and the discount rate β equal to one. Referring to equation (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 subsection 3.5 are shown in Table 3, where θ is the spillover, ρ 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 (13)). The standard errors are given in the parentheses. All estimates of

Table 3: Estimated Parameters for Model One.

Parameter	Imputed Data Set Number		
	1	2	3
θ	0.122	0.041	0.102
	(0.0575)	(0.00369)	(0.0161)
ρ	0.878	1.000	0.918
	(0.120)	(0.0794)	(0.0539)
r	1.076	1.100	1.100
	(0.696)	(0.0207)	(0.234)
Σ ($\times 10^4$)	1.173	1.224	1.542

the parameters are significant at the 10% level. Following Rubin (1987), we take the overall estimate for the parameters to be the average of the estimates. The variance of the parameters is

$$T = \bar{U} + \left(1 + \frac{1}{3}\right) B \tag{15}$$

where B is the variance of the estimates $\left(\frac{1}{2}\sum_1^3 (\hat{Q}_j - \bar{Q})^2\right)$, $\bar{U}$ is the average of the estimated variance $\left(\frac{1}{4}\sum_1^4 (U_j)^2\right)$, $\hat{Q}_j$ 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. All estimates of the parameters are significant at the 10% level.

Most of the variation in the moments comes from the capital estimates. Figure 1 shows each of the moments generated for data set one; the capital moments ($m3$ and $m4$) have values

Table 4: Estimated Parameters and Standard Errors.

Parameter	Value	Std. Error
θ	0.0883	0.0597
ρ	0.903	0.115
r	1.019	0.1868

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 (12). By setting $\delta = 0$ and $\beta = 1$, equation (12) becomes

$$K^*_{i,t} = \left(\frac{r_{i,t}}{\alpha_k P_t A_{i,t}} \right)^{\frac{1}{\alpha_k - 1}} \tag{16}$$

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 α_k is the coefficient of capital estimate in equation (4). In all of the regressions, the estimates of α_k are found to be slightly greater than one. Referring to equation (16), $\frac{1}{\alpha_k - 1}$ approaches infinity as α_k approaches one. The estimate for the optimal capital investment then grows large very quickly as α_k approaches one. Because of this problem, we require a different specification for the optimal capital investment.

5.2 Revised Optimal Capital Investment Decision

Following Xu (2008), we include a capital adjustment cost in the optimal capital investment decision equation:

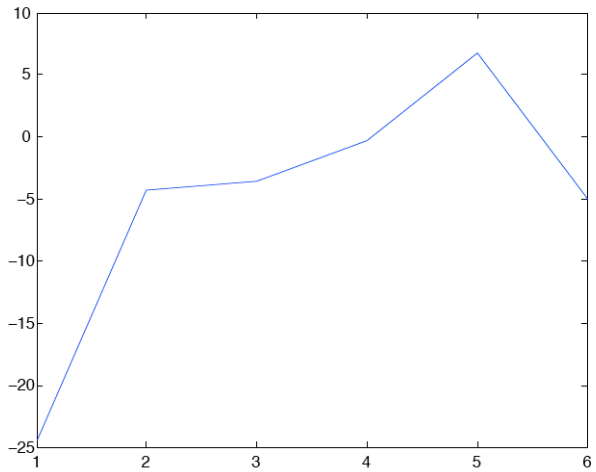
$$c(K_{i,t}, K_{i,t+1}) = c_a \left(\frac{I_{i,t}}{K_{i,t}} \right)^2 K_{i,t} \tag{17}$$

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.

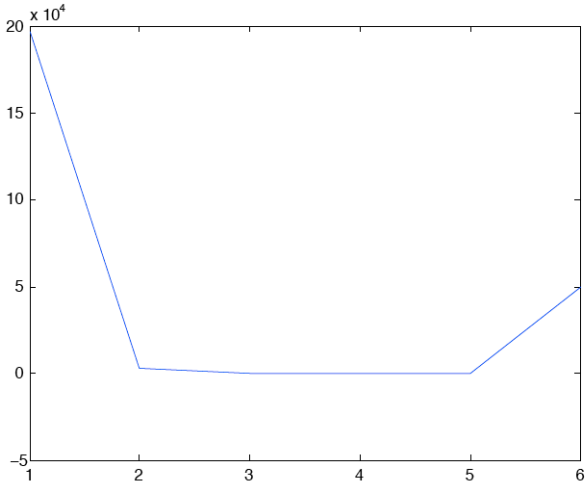
Substituting equation (17) into the original value function for a firm (equation (7)) produces the *revised* value function for a firm:

$$V(K_{i,t}) = \max_{K_{i,t+1}} \pi(K_{i,t}) - c_k I_{i,t} - c_a \left(\frac{I_{i,t}}{K_t} \right)^2 K_t + \beta V(K_{i,t+1}) \tag{18}$$

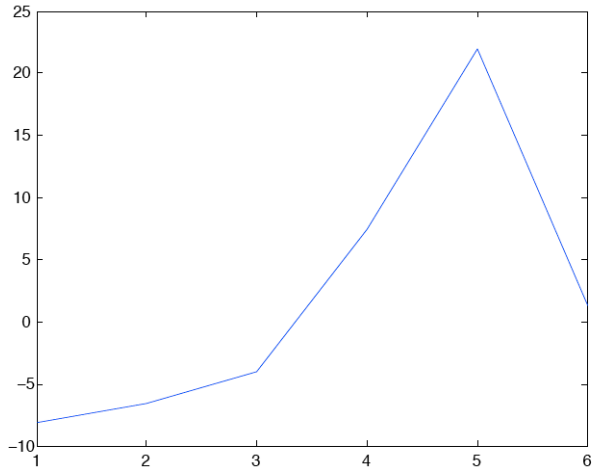
where $K_{i,t}$ is the capital stock of firm i at time t, c_k is the marginal cost of capital, δ is



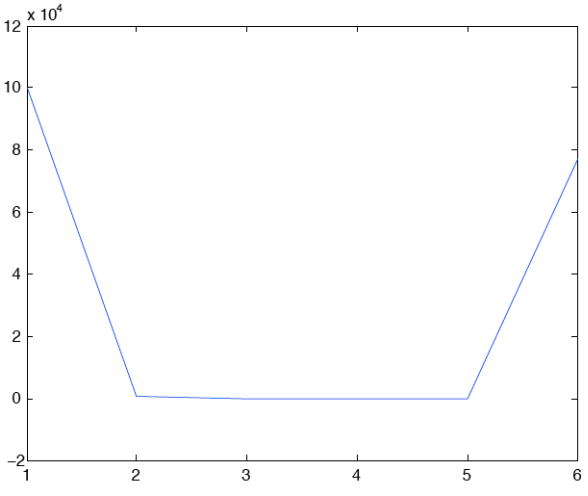
First Moment : Average Output



Third Moment : Average Capital



Second Moment : Output Std. Dev.



Fourth Moment : Capital Std. Dev.

Figure 1: Empirical Moments versus Year for the First Dataset.

the depreciation of capital, β is the discount factor, and c_a is the adjustment cost of capital. Substituting in the profit function gives:

$$V(K_{i,t}) = \max_{K_{i,t+1}} P_t A_{i,t} K_t^{\alpha_k} - r_t K_{i,t} - c_k(I_{i,t}) \\ -c_a \left(\frac{I_{i,t}}{K_{i,t}}\right)^2 K_{i,t} + \beta V(K_{i,t+1}) \tag{19}$$

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

$$\frac{\partial V(K_{i,t})}{\partial K_{i,t+1}} = -c_k - \frac{2c_a i_t}{K_{i,t}} + \beta \frac{\partial V(K_{i,t+1})}{\partial K_{i,t+1}} \tag{20}$$

Using the envelope theorem, the derivative of equation (19) with respect to $K_{i,t}$ is

$$\frac{\partial V(K_{i,t})}{\partial K_{i,t}} = \alpha_k P_t A_{i,t} K_{i,t}^{\alpha_k - 1} - r_t - c_k(1-\delta) \\ -c_a \left((1-\delta)^2 - \left(\frac{K_{i,t+1}}{K_{i,t}}\right)^2\right). \tag{21}$$

In period $t+1$ equation (21) becomes

$$\frac{\partial V(K_{i,t+1})}{\partial K_{i,t+1}} = \alpha_k P_{t+1} A_{i,t+1} K_{i,t+1}^{\alpha_k - 1} - r_{t+1} - c_k(1-\delta) \\ -c_a \left((1-\delta)^2 - \left(\frac{K_{i,t+2}}{K_{i,t+1}}\right)^2\right). \tag{22}$$

Substituting equation (22) into equation (20) and setting equal to zero gives

$$\alpha_k P_{t+1} A_{i,t+1} K_{i,t+1}^{\alpha_k - 1} - r_{t+1} - c_a \left[\left(1 - \left(\frac{K_{i,t+2}}{K_{i,t+1}}\right)^2\right) + 2\left(\frac{K_{i,t+1} - K_t}{K_{i,t}}\right)\right] = 0 \tag{23}$$

The policy function $K_{i,t+1} = f(K_{i,t})$ no longer has a closed form solution. To solve equation (23) for K_{t+1}, we use the following function approximation method.

Let $G(K_{i,t}, K_{i,t+1}, K_{i,t+2})$ represent equation (23) and let the optimal level of capital for the next period be of the form

$$f(K_{i,t}) = a + bK_{i,t} + cK_{i,t}^2 \tag{24}$$

where a, b and c are parameters to be estimated. To solve this approximation we 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 $t-1$. we 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

$$K^*_{i,t+1} = a + b\hat{K}_{i,t} + c\hat{K}^2_{i,t}. \tag{25}$$

5.3 Results

The best results were obtained for low values of c_a. The problem is, by including the revised optimal capital investment decision we also increase the computation burden significantly.[11] By increasing the accuracy of the capital estimate, we 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 5. It can be seen that the estimates are not significant at the 10% level, which they were in the previous estimate. we therefore accept the first estimates (Table 4) to be the final estimates. Due to time and computational constraints, we 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.

[11] 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 we are estimating an extra parameter) took over 29 hours.

Table 5: Estimated Parameters and Standard Errors Using the Revised Capital Estimate.

Parameter	Value	Std. Error
θ	0.15	0.5
ρ	0.9	2.8
r	1	2.8
c_a	0.1	0.3

5.4 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, we omit labour from our 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 our 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 our 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 (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, ρ, r) also

correct for the omitted variable bias. It is difficult to ascertain therefore whether the spillover is actually under-estimated, 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.

6 Discussion

6.1 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.

Within the PV industry there is rapid growth in production and capacity, and the industry

is moving towards being a less concentrated industry.[12] 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 our model, however, and we therefore leave this as an area of future research.

6.2 Policy Analysis

We 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%, we 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,

[12] See the overview of the PV industry in the appendix.

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.

7 Conclusion

A dynamic structural-empirical model is developed in order to estimate the size of the spillover of learning within the PV cell 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 different ways. There is currently no indication that these policies are the most effective or deserving means of supporting PV. The results of this paper provide a first step towards economic evidence of a possible market failure within the PV 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 paper. 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.

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Appendix

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.

A.1 The PV Production Process

we 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).[13][14] 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.

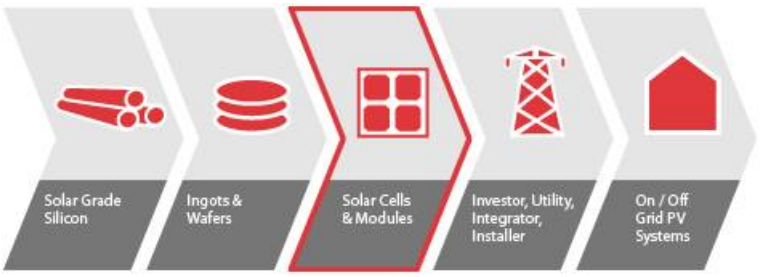

Figure 2: The PV Production Process.

A silicon wafer producer is typically not also a cell producer. PV cell producers perform a

[13]Source: www.suntech-power.com.

[14]Silicon PV cells represent the vast majority of PV production. Although we only consider *silicon cell* production in this section, the process is *similar* for most technology types.

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.

A.2 Growth of the PV Industry

As can be seen in Figure 3, PV production has been growing exponentially for almost the last three decades.

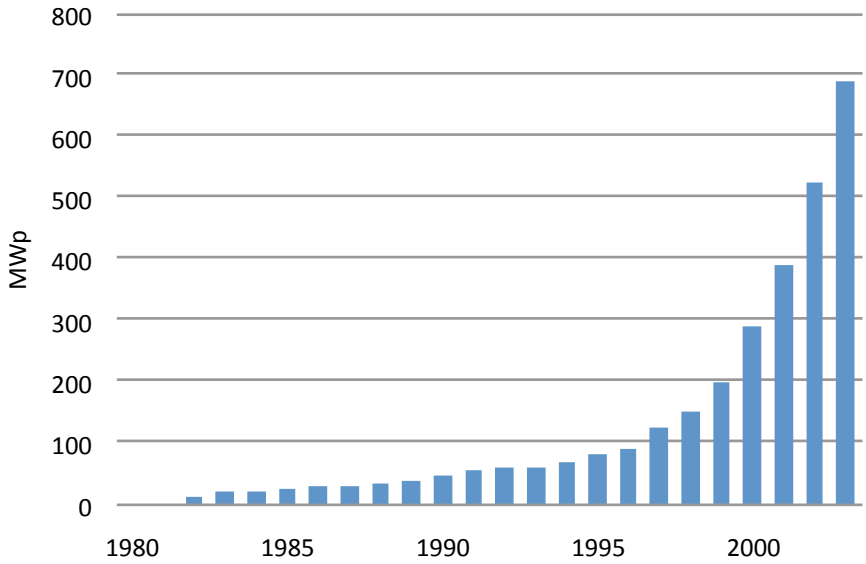

Figure 3: PV Module Production since 1980 (Santa-Fe-Institute (2009)).

The sample period being considered is 2003 to 2008. The total capacity and production for each year can be seen in Figure 4. 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)).

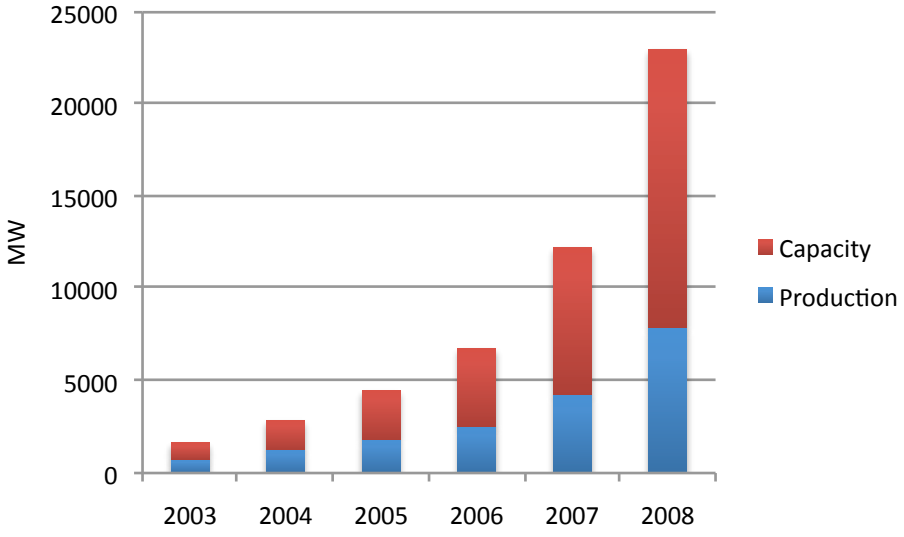

Figure 4: Cell Production and Capacity in the Years 2000 to 2008 (Photon-International (2000-2008)).

A.3 The Composition of the Industry

Referring to Table 6, 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 that 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.

A.4 The Learning Curve

As production experience accumulates, the learning effect leads to reductions in production costs. Figure 5 shows that the cost of PV modules decreased as production accumulated in

Table 6: The Top Five Cell Producers in the Years 2003 to 2008 (Photon-International (2000-2008)).

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

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.

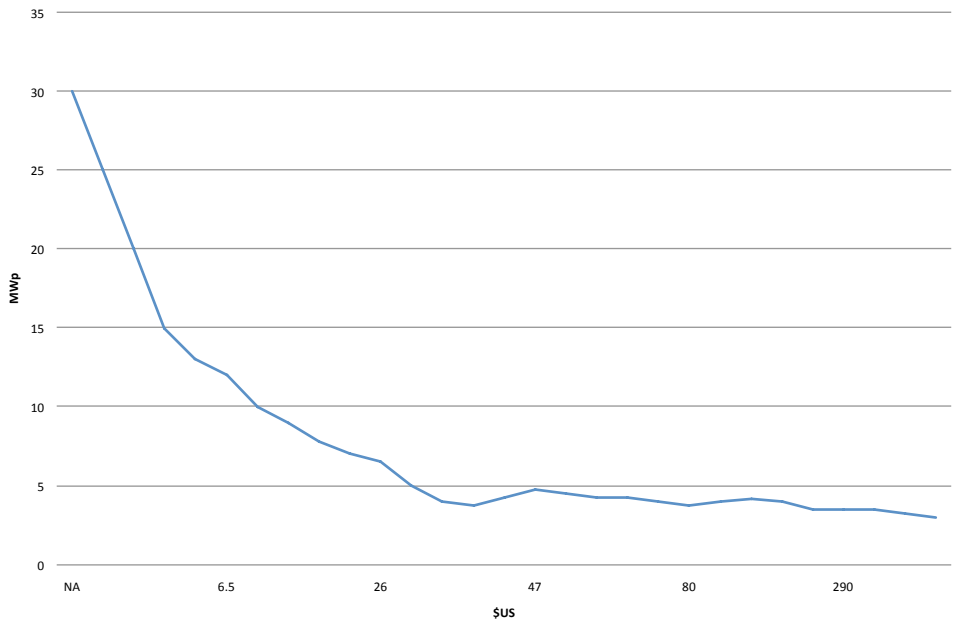

Figure 5: PV Module Production Versus Price (Santa-Fe-Institute (2009)).