Sun and Lemons: Getting over Information Asymmetries in the California Solar Market

Johannes Mauritzen
Department of Business and Management Science
NHH Norwegian School of Economics
Bergen, Norway
johannes.mauritzen@nhh.no
jmaurit.github.io

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Abstract

A large expansion of photovoltaic panel production in China coincided with a dramatic fall in the cost of solar photovoltaic systems in California and a boom in installations between 2009 and 2013. However the roll of local contractors that install the systems is not well understood. Using detailed data of approximately 125,000 solar installations in California between 2007 and 2014 I argue that the boom in installations can not be explained by cheaper Chinese panel production in isolation. Instead, the introduction of Chinese panels is closely intertwined with the introduction of an innovative business model at the contractor level that solves an asymmetric information problem. Solar panels are long-lived productive assets, where quality is important but costly for individual consumers to verify. The adoption of a leasing model by several large local installers solved the asymmetric information problem and led to the adoption of Chinese panels and in turn lower overall system prices and more installations. Using a multilevel regression, I model the firm level decisions of introducing a leasing model and adopting Chinese panels directly. I show a strong and significant interaction effect between these decision variables.

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1 Introduction

In the wake of the world-wide financial crisis that began in 2008, the Chinese government initiated a massive economic stimulus package. One of the side-goals of this package was to turn China into a top producer and exporter of solar panels. New and existing Chinese manufacturers of solar panels were provided inexpensive loans and other forms of subsidy in order to substantially build-out capacity. Within a few years, Chinese solar power manufacturers were beginning to export panels at prices significantly lower than established manufacturers, especially those with production based in Europe, Japan and the US [Lacey, 2011].

The role of cheaper Chinese panels has been widely acknowledged in driving the boom in installations of photovoltaic systems in California and elsewhere. However how the decisions and evolving strategies of local contractors facilitated the boom in installations is not well understood.

The economics of solar power is unique within power generation in that assets are often owned by individual consumers and small businesses. Large energy company will have considerable expertise in generation technologies and engineering, investment risk, electricity market structure and other specialized knowledge and competencies involved in generating electricity. A consumer or small business, on the other hand, can be expected to have much more limited knowledge and expertise.

Informational and behavioral issues therefor become important factors in analyzing investment decisions. For example Dastrup et al. [2012] argue that solar panels can not be considered a pure investment good, but are bundled also as a type of green conspicuous consumption. The authors back up this argument by showing how the installation of solar panels affects home prices in the San Diego area and finds evidence for a "solar price premium" and that this effect is positively correlated with how environmentally aware an area is. Bollinger and Gillingham [2012] study the the role of peer effects in solar power adoption. They find evidence that the adoption of solar panels by homeowners in a zip-code will increase the probability that other households in that zip-code will install solar panels.

In this article, I argue that the widespread adoption of Chinese panels is closely intertwined with a business model innovation at the local level that was meant to overcome information asymmetries of investing in a solar photovoltaic system. In particular, several large solar system contractors adopted a leasing business model. With a leased solar system, homeowners do not own the solar systems that are placed on their roofs and do not usually need to provide the initial capital for the system, but instead are offered electricity from the panels at prices lower than that of electricity from the grid over a defined period - often 20 years.

Cheaper Chinese panels, along with generous subsidies, helped make a leasing model financially feasible for contractors to offer consumers and businesses. Leasing models are, in turn, attractive to consumers and businesses for several reasons. They can allay both uncertainty about the complexities of owning and maintaining a solar panel system as well as about the quality of the installation done by the contractor. But another mechanism is likely also at play. The introduction of a leasing model helped overcome an asymmetric information problem relating to the uncertain quality of Chinese produced solar panels.

Solar panel systems are significant investments for households and businesses that need to last well over a decade in order to be financially profitable even with significant subsidies. At the same time, individual homeowners or small contractors would incur great costs in verifying the quality of the main component of a solar system: the solar panels. In this way the market for Chinese solar panels resembles the market for "lemons" in the seminal article by Akerlof [1970].

As Akerlof notes, with asymmetric information, rational consumers can be expected to prefer trusted brands and manufacturers. In the case of the solar power industry, this provides a barrier to entry to new, Chinese manufacturers and some pricing power to established manufacturers. In turn, this information asymmetry could potentially have delayed or even blocked a switching to cheaper Chinese panels even if the quality of Chinese panels are competitive with that of established manufacturers. With a barrier to entry for Chinese manufacturers, prices for solar panels and systems would likely be significantly higher.

Using a large sample of data from installations of solar panels in California between 2007 and 2014, I provide evidence that contractors were able to significantly bring down total system costs by both switching to cheaper Chinese panels and simultaneously introducing a leasing model. I argue that these companies were successful in overcoming the information asymmetries by owning the panels themselves since they are able to absorb the information asymmetry and associated risk - verifying the quality of the panels as a wholesaler.

I use a multilevel regression model that, resembling a difference-in-difference identification strategy, directly models the fall in system prices on contractor level decisions about switching to Chinese panels and a leasing model. I estimate a strong and significant interaction effect between switching to Chinese panels and introducing a leasing model. I suggest that companies who simultaneously introduced a leasing model and adopted Chinese panels gained a significant competitive advantage and were able to lower costs through both cheaper components and economies of scale. I will also discuss potential weaknesses of my identification strategy.

The analysis in this paper can be broken up into roughly two related parts. First, I present an overview of the market and its dynamics. I follow with both several simple, exploratory regression models as well as the main results from the multilevel regression. The results of this paper are important for understanding the rapidly expanding solar power industry. The research also has implications for market regulation, subsidies and trade policy.

2 The California Solar Initiative and the Market for Solar Photovoltaic Systems

I use data on approximately 125,000 solar power installations in the state of California between 2007 and 2014. The data is publicly available at `http://www.californiasolarstatistics.ca.gov/` and a cleaned data set is available on my website `jmaurit.github.io\#solar_lemons`. The data includes all installations covered by the California Solar Initiative, which provided rebates for installation of solar panels on existing single and multi-family homes, commercial and governmental buildings. Large utility-owned projects are notably not included in this program. The data set includes information on the size of the system, when it was installed, the amount of subsidy provided, the location of the installation to the scale of zip-code, the contractor who installed the system and the manufacturer of the panels and inverters used. Up until parts of the subsidy scheme began to expire in 2013, almost all residential solar panel installations in California came under the subsidy and are included in the dataset [Dastrup et al., 2012].

The California Solar Initiative was launched in January of 2007 and scheduled to last until 2016 or until the allocated funds of approximately 2.1 billion dollars were exhausted [California Public Utilities Commission, 2014]. As of the end of 2013, approximately 1500 megawatts (mW) out of a goal of 1940 mW was installed. The rebates covered customers of the largest three investor owned utilities - Pacific Gas and Electric Company, Southern

California Edison, and San Diego Gas and Electric - combined representing approximately 70 percent of California's load. The amount of the incentives is complex, being based on size of installation, and how much capacity has already been installed. In general, the incentives were designed to decline over time as more capacity is installed.

In the period 2007 to 2014, prices of solar power systems fell dramatically. Figure 1 shows the average total solar power system cost per kilowatt (kW) over time. In addition to a sharp fall in the system costs, the figure also shows that subsidies have shrunk while new installed capacity has generally continued to increase. The drop-off in installations seen towards 2014 reflects the exhaustion of rebates for customers of the Pacific Gas and Electric Company. This drop-off does not reflect total installations, as the data only includes installations that benefited from the rebate. Previous to the expiration of some of the subsidies in 2014, the dataset likely includes nearly all installations [Dastrup et al., 2012].

Comparing prices of leased systems to those that are sold out-right can be difficult because of the variation in what contractors report as the total cost for leased systems. Where the cost reported of a system that is sold out-right is simply the total price charged by the contractor, the cost of a leased system could be reported as either the Fair Market Value of the system, which is reported in tax filings or as an appraised sum of cost inputs. Some contractors will also include the cost of inverter replacements or roof replacements necessary for installation.

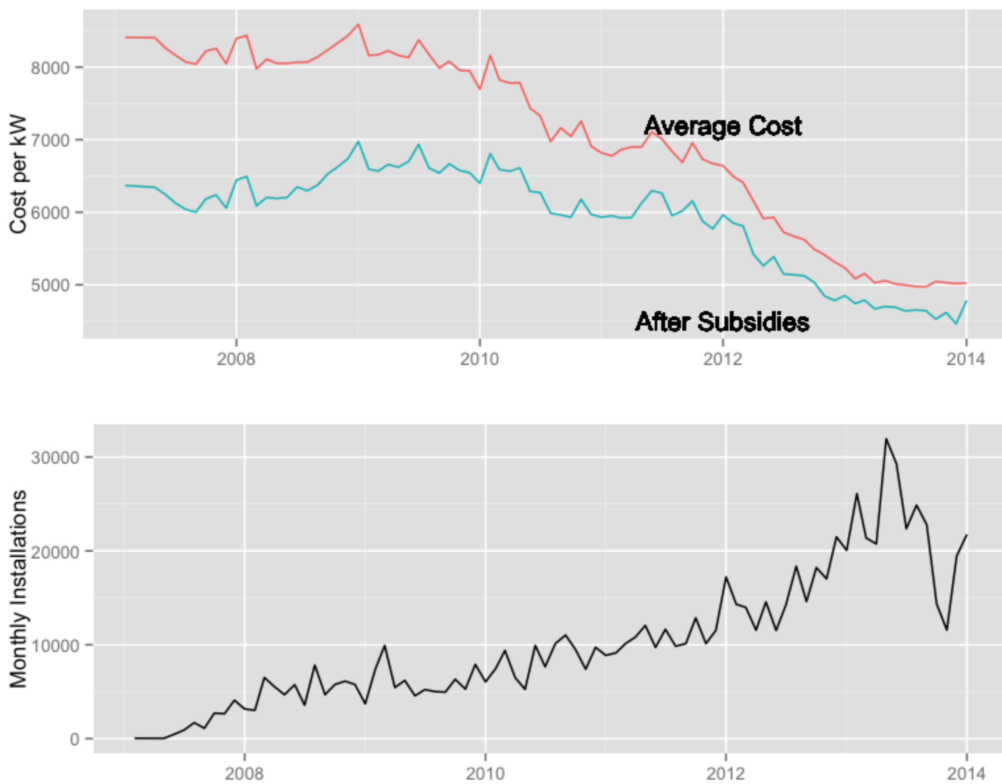

Figure 1: The green line shows the average unsubsidized cost of solar power systems over time, while the blue line shows the costs after state subsidies. The red line shows the average monthly number of installations of systems covered by the California Solar Initiative. The cost of solar power systems has fallen dramatically over the time period studied. Subsidies have been reduced in kind, however installations have continued a general upwards trend. The fall in installations seen towards the end of 2014 reflects the expiration of some of the subsidies and the fact that non-subsidized systems are absent from the data.

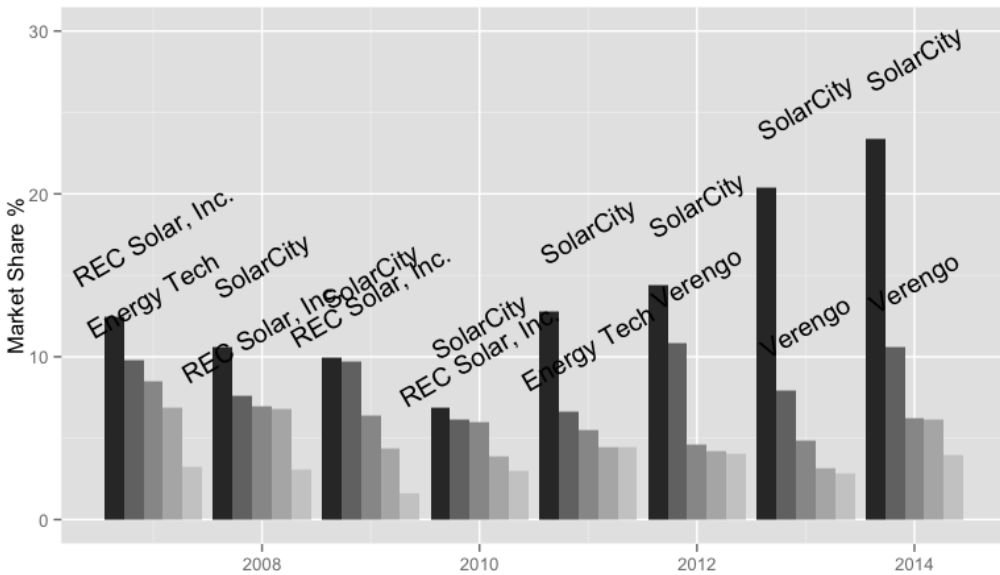

Figure 2: Marked concentration increased markedly over the period studied.

3 Lemons and the switch to Chinese panels

The steep drop in prices of solar panel systems in the period studied and especially since 2009 has a seemingly simple explanation. The expansion of low-cost production in China led to a large fall in global panel prices. However, the lowering of system costs is not just a function of global economies of scale, but also of the decisions made by contractors at the local level.

As figure 2 shows, market concentration has increased substantially over the time period studied. In particular, two contractors were able to gain large amounts of market share - Solar City and Verengo.

Figure 3 shows, the gain in market share by Solar City and Verengo coincided with a switch to Chinese panels. However, the figure also shows,

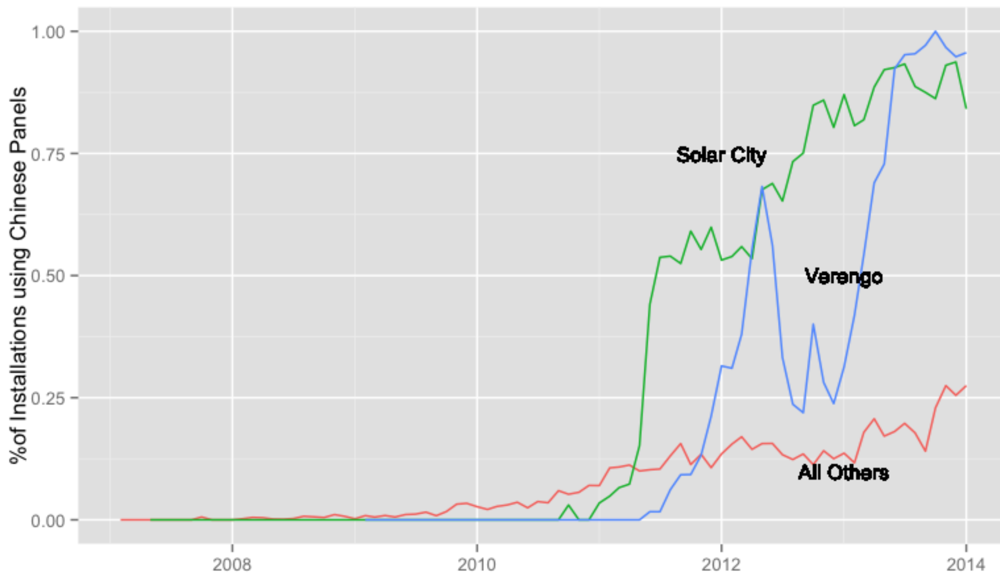

Figure 3: A few contractors, notable Solar City, were able to grab market share while switching to Chinese panels. However switching to Chinese panels alone does not sufficiently explain the increase in market share.

Solar City was not a first mover. Many contractors switched over to using Chinese panels well before Solar City did so, but it appears that being an early adopter of Chinese panels and the price advantage that conferred did not necessarily lead to increased market share alone.

A host of factors could be responsible for why some contractors were able to gain market share other than the price advantage of switching to Chinese panels. Advantages in financing, management practices, to building on the existing advantages of scale could, and likely did play a role to a certain exist.

However, the data suggests an alternative explanation backed up by a simple economic intuition. Solar panels are long-lived assets that currently

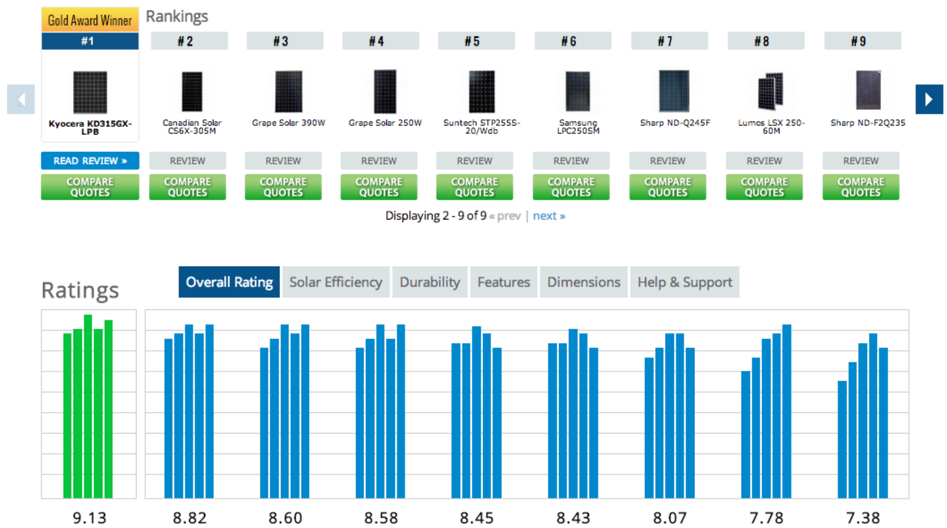

Figure 4: Websites are available for providing reviews of various solar panels, however new manufacturers that have not been on the market and have not been tested in California would not have been available here.

must last at least a decade in order to be financially profitable for the owner. More so, judging the quality of solar panels is beyond the technical abilities of the vast majority of consumers and thus most will rely on reputation and ratings of existing manufacturers. For example, figure 5 shows a screen shot of the website `http://solar-panels-review.toptenreviews.com/`, which provides reviews of solar panels based on past performance.

However, this presents a problem for Chinese manufacturers that have not had an earlier presence on the market. A lemons problem of asymmetric information arises. Consumers, with poor information on the quality of panels from unestablished Chinese manufacturers, will be weary of purchasing them. At a minimum they will demand a lower price than a comparable system with panels from an established manufacturer, and following the model by Akerlof, a market for systems using Chinese panels may even cease to exist entirely.

But a closer look at the data reveals that after 2010 many firms, notably Solar City, not only switched to Chinese panels but simultaneously switched to selling systems on a leasing model, as figure 3 shows. While verifying the quality of panels from a previously unknown manufacturer is expensive, a large contractor can take steps like having experts test the quality of modules and visiting manufacturing facilities that ordinary homeowners and business would find prohibitive. Having verified the quality of the panels, the contractor can then offer to build and own the system, offering to sell the electricity to the building owner at a price lower than offered by the local utility.

Using a leasing system is also superior to issuing a guarantee in overcoming the information asymmetry. A guarantee issued by a contractor to a homeowner is good only as long as the contractor remains solvent. Since the solar contractors are themselves often new firms, such a guarantee may not be seen as sufficient.

So far I have presented a descriptive evidence that adoption of Chinese panels and a leasing models in the California are closely intertwined and, in particular, that the adoption of a leasing model helped overcome asymmetric information related to the quality of unknown Chinese manufacturers of panels. In turn, the interaction of the adoption of a leasing model and Chinese

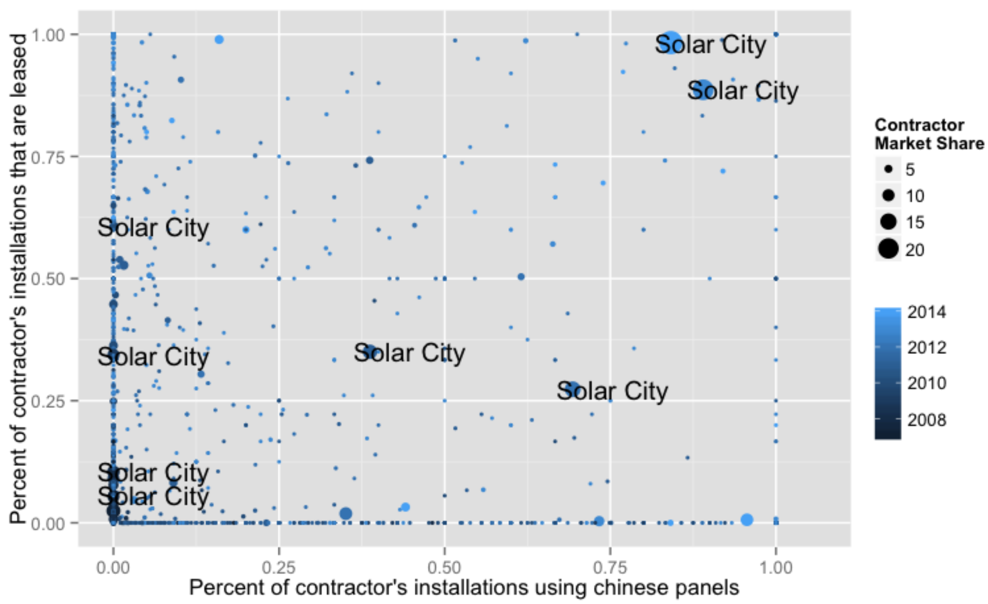

Figure 5: Each dot represents a contractor in a certain year, where the size of the dot represents the market share of the contractor, and the shade of blue represents the year - lighter shades being closer to the present. The placement on the x and y axis represents the percentage of the contractors' installations that year that used Chinese panels and were leased. After 2010 many contractors, notably Solar City, not only switched to cheaper Chinese panels but also moved to a leasing model of sales.

panels helped bring down prices and increase the popularity of solar power systems. I explore these predictions formally in the next session with regressions at the installation and contractor level as well a multilevel regression model.

4 Regression models

I begin with some simple regressions exploring the relationship between using Chinese panels and a leasing business model, as well as installation-level regressions of the adoption of Chinese panels and leasing on the fall in prices over time. At the contractor level, I run regressions looking at factors involved in gaining market share and lowering prices. I then provide a fuller analysis using a multilevel model that allows for a more causal interpretation, where I can directly model the contractor level choice of switching to Chinese panels and a leasing business model.

For the regression models I discard data where the system was self-installed, since the focus of this paper is on the strategies of contractors. For simplicity, I also only include data on installations from the top 50 panel producers. Of the initial approximately 124,000 installations in the data set, approximately 119,000 remain after these exclusions.

The most direct implication from the descriptive analysis presented above is that a link exists between switching to Chinese panels and using a leasing model. A simple logit model where the right-hand-side variable is whether or not a solar system is leased can be written as in equation 1.

$$lease_i = invlogit(\alpha + \beta timeYears_i + nationality_i + \sigma timeYears_i * nationality + \epsilon) \tag{1}$$

Here the variable $timeYears_i$ represents the time in year units, from January 1st, 2007 to when an installation i was installed. The reason time is measured from January 1st, 2007 is that this is when the California Solar Initiative officially opened and the earliest installation in the data set was installed shortly after. The $nationality_i$ represents a fixed effect for the nationality of the panel producer.

The results are best interpreted graphically, as in figure 6, but a table of estimated coefficients can be found in table 3. All coefficients are estimated to be statistically significant at the 5 % level.

Here the black lines represent model results for the probability of a system being leased using panels from Chinese manufacturers as well as comparisons with German and Japanese manufacturers - countries with large, established solar panel industries. The grey lines represent uncertainty of the estimates in the form of bootstrapped draws from the approximate posterior distribution. The jittered dots represent installations that are either leased (1) or sold outright (0), where a blue color represents the use of Chinese panels. While the probability of using a leasing model increases over time for systems using panels from all countries, the probability increases sharply for those using

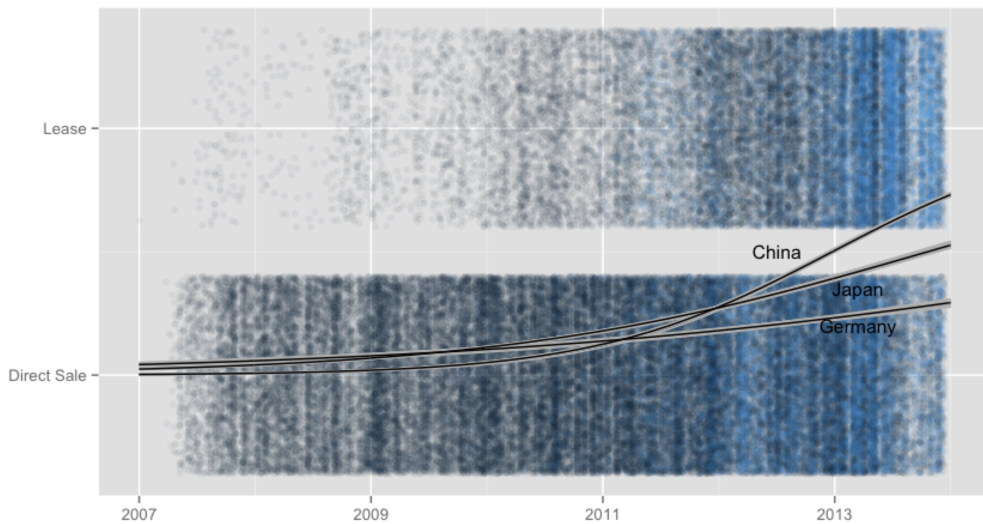

Figure 6: The figure shows results from a logit model of the probability of a solar system being leased as a function of time since February of 2007, nationality of the panel maker and their interactions. Systems with Chinese panels, mostly absent from the market before 2010, were substantially more likely to be used in leased systems than panels from more established Japanese and German manufacturers.

Chinese panels.

The regressions above indicate significant conditional correlations between the use of Chinese panels and a leasing model. However, the hypothesis that emerged from the descriptive analysis above was not necessarily that using Chinese models required a leasing model, but rather that it could confer an advantage. In turn, combining the use of Chinese panels and a leasing model would be expected to lead to an increase in market share. A regression model to explore this hypothesis can be written as in equation 2.

$$\begin{aligned} marketshare_j = \alpha + \beta_1 percChinese_j + \beta_2 percLease_j + \\ \beta_3 percChinese_j * percLease_j + year + \epsilon \end{aligned} \tag{2}$$

In these regressions, the data is aggregated to the contractor-year level, indexed by j. The variable *percChinese* represents the percent of all installations by a contractor using Chinese panels in a given year. Likewise *percLease* represents the percent of installations that are leased by a contractor in any given year. In addition interaction effects are included as well as year fixed-effects.

The results are presented in table 1. In the first column, year fixed effects are excluded. Here the coefficient on the main effect for using Chinese panels is not distinguishable from zero. This can be interpreted to mean that if a contractor does not lease solar systems, then increasing the percentage of Chinese panels is not associated with an increase in the market share. However the interaction term for percent Chinese with percent lease is strongly positive. The coefficient is easiest to interpret at the margin - given that a contractor uses only Chinese panels, a one percent increase in the share of systems they lease is associated with a one percent increase in market share.

In the third column I exclude the dominant contractor, Solar City from the data. The main effect for leasing remains essentially unchanged but the coefficient on the interaction term becomes insignificant. These results can be interpreted to mean that switching to a leasing model in general led to gains

	No F.E.	Year F.E.	excl. SCTY
(Intercept)	0.10***	0.41***	0.38***
	(0.01)	(0.05)	(0.03)
perc-chinese	−0.03	0.02	0.02
	(0.03)	(0.03)	(0.02)
perc-lease	0.31***	0.34***	0.31***
	(0.05)	(0.05)	(0.04)
perc-chinese:perc-lease	0.98***	0.91***	−0.04
	(0.14)	(0.14)	(0.10)
R^2	0.03	0.04	0.04
Adj. R^2	0.03	0.04	0.04
Num. obs.	6006	6006	5998

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 1: The results of these regressions can be interpreted to mean that given that a contractor uses only Chinese panels, a one percent increase in the share of leased systems leads to a one percent increase in market share. This effect, however, disappears when the leading contractor, Solar City is removed from the data.

in market share, where the largest gains were made by a a few companies that simultaneously switched to using Chinese panels as well as a leasing model. This interpretation has intuitive appeal given the costs of verifying the quality of solar panels. Actions like sending experts to inspect production facilities would be prohibitively expensive for all but the biggest contractors.

An important potential outcome of introducing a leasing model, is that by gaining acceptance of cheaper Chinese panels, the leasing model was able to bring down solar system prices in California. To explore this I start with a simple model at the installation level. I estimate the slope of log-costs over time with separate terms for whether systems were leased or used panels from Chinese manufacturers. The model can be written as in 3.

$$log(costPerKw_i) = \alpha + \gamma china_i + \tau lease_i + \beta timeYears_i + \sigma inter_i + \epsilon \quad (3)$$

Again, the model results are easiest to interpret in graphical form, presented in figure 7. The black lines represent the point estimates of the estimated coefficients while the grey lines again represent uncertainty in the form of draws from the approximate posterior distribution. A table of coefficients, all of which are estimated to be statistically significant at least at the 95% level, can be found in table 4 in the appendix. The model estimates that leased systems using Chinese panels enjoy a considerable cost advantage over non-Chinese systems, though that advantage has narrowed over time. The model results should be interpreted with care before 2010 as relatively few of the systems were both leased and used Chinese panels.

The results from the above regression provides evidence that both leasing and switching to Chinese panels played a significant role in lowering prices. However, the above installation-level model ignores the role of contractor-level variation. At the same time, models using data aggregated to the contractor-level ignores the substantial variation between installations by the same contractor. More so, the question of interest is not how the cost of leased systems using Chinese panels has changed over time, but rather how the choice by contractors to change to Chinese panels and a leasing model has affected system costs.

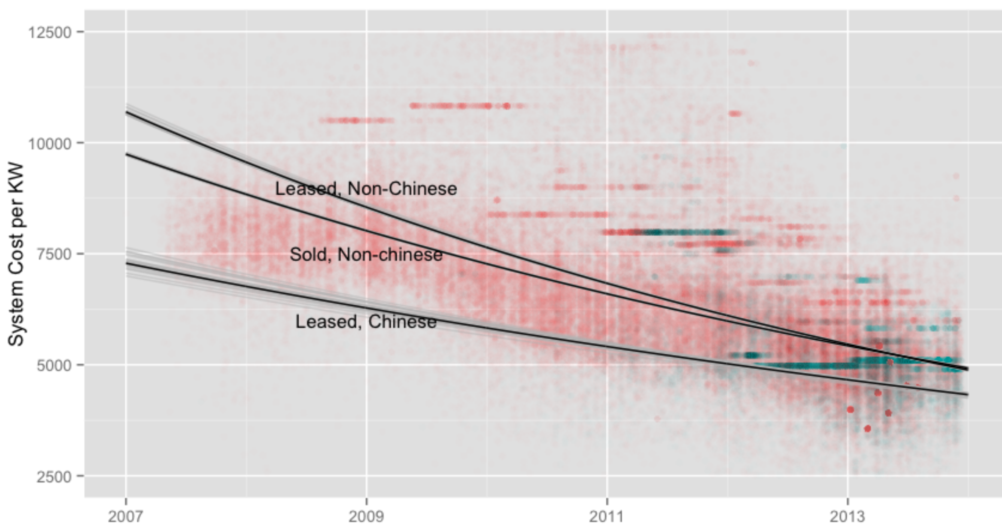

Figure 7: The figure shows model results from a log-linear model of solar system cost per kW as a function of time, whether a model was leased, and whether panels where from a Chinese manufacturer. The lines represent the model results while the dots represent the raw data on installations where a green color signifies installations that use Chinese panels. Systems with Chinese panels are substantially cheaper through the period studied, but only became widely popular after 2011.

In order to establish a clearer causal relationship between lower solar system costs and the decision to adapt Chinese panels and introduce a leasing model, I use a multilevel regression to model the contractor-level decisions directly. [1]

I include data between the years 2009 and 2013 as this was the period with the most dramatic price fall and with the most industry dynamics. Since I am interested in changes in behavior within a contractor in this period, firms that were not present in the full period 2009 to 2013 are excluded.

Following the notation from Gelman and Hill [2006] the model can be written as in equation 4. Here the log cost-per-kilowatt for each contractor j is modeled as a function of an intercept and installation-level data on the time of installation. The coefficients are represented by $a_{j[i]}$ and $b_{j[i]}$, where the i are included in order indicate that these coefficients are estimated on installation level data. The $b_{j[i]}$s can be interpreted as the average rate of price declines between 2009 and the end of 2013 for each of the 278 contractors in the data set. These installation-level coefficients are also constrained by a conditional probability distribution with group level predictors, represented by the vector of variables U_j and where $B_j = \{a_{j[i]}, b_{j[i]}\}$. Intuitively, the estimated B_j coefficients for each contractor are pulled towards the pooled distribution conditional on the contractor level predictors U_j.

[1] Multilevel models are often referred to as mixed effects models or random effects models, especially in the economics literature. However the language here can be inconsistent and confusing. I follow Gelman and Hill [2006] and Singer and Willett [2003] in calling them multilevel models.

$$
\begin{aligned}
log(costPerKw_i) \sim N(a_{j[i]} + b_{j[i]}timeYears_i, \sigma_y^2), i = 1, ..., n \\
B_j \sim N(U_j G, \Sigma_B), j = 1, ..., J
\end{aligned} \tag{4}
$$

The contractor level predictors that are of interest are defined as in equation 5: the change in percent of a contractor's installations that use Chinese panels between 2009 and 2013, and the change in the percent of a contractor's installations that are leased. Of particular interest, I include an interaction effect between these variables. G represents the vector of coefficients on the contractor level predictors U_j.

$$
\begin{aligned}
\delta_j^c = percChinese2013_j - percChinese2009_j \\
\delta_j^l = percLeased2013_j - percLeased2009_j
\end{aligned} \tag{5}
$$

The major advantage of this model is that the coefficients, B_j that represent the estimated price declines of solar systems from a contractor, j, are explicitly modeled as a function of the decisions made by the individual contractors: whether they chose to increase the percentage of Chinese panels used and whether they used a leasing model between the years 2009 and 2013. In this way, a causal link is established by simultaneously estimating price variation over time for each of the contractors, and variation between contractors as a function of the contractor decision variables.

The model resembles a difference-in-difference identification strategy from classical econometrics. I model the within-contractor change in price over time, but as where a classical difference-in-difference model will typically look at a single policy change or event, the multilevel structure of the model allows me to compare the decisions of each of the contractors in the dataset. Because I am measuring within-contractor variation over time, missing predictors that are correlated with the contractor but constant over time will will be controlled for by the contractor level intercept term, $a_{j[i]}$ and will not bias the results.

The exogeneity of the model is weaker than a difference-in-difference strategy, as the decision variables are not imposed on a random selection of contractors, like a policy change. Plausibly, some unobserved variable that is correlated with the decisions of the contractors could bias the results. When that is said, I have not been able to find any obvious missing variables that likely bias the results. More so, when the goal is to model outcomes of the decisions made by the contractors, a certain level of endogeneity is nearly unavoidable.

The multilevel model is fit using the R package lme4 [Bates et al., 2014b], which finds the maximum likelihood estimators of the coefficients through a penalized least squares routine.Another option would have been to do a fully Bayesian analysis that takes into account uncertainty of all the parameters of the model. However, given the large number of observations and large number of groups, the results from lme4, based partly on asymptotic approximations, should be sufficient. Conversely the computational cost of doing a full Bayesian analysis of such a large dataset with many groups is quite high.[2]

A summary of some of the regression results are presented in figure 2. The Estimates for σ_y and the the components of the vector σ_B, the estimated standard deviations at the group and individual levels are presented. The contractor level components are estimated to have a combined standard deviation of approximately .16 ($\sqrt{.153^2 + .044^2}$) while the estimated standard deviation for the unexplained individual level component is approximately .146. This can be interpreted to mean that given a contractor, the cost of an installation can be predicted with a standard deviation of .15 while costs could be estimated with a standard deviation of .22 ($\sqrt{.159^2 + .146^2}$) if one did not know the contractor. In other words, a substantial amount of the variance in the data can be ascribed to differences between the contractors. This provides some indirect support for my broader argument that contractor-level factors are important for explaining the fall in solar power system prices.

The estimates for the contractor-level predictors are also included in the table below, however it is impractical to present the 278 estimated within-contractor coefficients on the $time_years$ variable in table form. Instead, figure 8 shows the results of the multilevel regressions graphically. The first row

[2] I was unable to get a Bayesian model to converge using STAN after approximately 12 hours.[Stan Development Team, 2014]

	Model 1
(Intercept)	9.00*
	[8.98; 9.03]
change_lease	−0.05
	[−0.13; 0.04]
change_chinese	0.06
	[−0.01; 0.14]
time_years_a2009	−0.12*
	[−0.13; −0.12]
change_lease:change_chinese	0.10
	[−0.09; 0.30]
change_lease:time_years_a2009	0.04*
	[0.02; 0.06]
change_chinese:time_years_a2009	−0.04*
	[−0.06; −0.01]
change_lease:change_chinese:time_years_a2009	−0.05
	[−0.11; 0.01]
AIC	-55233.17
BIC	-55125.85
Log Likelihood	27628.58
Deviance	-55257.17
Num. obs.	56573
Num. groups: contractor	278
Std. Dev: contractor.(Intercept)	0.153
Std. Dev: contractor.time_years_a2009	0.044
Std. Dev: Residual	0.146

* 0 outside the confidence interval

Table 2: Summary of multilevel regression results. The contractor level components are estimated to have a combined standard deviation of approximately .16 while the estimated standard deviation for the unexplained individual level component is approximately .146. This can be interpreted to mean that given a contractor, the cost of an installation can be predicted with a standard deviation of .15 while costs could be estimated with a standard deviation of .22 if one did not know the contractor.

represents results when only the main effects of the contractor level predictors are included in $U_j = \{changeChinese_j, changeLease_j\}$.

In the top left panel, the estimated coefficients on the slope of the price change for all contractors is plotted as points in order of the change in the percent of Chinese panels the contractor used. The black line represents the estimated slope and intercept of the contractor-level predictor, $changeChinese_j$.

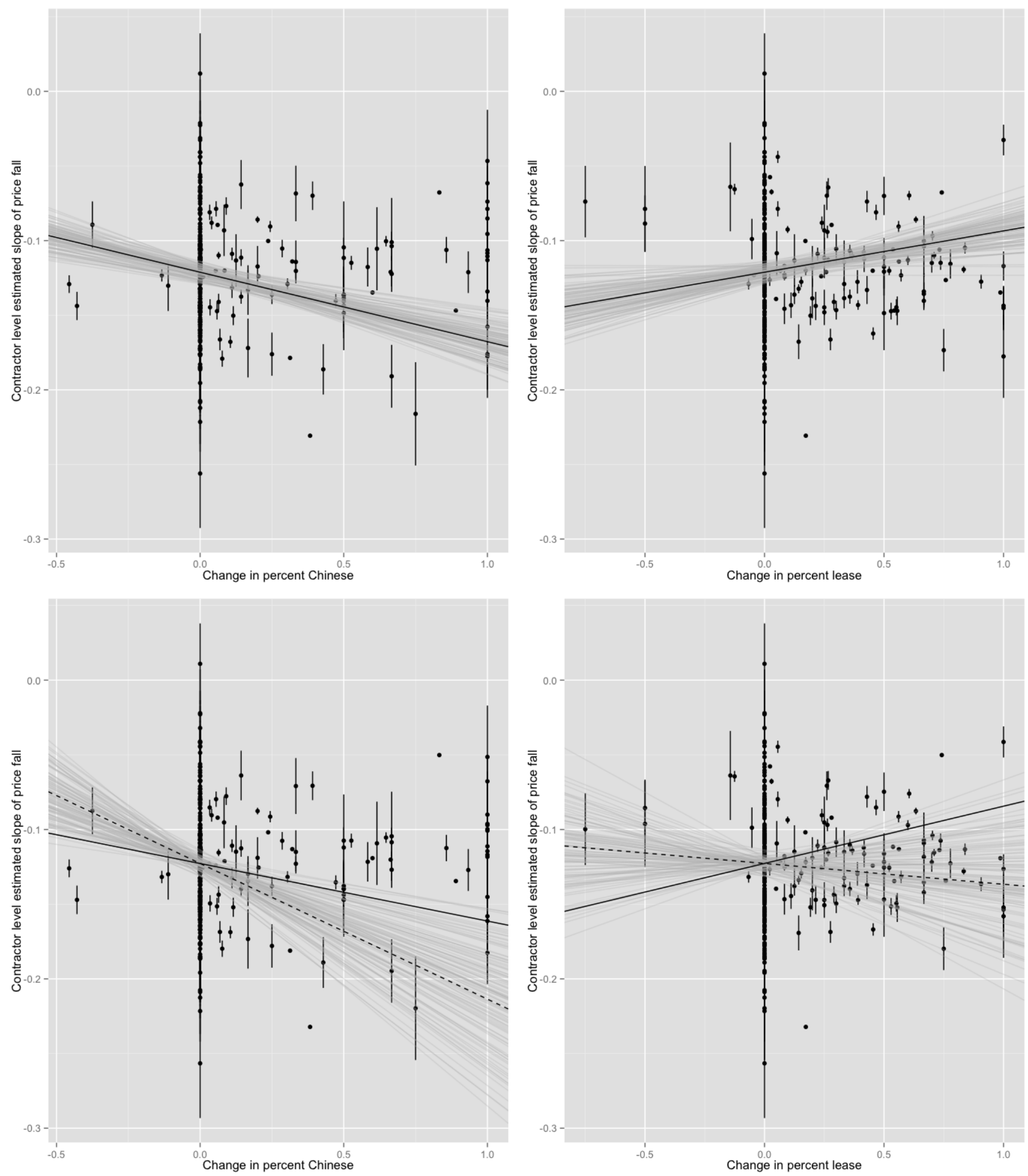

Figure 8: The top left panel shows that contractors that increased the share of installations using Chinese panels saw a steeper fall in costs over time. The lower left panel shows that those that also increased the share of leased panels, represented by the gray line, saw an even steeper fall in costs. The panels on the right show that all else equal, contractors that increased the share of leased installations saw less of a price fall, however those that simultaneously increased their share of installations with Chinese panels saw a steeper fall in prices.

The grey lines represent uncertainty in the form of bootstrapped simulations. Though substantial variation exists between contractors, the slope of the coefficient on $changeChinese_j$ is significantly negative. Contractors who switched to using Chinese panels saw, on average, a larger price drop.

In the top right panel, the estimated coefficients on the time variable are ordered in terms of the $changeLease_j$ variable. Here the contractor-level slope coefficient on $changeLease_j$ is estimated to be slightly positive. On the margin, companies that switched to using a higher percentage of leasing models, saw a smaller decline in prices than those that did not use a leasing model.

However, the main coefficient of interest is the interaction effect. In the bottom left panel, I show results from a regression model where I include an interaction term between $changeChinese_j$ and $changeLease_j$ to the vector of contractor-level predictors U_j. In the bottom left panel I show the estimated coefficient on the $changeChinese_j$ as the slope of the black line while the interaction term is added to the slope in the dotted line. Uncertainty of the estimated combined effect is represented by the grey lines.

The combination of changing to a higher percentage of leased systems and a higher percentage using Chinese panels had significant negative effect on prices. This can be interpreted to mean that simultaneously switching to using Chinese panels and to a leasing model provided an extra cost advantage beyond that which the cheaper panels provided in isolation. The previous analysis suggests that this may be related to increased economies of scale as companies who adapted a leasing model and Chinese panels were able to expand and grab market share.

The converse interpretation of the interaction effect is shown in the bottom right panel, the slope of the black line represents the estimated coefficient on $changeLease_j$, where the slope of the dotted line has the interaction term added. Contractors that increased the percentage of leases while not switching to Chinese panels had a less steep fall in their prices over time. However, when adding the interaction, the point estimate for the combined effect indicates a somewhat steeper fall in prices, however in this case the estimate is subject to a large degree of uncertainty.

The bottom two panels of figure 8 can be misleading in the sense that the dotted lines do not represent the total effect. This would include both the main effects of $changeChinese_j$ and $changeLease$, which in general have opposite signs.

To get a better idea of the magnitude and uncertainty of the estimated total and interaction effects, figure 9 shows results from 1000 simulated draws from the posterior distribution of the model in the form of histograms. The top two panels shows the total effect - the sum of estimated contractor-level slope estimates of the change to Chinese panels, change to leasing and the interaction estimate. The right panel shows just the interaction effect. The vertical line in both represents the upper 5 percent of simulated draws. Both the total effect and the interaction effect were of similar magnitude, with the distributions centered around -.05. As mentioned, this is because the main effects of changing to Chinese panels and changing to a leasing model have in general opposite signs.

The interaction effect is of special importance, especially relative to the main effect of switching to Chinese panels. I am interested in finding what the relative magnitude of switching to Chinese panels and switching to a leasing model compared to the effect of just switching to Chinese panels. To try to estimate this I create a new estimate, $\theta_{share} = \theta_{interaction}/\theta_{Chinese} * 100$. The histogram of the simulated θ_{share} are shown in the lower panel of figure 9. This distribution has a high variance, but more than sixty percent of the probability mass is at over 100 %. In other words, the model can be interpreted to mean that the interaction effect of both switching to Chinese panels and using a leasing model has a 60 percent probability of being at least as large as the effect of switching to Chinese panels alone and a 95 percent probability of being higher than zero.

Figure 10 shows some model checks. The top panel shows the actual data plotted against the predicted data in the form of a single draw from the posterior distribution. The model fit appears to be reasonable, though some notable outliers exist in the lower left-hand corner. In other words, the model over-predicts the costs of a few of the systems.

The lower panel, showing the predicted residuals[3] by contractor is perhaps more helpful. Of particular interest are the streaks visible for SolarCity and

[3]The residuals here are the difference between a single draw from the posterior distribution rather than from the point estimates in order to take account of uncertainty of all the coefficients.

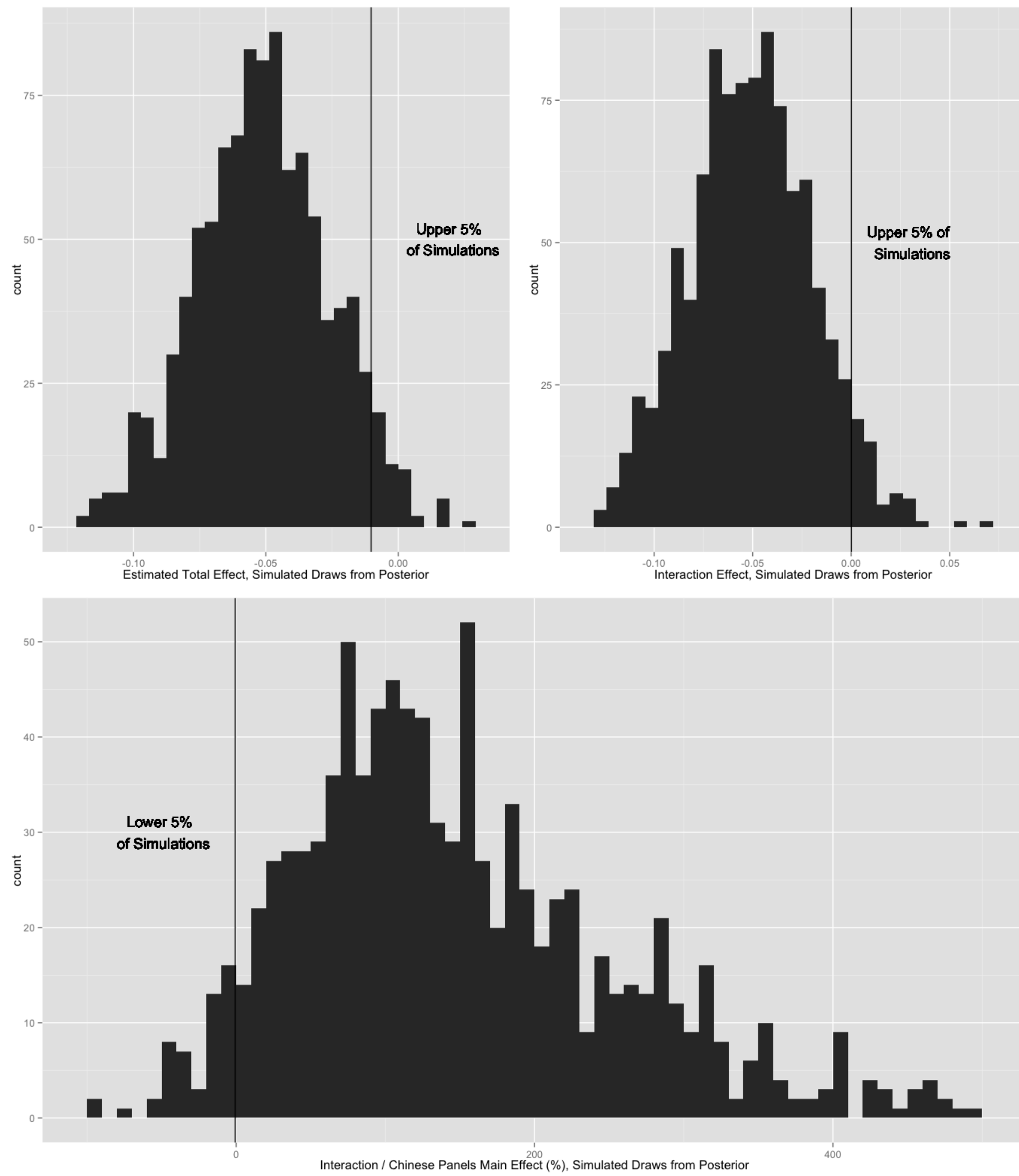

Figure 9: Histograms from 1000 draws from the posterior distribution. The model can be interpreted to mean that there is more than a 60 percent chance that the interaction effect is equal or more than the main effect of switching to Chinese panels and a 95 percent chance of being more than zero.

Sungevity. These are the result of reported costs for leased systems that stayed constant over a certain period of time while the model predicts a gradual fall in costs.

Given that the costs of systems that were sold outright were observed to fall steadily over time, these reported costs are likely overstated. Because of federal tax incentives that are based on total investment costs, the contractors have an incentive to overstate the costs of their leased systems. In fact Solar City is currently under investigation by the Internal Revenue Service for overstating costs [Solar City]. In turn, this implies that the estimated main effect for switching to a leasing model is likely biased upwards and the estimated positive effect of switching to a leasing model on the change in system costs is likely overstated. On the other hand the negative estimated interaction effect is likely underestimated and may in reality be larger in magnitude.

5 Conclusion

This paper has important implications for understanding the emerging solar power industry as well as for informing policies meant to encourage the adoption of solar power. Because solar power systems can be installed on roof-tops and that they in turn can compete with residential electricity prices, which are substantially higher than wholesale prices for electricity, solar power systems have become attractive for individual homeowners to install and oper-

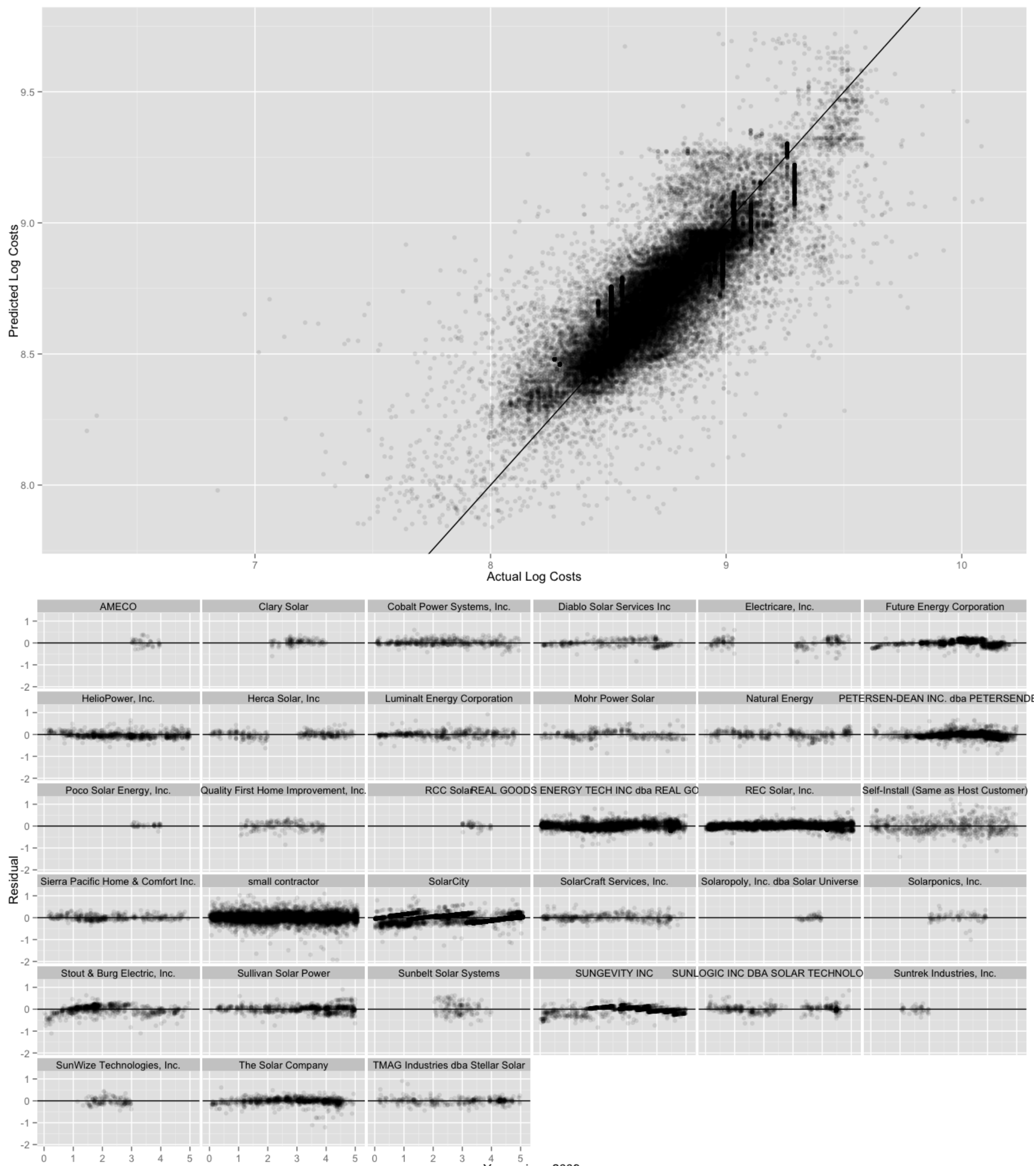

Figure 10: A plot of the simulated posterior residuals by contractor. The residuals are mostly centered around zero and no obvious patterns emerge other than some streaks for a few contractors. These show constant cost reporting over time from contractors using a leasing model.

ate. This also distinguishes solar power from most other forms of electricity generation. The decision of whether or not to invest is not made by an informed electricity utility executive, but rather regular home- and business-owners with limited industry knowledge and financial and engineering resources.

Uncertainty and information asymmetry becomes a major factor in the investment decision. This article has argued that the dramatic fall in solar power system costs in California between 2009 to 2013 and corresponding boom in installations can not be explained by new Chinese panel production in isolation. Instead, the simultaneous introduction of a leasing model helped overcome information asymmetries and uncertainty, at least partly related to the quality of Chinese panels.

This article has not explicitly set out to explore solar power policy, but several implications do emerge from this research. In Germany, also a leader in solar photovoltaic installations, only homeowners who themselves own their own solar system can collect government production subsidies. The flexibility of California s rules allowed for the introduction of leasing models and in turn lower overall prices.

Trade policy is also closely related to the subject of this article. In 2014, after the period studied in this article, tariffs of at least 30 percent were imposed by the US Department of Commerce on Chinese and Taiwanese solar panels. A full analysis of the merits and fairness of these sanctions are beyond the scope of this article, however this article clearly shows how competition from Chinese manufacturers drove down overall system costs and spurred increased installations. Subsidizing solar systems while at the same time imposing tariffs on imported panels seem like contradictory actions if the aim is to increase renewable energy production.

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A Software

For data cleaning and manipulation I used the python package Pandas [McKinney, 2012]. I use the R statistical programming package for all analysis in this article [R Core Team, 2013]. I use the R packages ggplot2 and ggmap for plotting [Wickham, 2009, Kahle and Wickham, 2013], plyr for data manipulation [Wickham, 2011], texreg for table formatting [Leifeld, 2013], and lme4 [Bates et al., 2014a] for implementation of multilevel models. All code for the analysis is also available at my website at `jmaurit.github.io\#solar_lemons`.

B Regression Tables

	Prob. of Lease
(Intercept)	-4.00^{***}
	(0.17)
time_years	0.58^{***}
	(0.03)
nationalityChina	-1.87^{***}
	(0.21)
nationalityGermany	0.89^{***}
	(0.21)
nationalityIndia	-14.32^{***}
	(3.44)
nationalityJapan	0.31
	(0.18)
nationalityNorway	2.96^{***}
	(0.21)
nationalitySouth Korea	-4.75^{***}
	(0.61)
nationalitySpain	-0.53^{*}
	(0.24)
nationalityTaiwan	-10.30^{***}
	(2.37)
nationalityUS	-0.14
	(0.18)
time_years:nationalityChina	0.41^{***}
	(0.04)
time_years:nationalityGermany	-0.26^{***}
	(0.04)
time_years:nationalityIndia	2.85^{***}
	(0.68)
time_years:nationalityJapan	-0.03
	(0.03)
time_years:nationalityNorway	-0.47^{***}
	(0.04)
time_years:nationalitySouth Korea	0.76^{***}
	(0.10)
time_years:nationalitySpain	0.12^{*}
	(0.05)
time_years:nationalityTaiwan	1.53^{***}
	(0.37)
time_years:nationalityUS	0.14^{***}
	(0.03)
AIC	123058.44
BIC	123252.16
Log Likelihood	-61509.22
Deviance	123018.44
Num. obs.	118890

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 3: Full results for logit model of the probability of a sysmem being leased.

	Log Costs
(Intercept)	9.18^{***}
	(0.00)
time_years	-0.10^{***}
	(0.00)
lease	0.09^{***}
	(0.01)
china	0.10^{***}
	(0.01)
time_years:lease	-0.01^{***}
	(0.00)
time_years:china	-0.03^{***}
	(0.00)
lease:china	-0.40^{***}
	(0.02)
time_years:lease:china	0.07^{***}
	(0.00)
R^2	0.38
Adj. R^2	0.38
Num. obs.	118890

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 4: Full model results of log costs of installed solar systems.