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Drivers of cost reduction in solar photovoltaics☆

Unni Pillai *

SUNY Polytechnic Institute, Albany, NY, USA

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ABSTRACT

Using a new dataset of costs, output, sales, technical characteristics, and capital expenditures of firms in the solar industry during 2005–2012, this paper investigates the factors that have contributed to the decline in the cost of producing solar panels. While previous studies have attributed learning-by-doing and economies of scale as important drivers of cost reduction, these do not have any significant effect on cost once four other factors are taken into account, namely, (i) reduction in the cost of a principal raw material, (ii) increasing presence of solar panel manufacturers from China, (iii) technological innovations, and (iv) increase in investment at the industry level. These findings suggest that the upstream industries that supply the solar panel industry with raw materials and capital equipment have been important contributors to the reduction in the production cost of solar panels.
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1. Introduction

The solar photovoltaic industry has expanded rapidly in the last few years. Annual production of solar panels has increased by a factor of sixteen during the period 2005–2012, growing at an average annual rate of 56% during the period.[1] Generation of electricity through solar panels was more costly than generation through conventional sources like coal or natural gas for the period 2005–2012 (see Woodhouse et al. (2011), Tidball et al. (2010) and Prior (2011)). The rapid expansion of the industry in the face of this cost disadvantage has occurred because of generous subsidies in many countries.[2] These government subsidies have often been advocated on the grounds that support to the solar industry will lead to the expansion of solar electricity generation and reduction in production cost and price of solar panels, an assumption which has mostly been justified on the grounds that there are learning externalities and static economies of scale in the industry (see Benthem et al. (2008), Algoso et al. (2005), and Shrimali and Baker (2011)).

There have been numerous studies, across many industries, documenting decreases in unit production cost occurring alongside increases in variables used to proxy learning.[3] Different variables have been used to proxy for learning, with cumulated output and cumulated investment being the two popular ones.[4] Critiques of the learning studies have pointed out that learning curves do not explain the process by which cost reduction occurs, which has led many researchers to look for explanatory factors which might be correlated with cumulated firm or industry output.[5]

In the solar panel industry, most studies have used cumulated industry output as a proxy for learning, assuming a relationship of the form $c(Y) = aY^{-b}$, where c is the unit production cost and Y is the cumulated output. The reduction in unit production cost with increases in cumulated output is usually stated in terms of the learning rate, which is the

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* College of Nanoscale Engineering and Technology Innovation, SUNY Polytechnic Institute, 257 Fuller Road, Albany, NY – 12203, USA.
E-mail address: usadasivanpillai@sunycnse.com.

[1] The annual production data were taken from the dataset compiled by Earth Policy Institute, available at http://www.earth-policy.org/data_center/C23.

[2] Frondel et al. (2010) estimate the cost of subsidies to solar generation systems during 2000–2010 in Germany to be over 53 billion euros. The California state government has allocated 2.16 billion dollars for subsidies to solar during 2007–2016 (see CPUC (2009)). In 2012, Italy spent over $8.8 billion on subsidies to solar electricity (see http://www.pv-magazine.com/news/details/beitrag/a-look-at-italys-latest-conto-energia-100008223/#axzz2IioZQ4nZ). A number of studies examine the impact of subsidies to renewable energy products on adoption of these products—see Hughes and Podolefsky (2013) and Chandra et al. (2010).

[3] These include Wright (1936) in the aircraft industry, Rapping (1965) in the ship building industry, Epple et al. (1996) in the truck manufacturing industry, and Lieberman (1984) in the chemical industry.

[4] For example, Sheshinski (1967) found that cumulated output and cumulated investment gave better results than calendar time in explaining improvements to productivity (which is inversely related to unit production cost) in many manufacturing industries. Dimensions of learning can vary across industries, see Argote (2013) for a good description of learning in different industries.

[5] These attempts have had mixed results, with Adler and Clark (1991), Mishina (1999), Jarmin (1994), and Lieberman (1984) finding that other variables only augment the effect of learning or have no effect at all. Revisiting Rapping's (1965) study on learning in the ship building industry, Thompson (2001) finds that properly accounting for capital deepening halves the size of the learning effect estimated in Rapping (1965). Sinclair et al. (2000) find that cost reductions in a big chemical company which appear to be the result of learning were in fact the result of R&D and related activities undertaken by the company.

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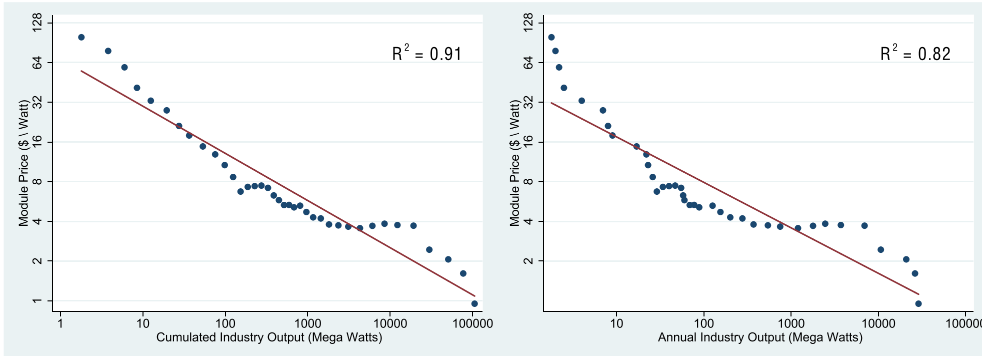

(a) (b)

Fig. 1. *Notes:* The graph on the left, plotting module price against cumulated industry output, is often referred to as the learning curve. The slope of the regression line corresponds to a price decline of 21.5% for every doubling of cumulated output. The graph on the right shows the module price against annual industry output. The slope of the regression line corresponds to a price decline of 21% for every doubling of current output.

percentage reduction in cost that occurs when cumulated output doubles.[6] Since cost data are usually unavailable, price is usually used to proxy cost. The left graph in Fig. 1 plots the price against cumulated industry output for 1970–2012, which indicate a learning rate of 21.5%.[7] Similarly, the right graph in Fig. 1 indicates that price also shows a log-linear relationship with current industry output, with the negative slope often perceived as indicating the presence of economies of scale in production.[8]

However, this paper finds that cumulated industry output (or other proxies for learning like cumulated firm output, cumulated firm investment, or cumulated industry investment) and current industry output (or other proxies for economies of scale like current firm output or plant size) do not have a statistically significant effect on production cost once other relevant factors are taken into account. The next section examines these factors in detail.

2. Overview of the solar panel industry

The ability of some materials to convert sunlight to electricity, the photovoltaic effect, was first observed in the mid nineteenth century. Since then, there has been much progress in the manufacture of solar cells that use such photovoltaic materials to produce electricity from sunlight. The most popular technology for making commercial solar cells is the crystalline silicon technology, which accounted for over 90% of the industry output in 2012. This paper focuses on sources of cost reduction in crystalline silicon solar panels.

The production of crystalline silicon solar panels begins with the manufacture of the high-purity polysilicon, which is then subjected to many chemical processes to make a solar cell, the basic electricity-producing unit. Many solar cells are strung together to make a solar panel (also called a solar module), which are the square panels seen on rooftops. The focus of this paper is on firms that manufacture solar panels, though most of the firms in the dataset used in this study are vertically integrated and also manufacture solar cells. Solar panels are rated in terms of the electric power that they can generate, stated in watts, and firm and industry output are quantified in terms of watts produced. Fig. 2 shows the reductions in price per watt and cost per watt for the period 2005–2012.[9]

Fig. 2. Reduction in price and cost of solar panels (2005–2012). *Notes:* The cost per watt and price per watt are the averages of these variables for the fifteen firms in the dataset. See Section 4 for details.

A cursory examination of the firm level data used in this paper suggests a number of reasons that could have contributed to the decline in cost per watt seen in Fig. 2. Four factors that have commonly been considered as important drivers of cost reduction show up in the data (see Fig. 3).[10] First, all firms in the dataset show increases in the light-to-electricity *conversion efficiency* of their solar panels, often referred to as just efficiency in the industry (Fig. 3a). Efficiency measures the ability of the solar panel to convert a given amount of light to electricity, and everything else remaining the same, higher conversion efficiencies result in lower cost per watt.[11] Second, the price of polysilicon, the main raw material used in the manufacture of solar panels, has changed significantly during 2005–2012 (Fig. 3b). Third, all firms have reduced the amount of polysilicon needed to make a watt of solar panels (Fig. 3c). Fourth, the average size of manufacturing plants of each firm has also increased over time (Fig. 3d). Nemet (2006) argues that increase in plant size was the main driver of cost reduction in solar panels during 1975–2002.

The data also point to two other factors that have not been considered before in the literature. The international composition of solar

[6] Suppose $c = aY^{-b}$, and cost changes from c_0 to c' when output doubles. Then when output doubles, cost reduces by a factor $\frac{c'}{c_0} = 2^{-b}$. Hence the percentage reduction in cost (learning rate) is $LR = \left(1 - \frac{c}{c_0}\right) * 100 = \left(1 - 2^{-b}\right) * 100$.

[7] Williams and Terzian (1993) estimate that solar panel prices on the global market followed a learning rate of 18% between 1976 and 1992. IEA (2000) and Van der Zwaan and Rabl (2004) both find a learning rate of around 20%.

[8] The data for Fig. 1 were taken from the dataset compiled by Earth Policy Institute.

[9] The industry average gross margins for the years 2005–2012 were 17%, 20%, 21%, 19%, 21%, 22%, 11%, and 2%, respectively.

[10] Nemet (2006) and Swanson (2006) discuss these four factors.

[11] For example, if a solar panel has an efficiency of 15%, it means that it can convert 15% of the light energy that falls on it to electrical energy.

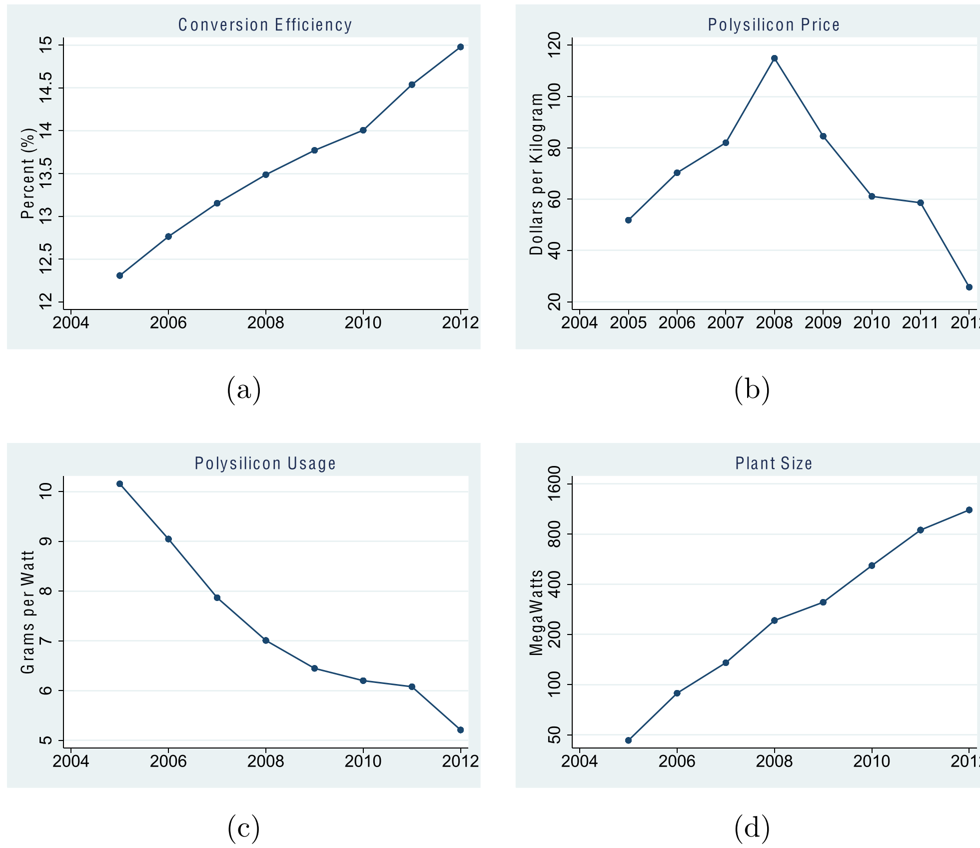

Fig. 3. *Notes:* Graph (a) shows the average light-to-electricity conversion efficiency of firms in the dataset. Graph (b) shows the industry price of a kilogram of polysilicon, calculated as the weighted average of prices of six leading polysilicon manufacturing firms. Graph (c) shows the average quantity of polysilicon needed to produce one watt of solar panels. Graph (d) shows a weighted average of plant size of firms in the dataset. See Section 4 for details on how the data on these variables are collected.

panel producers changed during 2005–2012, with the fraction of the panels produced by firms from China increasing throughout the period. The reported production cost of firms from China is lower than that of firms from other parts of the world (see Fig. 4).[12] Increasing penetration of lower cost firms from China has contributed to the decrease in average production cost of solar panels.

Finally, the data on annual capital expenditures and capacity addition in the industry indicate that the price of capital equipment is

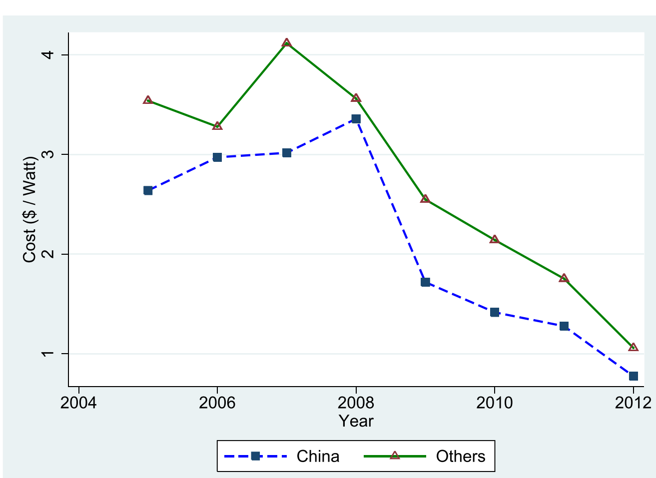

Fig. 4. Average cost of solar panels from China and from other countries.

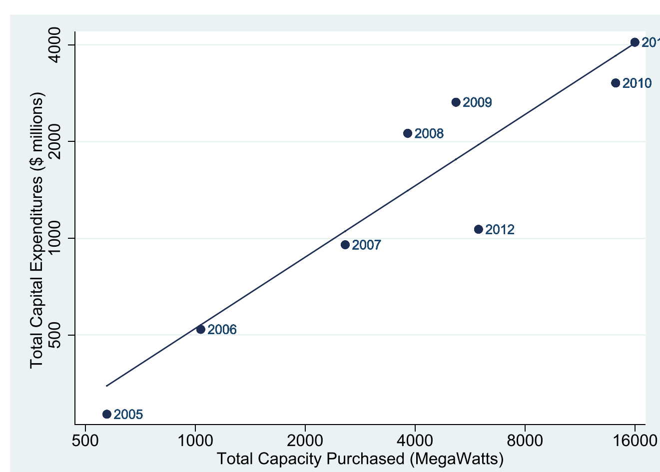

Fig. 5. Capital costs is a concave function of the quantity of capital equipment purchased by the industry (slope = 0.73). *Notes:* The x-axis is the total capacity added in a year by the firms in the dataset, and the y-axis is the total capital expenditures of firms in that year. The variables are plotted on a log scale and the graph indicates a relationship of the form $\textit{Capital Expend} = \textit{Capacity Purchased}^{0.73}$. The coefficient of 0.73, less than one, indicates that the price of a unit of capacity (or physical capital) decreases as more capacity is purchased. The capital equipment used by solar panel manufacturers are produced by a different group of companies. The major capital equipment producers include GT Solar, Applied Materials, Centrotherm, and Meyer Burger.

[12] See Section 5.3 for quantification of the cost difference and a discussion on possible origins of the difference.

lower in those years in which the industry purchases a higher amount of capacity. Fig. 5 shows a concave relationship between industry capital expenditures and total capacity added by the firms, suggesting that unit capital cost decreases as the industry purchases more capacity.

The features of the solar technology and industry outlined above are used in the next section to develop a model of production used in the regression analysis.

3. Model

The electric power output of a solar panel manufactured by firm j can be written as the product of the light energy that falls on the panel, the light-to-electricity conversion efficiency of the panel, and the physical area of the panel, i.e.

$$y_{jt} = E_{jt} A_{jt} S, \tag{1}$$

where y_{jt} is the electric power output in watts, E_{jt} is the light-to-electricity conversion efficiency of solar panels produced by firm j, A_{jt} is the area of solar panels manufactured by firm j, and S is the solar constant which is a measure of the light incident on the panel.[13] Output of solar panels is stated in terms of watts produced under standard test conditions that keep S constant, and hence S plays no role in the analysis in this paper. The total area of solar panels produced, A_{jt}, represents the physical output of the production process, and conversion efficiency E_{jt} converts the physical output in area to electrical output y_{jt} measured in watts.

The production possibilities for the physical output, A_{jt}, are captured using a production function. Capital and material are the key inputs in the solar panel production process (see Goodrich et al. (2011)).[14] Two observations indicate substitution possibilities between capital and materials in the industry. First, the quantity of polysilicon needed to produce 1 watt of solar panels shows substantial variation across firms and over time in the data. Second, Goodrich et al. (2013a) describe how some kinds of capital equipment used in production process can reduce the quantity of polysilicon needed. To allow for substitution possibilities, the production process is captured using a Cobb–Douglas production function, with capital K and materials M as inputs. To incorporate improvements in material usage over time (see Fig. 3c), assume that a material input of M translates to an effective material input of $\frac{M}{u}$. As u decreases, less material is needed to achieve the same output. To allow for possible learning economies, output is assumed to vary as X^{θ}, where X is the accumulated experience measured through cumulative industry and firm output in the empirical analysis.[15] These assumptions can be captured using the production function,

$$A_{jt}(K_{jt}, M_{jt}) = e^{\lambda t} X_{jt}^{\theta} K_{jt}^{\alpha} \left(\frac{M_{jt}}{u_{jt}}\right)^{\delta} \eta_{jt} \tag{2}$$

where K_{jt} is the capital used by firm j, M_{jt} is the materials used by firm j, u_{jt} is a measure of the unit material requirement, X_{jt} is a measure of the experience accumulated through learning involved in the production process, and η_{jt} is the error term. The factor $e^{\lambda t}$ captures the effect of any variable that changes systematically over time and is not captured through the other variables, X, K, M, or u. Substituting Eq. (2) into Eq. (1) gives the final production function,

$$y_{jt} = e^{\lambda t} E_{jt} X_{jt}^{\theta} K_{jt}^{\alpha} \left(\frac{M_{jt}}{u_{jt}}\right)^{\delta} \eta_{jt} \tag{3}$$

Solar panel firms take the rental rate of capital equipment and price of polysilicon as given.[16] Firms choose M_{jt} and K_{jt} to minimize the cost of production,

$$C_{jt} = v_t M_{jt} + r_t K_{jt} \tag{4}$$

where v_t is the price of polysilicon and r_t is the rental rate of capital equipment, both of which are the same across firms. Cost minimization leads to the following average cost function,

$$\bar{c}_{jt} = \left(e^{\lambda t}\right)^{-\frac{1}{\alpha+\delta}} E_{jt}^{-\frac{1}{\alpha+\delta}} y_{jt}^{\frac{1-\alpha-\delta}{\alpha+\delta}} X_{jt}^{-\frac{\theta}{\alpha+\delta}} \left(u_{jt} v_t\right)^{\frac{\alpha}{\alpha+\delta}} r_t^{\frac{\delta}{\alpha+\delta}} \eta_{jt}^{-\frac{1}{\alpha+\delta}} \tag{5}$$

A simple way to incorporate the strong concave relationship between capital expenditures and capacity added seen in Fig. 5 is to assume that the rental rate of capital equipment decreases with increase in total capital expenditures of all firms,

$$r_t = I_t^{-\mu} \tag{6}$$

where $I_t = \sum_{j=0}^{N} I_{jt}$ is the total capital expenditure of all firms in the industry. Substituting Eq. (6) into Eq. (5) and taking logs gives the equation used for the regression analysis,

$$\begin{aligned} ln(\bar{c}_{jt}) = {} & \beta_0 + \beta_t t + \beta_E ln(E_{jt}) + \beta_y ln\left(y_{jt}\right) + \beta_X ln(X_{jt}) + \beta_u ln(u_{jt}) \\ & + \beta_v ln(v_t) + \beta_I ln(I_t) + \epsilon_{jt}, \end{aligned} \tag{7}$$

where the coefficients $\{\beta_t, \beta_E, \beta_y, \beta_X, \beta_u, \beta_v, \beta_I\}$ are functions of $\{\lambda, \theta, \alpha, \delta, \mu\}$. The next section describes the sources of data for variables in Eq. (7).

4. Data

The empirical analysis is done using a novel panel dataset of leading solar panel manufacturers assembled from a number of different sources. The dataset covers 15 leading solar panel firms over the years 2005–2012. The choice of firms and the time period were both dictated by the availability of cost data, which are collected in this study from the cost of goods sold (COGS) reported by firms in their annual reports or filings at the U.S Securities and Exchange Commission (SEC). Prior to 2005, a good majority of solar panels were produced by product divisions that were part of large oil corporations like British Petroleum (BP) and Shell Corporation, or Japanese conglomerates like Sharp, Kyocera, Sanyo, and Mitsubishi.[17] None of the six companies above report the cost of goods sold (COGS) or other cost information separately for their solar product division in their annual reports or other stock exchange filings.[18] The early 2000s saw the emergence of pure play solar companies, many of whom registered as public companies by 2005. As the pure play solar companies grew, the oil corporations and Japanese conglomerates became much less significant in terms of their market share.[19] For these reasons, 2005 was the first year that the cost data were available for a good cross-section of the companies, and hence 2005 is taken as the starting point in the analysis.

[13] The equation follows from the definition of conversion efficiency, see Goodrich et al. (2013a).

[14] Labor is a relatively less important factor, especially for the period 2005–2012 considered in this study, when most of the production plants were automated to a large extent.

[15] A value of $\theta = 0$ implies that there are no learning economies.

[16] This is a reasonable assumption since all firms included in this study purchase capital equipment from upstream equipment manufacturing firms, and all but one of the firms purchase polysilicon from upstream polysilicon manufacturing firms. The solar panel industry is fragmented, and hence, it seems reasonable to assume that the downstream panel firms have little individual control over the price of capital equipment and materials provided by the upstream firms.

[17] These six companies (BP, Shell, Sharp, Kyocera, Sanyo, and Mitsubishi) accounted for 72% of the total world production of solar cells in 2001 and 63% of the total in 2004.

[18] Many of the remaining companies involved in solar production are small companies scattered across different countries, which were not publicly listed and hence did not divulge any cost information. Examples include Photowatt in France and Isofoton in Spain.

[19] For example, in 2010, the six companies mentioned earlier accounted for only 13% of total world production.

Table 1
Data summary.

Year	Companies	Shipments in Dataset		Company revenues				Company Shipment Share			
		(million watts)	(% of world production)	(Million $)				(% of World Production)			
				Mean	S.D.	Min	Max	Mean	S.D.	Min	Max
2005	9	217	13	99	84	27	286	1.2	0.9	0.2	3.0
2006	11	455	20	184	149	46	472	1.8	1.3	0.6	5.3
2007	12	1080	32	400	339	70	1332	2.6	2.7	0.5	10.5
2008	12	1962	33	692	446	112	1786	2.7	2.0	0.4	7.7
2009	15	3501	39	568	461	12	1606	2.6	2.3	0.3	7.5
2010	15	8043	39	1040	698	302	2766	2.6	2.1	0.6	7.5
2011	14	12080	37	1179	818	246	3014	2.5	1.9	0.4	6.5
2012	11	12,176	38	923	495	276	1763	2.5	2.2	0.3	7.1

Notes: The company revenues are taken from the dataset used in the study (see Section 4). The annual world production is taken from the dataset compiled by the Earth Policy Institute.

Omitting the oil corporations and Japanese conglomerates leaves fifteen major companies who report their solar panel production costs. The rest of the market is held by companies that do not report usable cost data in their reports or by small companies which are not publicly listed.[20] The data include a cross-section of leading European, U.S., and Chinese companies.[21] The companies in the dataset cover 13% of total world production during 2005, the coverage increases to 38% in 2012 (see Table 1). The companies included are fairly large, with annual revenues ranging from twelve million to three billion dollars. The production shares vary from less than a percent to over 10% of total world production. The dataset includes companies producing both polycrystalline and monocrystalline silicon solar panels, the two prominent technologies within the crystalline silicon technology. The dataset also includes firms which are vertically integrated and those which are not.[22]

The dataset contains an unbalanced panel of firms. Once a firm enters the industry, the dataset contains annual observations on the firm till the end of the time period or until it exits the industry. Data are not available for the earlier years for some of the firms, either because they had not yet entered the industry or because they were not publicly listed and hence did not disclose their COGS. The percentage of solar panels in the dataset that were produced by firms from China increased from 32% in 2005 to 82% in 2012.[23]

For each company, annual data were collected on COGS, revenue, shipments, and capital expenditures. For the U.S. companies, the data were collected from their annual 10-K statements. All the companies in the dataset that are based in China are registered in U.S. stock exchanges, and hence file an annual 20-F statement with the U.S. SEC. The format for the 20-F statement is similar to 10-K statement, providing comparability between the data used for companies based in U.S. and China.[24] For the companies based in Europe, the data were obtained from their annual reports.[25] All companies report their annual shipment of solar panels in watts.

The use of cost data derived from annual reports of companies has sometimes been criticized in the literature. But there a number of reasons to believe that concerns raised are less severe for the cost data that are used in this study. First, all the companies considered in the analysis are pure solar companies, so the variable costs they report in annual statements are those associated with solar production alone. Second, many of the companies state in their annual reports that a substantial fraction of the COGS that they report are material costs, which are usually correctly reflected in annual reports. Third, the unit cost of production is the most closely watched metric in the industry, and market analysts routinely publish estimates of the unit costs for different companies using their own methods.[26] It is quite likely that the close scrutiny by industry observers puts a heavy burden on the firms to report their costs truthfully.

The dependent variable, average variable cost of producing solar panels for each firm, $(\overline{c}_{jt})$, was obtained by dividing COGS by annual shipments. The costs were converted to base 2011 using the U.S. Consumer Price Index. The mean, standard deviation, minimum, and maximum values of the variables in Eq. (7) are shown in Table 2.[27] The data sources for the explanatory variables are described below.

The light-to-electricity conversion efficiency numbers reported by firms are inadequate for use in this paper since all firms reveal only the best (highest) efficiencies obtained in their research laboratories, and these can differ from the efficiencies of panels sold to customers.[28] The efficiencies for all panels sold by each company were obtained from the Photon database, and a weighted average of the efficiencies of the panels sold by each company in a year was calculated.[29] The weight for each panel was the quantity share of the panel among all the panels sold by the company in California during that year.[30]

Plant size was used as one of the proxies for economies of scale in production. The size of plants (in watts) owned by each company was collected from their annual reports, and an average plant size variable was constructed for each company for every year. For the price of polysilicon, an industry average price was used since very few solar panel companies in the dataset revealed their purchase price of

[20] The solar panel industry is quite fragmented, GTM (2012) reports that the top 15 panel companies only accounted for 47% of worldwide panel sales in 2011 and 50% in 2012.

[21] The companies in the dataset are Suntech Power, Yingli Green Energy, Trina Solar, Canadian Solar, Hanwha Solarone, LDK Solar, ReneSola, Sunpower Corporation, Evergreen Solar, Solarworld AG, Aleo Solar, Solar Fabrik, Centrosolar. and Renewable Energy Corporation.

[22] All companies considered here report the revenue and COGS for the solar panel sales separately from the revenue and COGS of other segments.

[23] For the intermediate years, the market share of firms from China were 53% in 2006, 70% in 2007, 66% in 2008, 66% in 2009, 73% in 2010, and 78% in 2011.

[24] The cost of goods sold (COGS) for the companies in the dataset filing 10-K and 20-F includes the cost of materials, direct labor cost, utilities and depreciation of capital, and excludes the expenses on R&D, marketing and general administration. Hence the COGS reported by these companies is a good measure of their variable cost of production.

[25] While some of the European companies report the cost of goods sold, a few report only the earnings before income and taxes (EBIT). Subtracting the sum of EBIT and reported expenses on R&D, marketing, and general administration from the annual revenues gives a measure of the variable cost of production that is comparable to the COGS reported by companies registered on U.S. stock exchanges.

[26] For example, Greentech Media publishes "PV Technology, Production and Cost Outlook" with cost estimates for the major solar panel manufacturers.

[27] The cross-sectional variation in panel cost, efficiency, plant size and polysilicon, usage seen in Table 2 allows the coefficients in regression Eq. (7) to be estimated with a high level of statistical significance (see Table 3). The two variables that are same across firms, polysilicon price and industry investment, show considerable variation over time. Even for the years in which the average panel cost did not change much (2005–2008), there was a lot of variation in the explanatory variables, both across firms and across years.

[28] All companies also sell a few different panels every year, and efficiencies can vary across these panels.

[29] Photon tests the technical characteristics of panels in its laboratories and makes the test data available in its online database.

[30] California was chosen as the market to calculate the weights because detailed data on all solar installations in California are available from the dataset maintained by California Solar Center. The dataset includes the product numbers for each panel, which allows matching the panels with the Photon database to locate the efficiency of the panel. California is also a fairly large market, and all of the companies used in this study sold in California. For the years in which California data were not available, the model numbers of panels sold by each company in a year was obtained from reports in the Photon Magazine of spot market sales of solar panels in Germany.

Table 2
Data summary.

Year	Unit cost ($/watt)				Efficiency %				Poly usage (Grams/watt)				Plant size Megawatts				Capital expend. Million $			
	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max
2005	3.3	1.3	2.4	6.3	12.4	1.7	10.5	16.2	1.0	1.5	6.5	11.0	52	47	15	150	43	25	8	72
2006	3.1	0.4	2.7	4.2	12.8	1.3	11.5	16.2	9.1	1.2	6.5	10.0	89	71	25	270	121	233	5	812
2007	3.7	1.1	2.8	6.5	13.2	1.3	12.1	16.9	7.9	1.2	5.0	9.1	135	139	25	540	98	75	1	210
2008	3.5	0.6	2.6	4.7	13.5	1.2	12.4	17.2	7.0	1.2	5.0	8.5	243	263	31	1000	239	203	14	725
2009	2.1	0.5	1.4	3.1	13.8	1.3	12.5	18.0	6.5	1.2	3.9	8.2	312	272	45	1000	232	263	7	829
2010	1.8	0.5	1.0	3.0	14.0	1.2	13.2	18.0	6.2	1.2	3.6	7.8	518	343	126	1200	236	241	3	861
2011	1.5	0.3	1.1	1.9	14.5	1.1	13.8	18.1	6.1	1.00	4.5	7.5	845	547	152	1900	296	279	2	877
2012	0.9	0.2	0.7	1.2	15.1	1.3	14.5	19.1	5.2	0.78	4.0	7.0	1115	542	438	2400	130	96	22	309

Notes: See Section 4 for sources of data.

polysilicon. The annual revenues of major polysilicon companies were divided by the annual shipments to obtain the average selling price of polysilicon for each company, and a weighted average of these prices was taken as the industry average price.[31] The data on polysilicon usage for each company were obtained from their annual reports and from articles in industry magazines. The annual capital expenditures undertaken by each firm where obtained from their annual reports, and firm level capital expenditures were added up to obtain the total annual industry capital expenditure. The next section reports the results from the regression analysis.

5. Results

The results of the regression analysis are reported in Table 3. The dependent variable is the average variable cost, and the results in each of the columns (1)–(10) are discussed below. Columns (1)–(3) show the effect on cost of time, cumulative industry output, and plant size considered individually, and column (4) shows the results when the full list of variables in Eq. (7) are used. Columns (5) and (6) show the results when annual industry investment is replaced by annual firm investment and cumulated industry investment, respectively. Column (7) shows the result when only the statistically significant variables are used in regression, and columns (8)–(10) shows the results when firm fixed effects are added.

5.1. Learning and economies of scale

As can be seen from column (1), time is statistically significant with the coefficient indicating a 21% average annual reduction in cost over the time period. Column (2) shows the estimate of a learning curve with the cumulative industry output as a proxy for learning. Cumulative industry output is significant, with doubling of output reducing the average cost by around 19%. If cumulative firm output is used instead of cumulative industry output, the learning rate decreases to 16%.[32] The third column estimates static economies of scale, using plant size as a proxy. Plant size is also significant, with doubling of plant size leading to a 22% reduction in cost. Using current firm output as a proxy for economies of scale also gives a significant coefficient, with doubling of current output corresponding to an 18% reduction in cost. However, proxies for learning (cumulative industry output or cumulative firm output) and economies of scale (current output or average plant size) become insignificant in the regression when the list of explanatory variables are expanded to include variables in Eq. (7), as shown in column (4).[33] The impact of each of the significant variables on cost is discussed below.

5.2. Polysilicon price and polysilicon usage

Polysilicon price is significant in all the regressions including the ones where firm fixed effects are included. The result in column (7) indicates that 1% decrease in polysilicon price leads to a 0.9% decrease in cost of production.[34]As indicated in column (7), a 1% reduction in polysilicon usage leads to a 0.52% reduction in cost.

5.3. China dummy

The China dummy variable is significant in all regressions where it is included.[35] The coefficient −0.24 on the dummy for China indicates that production cost of firms from China were 22.4% lower than that of firms from other countries during the period of the study.[36] The computed cost difference is close to the 23% difference found in Goodrich et al. (2013b). It is to be noted that the costs of firms from China are lower even after accounting for differences in technological factors like conversion efficiency and polysilicon usage.[37]

5.4. Efficiency

A 1% increase in efficiency leads to almost 1% reduction in average cost, as indicated in column (7), which is also the impact that Nemet (2006) uses in his model. Note that both the initial efficiency of the firm and its annual (current) efficiency were included in the regression. Initial efficiency was included because firms often use proprietary processing steps that increase their efficiency but also adds to cost, and hence one would expect a higher efficiency to be associated with higher costs in a cross-section of firms, while higher efficiency would be associated with lower costs for a given firm over time.[38] These two effects

[31] The polysilicon companies used were Wacker Chemie, REC, LDK, GCL Poly ,and Daqo Corporation.

[32] Result not shown in Table 3.

[33] Nemet (2006) finds plant size to be an important contributor to the reduction in panel costs. One possible reason for the different result from this paper is that Nemet considers the time period 1975–2001. During the early years, plant size was quite small, and the benefits to scaling up were probably much higher at lower plant sizes. In contrast, plant sizes were very high for the time period considered in the current study, reaching an average of 1GW across the firms in the dataset, for the year 2012.

[34] Yu et al. (2012) contains a detailed empirical analysis of factors that affected polysilicon price during 2004–2009.

[35] The dummy variable was omitted in the firm fixed effect regressions.

[36] The percentage reduction in cost is just $(1-e^{-\beta_c}) * 100$, where β_c is the estimated coefficient on the dummy.

[37] Two studies point to possible factors that might explain the cost difference between firms from China and elsewhere. In 2012, the U.S. International Trade Commission conducted an investigation in response to a petition by some U.S. firms that Chinese firms were receiving subsidies from government and selling at less than fair market value in the U.S. In its findings (summarized in USITC (2012)), the commission concluded that Chinese firms had received subsidies from the government. The second study, Goodrich et al. (2013b), uses an engineering-type factory model to estimate cost differences between U.S. and China. They conclude that subsidies provided by the provincial governments in China (which include low-cost land, free factory space, and subsidized electricity) as well as supply chain advantages (benefits from having a dense regional network of suppliers to supply the scaled up industry in China) contribute to the cost difference between firms in China and the U.S.

[38] See Saga (2010) for a discussion on manufacturing process requirements for solar cells of different efficiencies and the implication for production costs.

Table 3
Estimates of average cost function parameters. Dependent Variable — Average Variable Cost.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
								(With firm fixed effect)		
Time (t)	−0.21***			−0.25						
	(−0.014)			(0.18)						
Cumul. ind output (X_t)		−0.30***		0.36						
		(0.02)		(0.26)						
Plant size			−0.35***	−0.02						
			(0.03)	(0.03)						
China dummy				−0.21***	−0.24***	−0.24***	−0.24***			
				(0.05)	(−0.03)	(0.03)	(0.03)			
Polysilicon price (v_t)				0.77***	0.92***	0.97***	0.91***	0.96***	1.00***	1.00***
				(0.13)	(0.06)	(0.09)	(0.05)	(0.07)	(0.07)	(0.07)
Polysilicon usage (u_{jt})				0.51***	0.50***	0.55***	0.52***	0.37*	0.54***	
				(0.10)	(0.10)	(0.10)	(0.10)	(0.91)	(0.07)	
Intial firm efficiency				0.58*	0.59**	0.68**	0.61**			−1.64***
				(0.31)	(0.30)	(0.31)	(0.30)			(0.54)
Annual firm efficiency (E_{jt})				−0.87**	−0.92**	−1.07***	−0.98***	−1.01*		
				(0.40)	(0.37)	(0.39)	(0.38)	(0.62)		
Annual industry investment (I_t)				−0.27***	−0.27***	−0.33***	−0.26***	−0.30***	−0.33***	−0.35***
				(0.07)	(0.04)	(0.09)	(0.04)	(0.05)	(0.05)	(0.05)
Annual firm investment (I_{jt})					−0.02					
					(0.01)					
Cumul. industry investment						0.06				
						(0.06)				
R^2	0.71	0.65	0.64	0.93	0.93	0.92	0.92	0.93	0.93	0.93
Obs	99	99	97	97	97	96	98	98	99	98

Notes: Standard errors are given in brackets. Cumulated industry output is used as proxy for experience, using cumulated firm output instead gives similar results. Plant size is used as proxy for economies of scale, using current firm output instead gives similar results.
* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

can be captured with two variables, the efficiency of the firm in the first year of the study and the efficiency of the firm in the current year. As expected, the coefficient on initial efficiency is positive while that on current efficiency is negative.

5.5. Industry investment

As shown in columns (4) and (7)–(10), annual industry investment has a statistically significant impact on costs. Firm level investment is not statistically significant, as can be seen from column (5) where annual industry investment is replaced by annual firm investment. To check whether the effect of industry investment is because of any learning associated with capital equipment, cumulated industry investment was added to the list of explanatory variables. The results are shown in column (6); the coefficient on cumulated industry investment is also not significant. The decrease in production cost could be because of the decrease in purchase price of capital equipment as total industry investment increases (see Fig. 5).[39] The decrease in purchase price of capital equipment could be the result of economies of scale in the production of capital equipment, further investigation of the upstream capital equipment market is necessary to provide more insight into the impact of industry investment on the cost of production of solar panels. The regression results in column (7) show that a 1% increase in investment in the industry is associated with a 0.26% reduction in cost.

[39] New capital equipment can be better than the one that it is replacing, and this is plausibly one explanation why industry investment seems to be associated with lower panel costs. But note that new capital equipment in the solar industry is often better in the sense that it can produce solar panels with higher light-to-electricity conversion efficiency and lower polysilicon usage, two variables which are already captured in the regression equation (Eq. 7).

5.6. Firm fixed effects

In column (8), a firm fixed effect is added to the explanatory variables, and the China dummy and initial efficiency are removed since they are collinear with the firm fixed effect. Adding in the fixed effect results in coefficients that explain variation in cost within firms. As column (8) shows, polysilicon price and industry investment remain significant at the 1% level while efficiency and polysilicon usage are now significant only at the 10% level. This happens because polysilicon usage and efficiency are correlated within a firm, and there is not enough years of data to separately discern the within-firm effect of these two variables on cost. When only one of these two variables is included in the regression, both these variables remain significant at the 1% level. Column (9) shows the result when only polysilicon usage is included, and column (10) shows the results when only efficiency is included.

6. Contributions to cost reduction

The estimates in Section 5 can be used to decompose the reduction in average cost into contributions from the different factors, similar to growth accounting methods used in economics since Solow (1957). The industry average values of cost and the variables that affect cost (as indicated in column (7) of Table 3) are used for this accounting exercise. Setting the coefficients for time (β_t), experience (β_X), and output β_y all equal to zero in Eq. (7) and differentiating with respect to time gives,

$$\frac{\dot{c}}{c} = \beta_E \frac{\dot{E}}{E} + \beta_u \frac{\dot{u}}{u} + \beta_v \frac{\dot{v}}{v} + \beta_I \frac{\dot{I}}{I} + \frac{\dot{\eta}}{\eta}, \qquad (8)$$

where the dots over the variables indicate the derivative with respect to time. Hence the explained portion of the growth rate of cost is the weighted average of the growth rates of the efficiency $\frac{\dot{E}}{E}$, polysilicon

Table 4
Contribution of different factors to reduction in cost.

Annual growth rate of unit cost	**−20.9 %**
Contributing factor	Percent contribution (%)
Efficiency	−2.1
Polysilicon price	−7.0
Polysilicon usage	−5.0
Industry investment	−5.3
Total contribution from four factors	**−19.4**
Residual	−1.5

usage $\frac{\dot{u}}{u}$, polysilicon price $\frac{\dot{v}}{v}$, and industry investment $\frac{\dot{i}}{I}$, the weights being the coefficients estimated in Section 5. The annual growth rate of each variable is computed as the log difference of the variable between the two time periods.[40] The average of the annual contributions of each factor is shown in Table 4.

Decrease in polysilicon price was the largest contributor to the decrease in costs, accounting for 7% of the 21% decline in costs with decrease in polysilicon usage adding another 5%.[41] Increase in annual industry investment and improvements in efficiency explain 5.3% and 2.1% respectively of the of the annual 21% reduction in cost. [42]

7. Conclusion

The reduction in average production cost and price of solar panels during 2005–2012 has been driven by reduction in the price of polysilicon, improvements in technology, increasing market penetration of lower cost firms from China, and increases in industry investment. Learning externalities and static economies of scale do have any significant explanatory power over solar panel cost, once the other factors are taken into account. These results suggest that government policies aimed at reducing the cost of solar panels should target technological advancements not only in the solar panel industry but also in the upstream industries manufacturing polysilicon and the capital equipment used in solar panel production.

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[40] If the annual growth rate of c is g_c, so that $c_{t+1} = c_t e_c^g$, then the annual growth rate can be calculated from data as $g_c = lnc_{t+1} - lnc_t$.

[41] Decreases in thicknesses of the solar cells and reduction in material loss during the manufacturing process were the main drivers of the decrease in polysilicon usage (see Fischer et al. (2012)).

[42] Efficiency improvements play a smaller role in cost reduction here compared to Nemet (2006), because efficiency increases were much larger in Nemet's dataset (from 6.5% to 13.5%) than in the dataset used in the current paper (from 12.4% to 15.1%). Polysilicon price and polysilicon usage plays a more prominent role here compared to Nemet (2006), because polysilicon cost as a fraction of total panel cost was a much higher fraction for the time period considered in this study (2005–2012), than in the time period considered in Nemet's (2006) study (1975–2001).