

A Model for Commercial Adoption of Photovoltaic Systems in California

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To promote the installations of solar photovoltaic (PV) systems efficiently, it is important to quantify the impact of government incentive programs and solar PV system life-cycle costs on customer adoption. In this paper a model for commercial solar PV adoption is developed with explanatory variables such as government incentive programs and solar PV system installation costs. The adoption model is built on top of the Generalized Bass diffusion framework. The model is applied to forecast commercial solar PV adoption in Southern California. Asymptotic standard errors of the parameter estimates are calculated to verify the significance of the explanatory variables. Empirical results show that decreasing solar PV installation costs and government incentive programs are the main forces that drove the growth of commercial solar PV adoption. In the case of Southern California, we also discover that government incentive programs and PV installation costs have a much higher impact on large commercial customers than small commercial customers. Our Generalized Bass diffusion model of commercial solar PV adoption yields a lower root-mean-square error (RMSE) than the basic Bass Diffusion model. In addition, the commercial solar PV adoption model predicted that the eventual adoption rate of solar PV system is higher for large commercial customers.

Keywords: Generalized Bass Diffusion Model; Innovation Diffusion; Nonlinear Regression Models; Photovoltaic Energy

I. INTRODUCTION

Solar energy, including both the solar thermal and photovoltaic, grew rapidly in the U.S. from 64 trillion Btu in 2001 to 427 trillion Btu in 2014⁴¹. The U.S. solar energy's share of total new electricity generation capacity increased from 10% in 2012 to 32% in 2014¹⁹. In particular, the small-scale distributed solar PV system, which accounts for 33% of the total solar generation has grown significantly in the United States over the past several years⁴⁰. As a vital component of the U.S. renewable energy portfolio, continuing adoption of solar PV systems is key to both reducing greenhouse gas emissions and building a clean energy workforce. For example, the solar industry workforce in the United States grew more than 50% in the past four years and now employs more than 140,000 workers³⁵.

To stimulate the growth of the solar PV market, the federal and state governments have been supporting research and strengthening U.S. solar manufacturing capabilities to drive down the installation cost of solar PV³⁵. In addition, the U.S. imported a significant portion of solar equipment from Asia^{11,20,24}. The boom in global solar module production also led to a precipitous decline in solar PV module prices. In California, the median installed cost for systems of 10-100 kW-dc in size dropped 56% from \$10.7/W-dc in 2001 to \$4.7/W-dc in 2013³. In addition, the federal and state governments developed many incentive programs to directly promote the adoption of solar PV systems. At the federal level, the Investment Tax Credit (ITC) was implemented in 2006, which provides 30% tax credit for solar systems on residential and commercial properties³⁰. At the state level, California has been leading the way by implementing an array of incentive programs including the California Solar Initiative (CSI), the New Solar Homes Partnership (NSHP), the Self-Generation Incentive Program (SGIP), etc^{8,10,39}.

The drop in solar PV cost and direct government incentives have contributed to the rapid growth in the penetration of small-scale distributed solar PV systems in the energy market. However, there is a lack of rigorous analyses that quantify the impact of government incentives and solar PV costs on adoption. Such

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analyses will provide critical and useful feedback to government agencies to improve the design of future renewable energy incentive programs, and serve as the basis of forecasting the adoption.

Several diffusion models have been developed to describe the adoption of new products and technologies. The Bass Model (BM)⁴ is a simple but effective model which described the empirical adoption of a wide range of products and services. The BM was extended to the Generalized Bass Model (GBM)⁶, by including decision variables such as price, marketing effort, etc. In the BM⁴, the model parameters were estimated by ordinary least squares (OLS). A maximum likelihood estimation (MLE) approach was proposed by Schmittlein and Mahajan²⁸, and it fits better to the observations than OLS and allows for one-step ahead forecasts. A nonlinear least squares approach was proposed by Srinivasan and Mason³², and it corrects the underestimates of standard errors of the estimated parameters in the MLE approach.

Many researchers have studied the mechanics of residential solar PV adoption using various approaches. Rai and McAndrews²⁵ and Schelly²⁷ analyzed multiple factors that influence residential customers' decisions on solar PV adoption. These factors include government incentives and solar PV costs. However, these analyses were conducted in the form of surveys and interviews. Agarwal et al.¹ used BM without any decision variables to model residential solar PV adoption. The model parameter estimates were not as robust as the MLE and nonlinear least squares approach. GBM was used by Guidolin and Mortarino¹⁶ to model adoption patterns of PV systems in many countries. In the GBM, institutional measures, policies, and government interventions were modeled as perturbations in the form of exponential shocks and rectangular shocks. The model proposed was helpful in explaining the impact of short-term interventions, such as a moment of opinion change due to social incidents. However, it did not clearly explain the effects of long-term interventions such as solar PV incentive programs and the dropping installation cost of PV systems on adoption.

Since its emergence in 2007, the third-party ownership (TPO) model has earned a significant share in the solar PV market⁴². The rapidly growing third-party PV ownership has prompted a few researchers to study its impact on residential solar PV adoptions.¹³ found that the introduction of third-party PV ownership enticed a new demographic to adopt residential PV systems which increased the total demand for PV systems. The economics of buy or lease a residential PV system is studied in²⁶. It is shown that the choice of contract type and payment structure have implications for the total cost to residential solar PV customers over the lifetime of the contract¹².

To the best of our knowledge, this paper is the first to study adoption of distributed commercial PV systems. The adoption of commercial PV systems include both purchasing/owning the solar PV system and deployment of solar PV system through a TPO contract.²⁹ Note that the drivers and barriers to distributed commercial PV adoption are different from that of residential adoption. For example, a higher percentage of buildings are leased in the commercial sector than the residential sector^{37,38}. Therefore, the commercial PV adoption faces bigger challenges in the form of incentive splitting between the building owner and multiple-tenants. In addition, many limited liability companies (LLC) that own commercial properties have low credit ratings which make solar financing more difficult. Finally, though the total number of commercial customers are smaller than residential customers, their average solar PV size is much larger. Figure 1 shows the number of solar PV installations, and Figure 2 shows their average solar PV size each year in Southern California. From 2001 to 2014, the number of commercial installations were only about 3% of the total installations of all types, but the commercial solar PV capacity was about 40% of the total installed PV capacity.

Compared with other related work, this paper makes the following unique contributions:

1. This paper develops a GBM for commercial PV adoption, which quantifies the impact of solar PV costs and government incentive programs on the adoption.
2. The GBM for commercial PV adoption is also capable of forecasting the eventual commercial PV adoption rate and quantifying the delayed effect of explanatory variables on adoption.
3. The model is applied to fit the empirical commercial PV adoption data in Southern California. Nonlinear least squares is applied to estimate the model parameters and their asymptotic standard errors. The empirical results show that large commercial customers are more susceptible to the influence of PV costs and government incentives than small commercial customers.
4. By changing the cost and incentive rates fed into the model, adoption curves can be forecasted under different cost and policy conditions. This can be a useful tool for the government to evaluate its renewable energy technology incentive policies.

The rest of the paper is organized as follows. Section II reviews the Bass Model and Generalized Bass Model. Section III presents the model for commercial PV adoption. In Section IV, the solar PV adoption model is fitted and validated using historical adoption data. Section V quantifies the impact of federal and state incentives on California commercial PV adoption. Section V presents the conclusions and policy

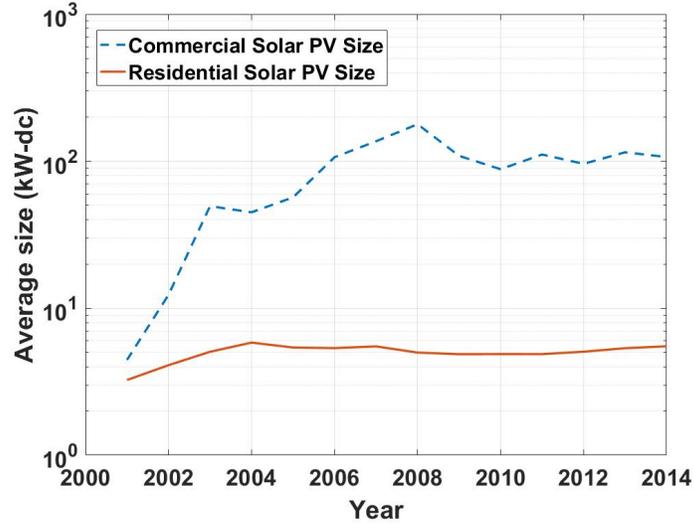


FIG. 1: Average installed PV size by customer type in Southern California

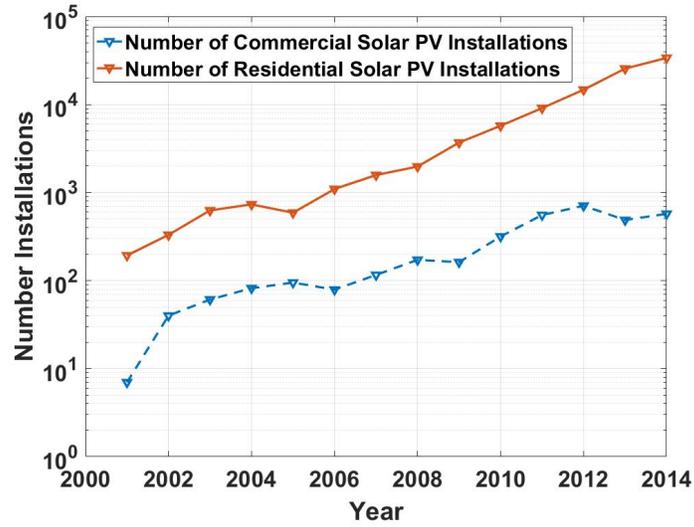


FIG. 2: Number of solar PV installations by customer type in Southern California

implications of the work.

II. OVERVIEW OF BASS MODEL, GENERALIZED BASS MODEL AND PARAMETER ESTIMATION APPROACHES

A. Bass Model and Generalized Model

The Bass diffusion model is a well-established model of innovation and technology adoption in the market. It can be described by the following formulation⁴:

$$\frac{f(t)}{1 - F(t)} = p + qF(t) \quad (1)$$

$F(t)$ is the cumulative adoption function. $F(t) \rightarrow 1$ as $t \rightarrow \infty$. $f(t) = \frac{dF(t)}{dt}$ is the adoption rate. The left hand side of the function describes the conditional adoption rate at time t , and it is controlled by two factors: p and q . p is the innovation factor, describing innovative adopters who are willing to adopt the product themselves, and q is the imitation factor, describing the adopters who follow other adopters' use of the product. Both p and q are positive.

The solution of equation (1) is as following⁴:

$$F(t) = \frac{1 - e^{-(p+q)t}}{1 + \frac{q}{p}e^{-(p+q)t}} \quad (2)$$

$$f(t) = \frac{\frac{(p+q)^2}{p}e^{-(p+q)t}}{\left(1 + \frac{q}{p}e^{-(p+q)t}\right)^2} \quad (3)$$

To include marketing effort factors in the diffusion model, Frank M. Bass introduced the generalized Bass model⁶. The GBM is described as follows:

$$\frac{f(t)}{1 - F(t)} = [p + qF(t)]x(t) \quad (4)$$

where $x(t)$ is called ‘‘current marketing effort’’, reflecting the influence of market factors on the adoption rate at time t . Define the cumulative marketing effort $X(t) = \int_0^t x(\tau)d\tau$ and let $X(0) = 0$. The solution of (4) is given by:

$$F(t) = \frac{1 - e^{-X(t)(p+q)}}{1 + \frac{q}{p}e^{-X(t)(p+q)}} \quad (5)$$

$$f(t) = x(t) \frac{\frac{(p+q)^2}{p}e^{-X(t)(p+q)}}{\left(1 + \frac{q}{p}e^{-X(t)(p+q)}\right)^2} \quad (6)$$

$x(t)$ is a function of one or more decision variables. For example, product price was chosen as a decision variable by Bass et al.⁶. Under the argument of diminishing returns, $x(t)$ can be defined as below:

$$x(t) = 1 + [(dPr(t)/dt)/Pr(t)]\beta_0 \quad (7)$$

where $Pr(t)$ is the price at time t , and β_0 is a weight coefficient expected to be negative. Let $\Phi_0(t) = \ln \frac{Pr(t)}{Pr(0)}$, then

$$X(t) = t + \beta_0\Phi_0(t) \quad (8)$$

B. Parameter Estimation Methods

In this subsection, we describe how to perform parameter estimations for diffusion models. Let M denote the total customer population. The eventual cumulative solar adoption denoted by m is only a portion of M . Define the eventual adoption rate c ($0 \leq c \leq 1$) such that $m = Mc$. To estimate the parameters, we use the observation of a series of historical adoption s_i , ($i = 1, 2, 3, \dots, N$), which is the number of solar PV systems installed in time interval i . For example, let s_i be the number of adopted solar PV systems in month i and let $t_i = i$. Then from (1), the following is derived:

$$mf(t_i) = mp + (q - p)(mF(t_i)) - (q/m)(mF(t_i))^2 \quad (9)$$

In the work of Agarwal et al.¹, Bass⁴, $mf(t_i)$ was replaced by s_i , and $mF(t_i)$ was replaced by $\sum_{j=1}^i s_j$. Then OLS estimation can be applied to (9) to estimate parameters p , q , and m . The OLS approach has two drawbacks. First, the replacement is not precise because it uses the aggregated adoption of time intervals

to replace instantaneous adoption rates. The diffusion model is time continuous, but it is estimated using discrete time series data. Second, disturbances such as noise and parameter misspecifications were not appropriately modeled.²⁸ showed that there is bias in such methods.

To overcome these drawbacks, nonlinear least squares estimation was proposed by Srinivasan and Mason³², which also yields valid estimation of the standard errors of the estimators. The disturbance is modeled as follows:

$$s_i = m[F(t_i) - F(t_{i-1})] + u_i \quad (10)$$

where $F(t_i)$ can be in forms of either (2) or (5). u_i is the net disturbance of sampling errors, the impact of excluded factors, misspecified parameters, etc. Then the parameters in $x(t)$, p , q , and m can be estimated by the nonlinear least squares (NLS) approach:

$$\min \sum_{i=1}^N \{m[F(t_i) - F(t_{i-1})] - s_i\}^2 \quad (11)$$

In this paper the NLS approach is used to estimate the model parameters.

III. COMMERCIAL SOLAR PV ADOPTION MODEL

A. Choice of Decision Variables

To apply the GBM, appropriate decision variables need to be chosen first. As mentioned in Section I, two explanatory variables have significant influence on PV adoption: installed PV system costs and government incentives. The installed PV system costs include the PV module price and non-module costs such as inverters, mounting hardware, labor and permitting fees, and installer profit. Government incentives include both federal level and state level incentive programs. They can be in forms of tax credits like the ITC, rebates like the CSI, etc.

Government incentives have different impacts on different groups of commercial customers. Based on PV system sizes, the adopters can be divided into 3 groups: 0-10 kW-dc, 10-100 kW-dc, and 100-1000 kW-dc. Figure 3 depicts the percentage of commercial customers in each group who applied and received California solar PV installation incentives on an annual basis. From 2007 to 2014, 88.27% of commercial customers in the 100-1000 kW group received state level incentives, whereas 63.22% of customers in the 10-100 kW group received incentives; only 34.20% of customers in the 0-10 kW group received incentives. Though no information is available on the application rate of the ITC, it can be inferred that the ITC may also have a higher application rate in the 100-1000 kW range than the other two ranges. A decision variable should describe a factor that impacts most of the PV adopters. If there is a large portion of adopters who do not apply for incentive programs, then the incentive may not be a good decision variable. In this case, the incentive can be a suitable decision variable for the 100-1000 kW group, probably a suitable decision variable for the 10-100 kW-dc group, and not a good decision variable for the 0-10 kW-dc group. Therefore, in the 0-10 kW-dc group, we use only the cost as the decision variable, while in the 10-100 kW-dc group and the 100-1000 kW-dc group we use both incentives and the cost. We can verify if the incentive is a suitable decision variable by checking the significance level of parameter estimates.

One may propose that savings in electricity bills are also important factors. This is true, because customers with solar PV systems consume less electricity from utility companies. This factor is also related to government policy. For example, the Net Energy Metering program(NEM)³³ is supported by the government in California, and the program allows customers with solar PV to pay their utility bills based on the net energy consumption from the grid. If the solar PV generates more energy than a customer's consumption, the energy can be sold to utility companies at the retail price.

Electricity bill savings are not considered in our model, because savings are difficult to estimate for a large group of potential commercial customers. The estimation of savings is difficult for two reasons. First, the tariff rates of utility companies are hard to forecast. There are many different types of tariffs for commercial customers, and they change frequently. To make the issue more complicated, the growth of solar PV adoption can affect the tariff in turn⁷. The second reason is that it is difficult to forecast each customer's electricity usage pattern in the long term. The electricity usage patterns of commercial customers depend on a variety of factors such as their locations, business, and building types.

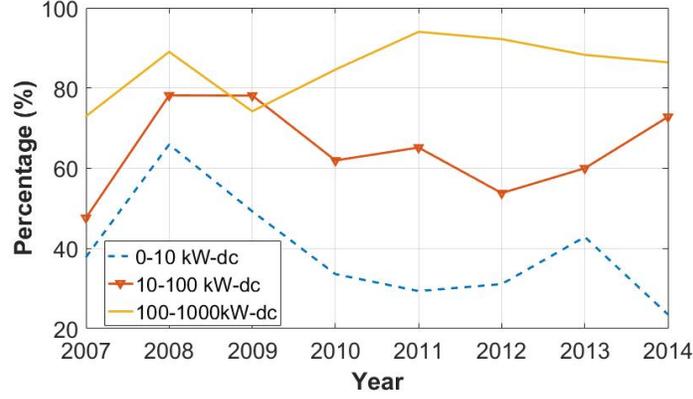


FIG. 3: Percentage of commercial PV installations that benefited from the CSI program in 3 size ranges.

Overall, in the solar PV adoption model, the installation cost is one general decision variable for all customer groups, and the incentive is another decision variable for the customer groups that have high incentive adoption rate.

B. Commercial Solar PV Adoption Model with Costs and Incentive Rates as Decision Variables

In this subsection, we address the question of how to map incentives and costs to $x(t)$ in the GBM. When the installation cost is the only decision variable, $x(t)$ and $X(t)$ can be defined as (7) and (8). When both the incentive and the cost are decision variables, they are mapped to $x(t)$ in the following way. Government incentive programs have varying rates, which can be transformed into monetary savings. Then the monetary saving is combined with the solar PV cost. Let $Pr(t)$ be the solar PV cost at time t , and $INC(t)$ be the money saved from incentive programs at time t . Both $Pr(t)$ and $INC(t)$ have the unit of \$/W-dc. Then we define the net expense $E(t)$ of installing solar PV as follows:

$$E(t) = Pr(t) - INC(t) \quad (12)$$

Similar to (7), with the law of diminishing returns, $x(t)$ is derived as follows:

$$x(t) = 1 + [(dE(t)/dt)/E(t)]\beta_0 \quad (13)$$

where β_0 is a weight coefficient expected to be negative. Let $\Phi_0(t) = \ln \frac{E(t)}{E(0)}$, then

$$X(t) = t + \beta_0 \Phi_0(t) \quad (14)$$

From (5), the cumulative solar PV adoption function at time t is:

$$F(t) = \frac{1 - e^{-[t+\beta_0\Phi_0(t-d)](p+q)}}{1 + \frac{q}{p}e^{-[t+\beta_0\Phi_0(t-d)](p+q)}} \quad (15)$$

In (15) a variable d is introduced to represent the effect of time delay. d represents the time lag between the time when new incentive program or pricing information is made available and the time when a PV system is installed using the new information. d includes the decision making time for commercial customers, the time taken to apply for incentive programs and acquire necessary permits, time for installation, etc. When fitting the GBM, M is known, so c can be estimated directly. The NLS parameter estimation problem (11) can be reformulated as:

$$\min \sum_{i=1}^N \{Mc[F(t_i) - F(t_{i-1})] - s_i\}^2 \quad (16)$$

M and s_i are exogenous variables. p , q , β_0 , d , and c are model parameters that need to be estimated by solving NLS problem. For simplicity in estimation, define $b = p + q$ and $a = q/p$. Then the parameters to be estimated are c , d , a , b , and β_0 .

IV. CASE STUDY

In this section, a case study is conducted to validate the usefulness of the proposed GBM in modeling the commercial solar PV adoption. The historical PV adoption data, from 2001 to 2014 in the service territory of Southern California Edison³¹, is used in the empirical study. For California solar PV adopters, the major incentive programs considered include the CSI at the state level and the ITC at the federal level. The impact of these two incentive programs and the PV cost is analyzed in this section. The GBM parameter fitting results will be presented and compared with the BM.

A. Description of Datasets

The raw datasets include four parts: 1) commercial customers' aggregated electrical energy usage; 2) solar PV adopters' information; 3) historical installed PV cost; and 4) historical information about incentive program applications. The details of the datasets are as follows:

1) There are about 676000 commercial electric customers in SCE's service territory. These commercial customers are divided into various groups based on building/business types derived from the North American Industry Classification system. In each building type, customers are further divided into several subcategories based on their annual electricity usage. The average annual usage for customers in each subcategory is recorded.

2) Information on 3000 commercial solar PV adopters was gathered, including their adoption dates, PV system sizes, annual electricity usages, and building types from 2001 to 2014. The 3000 commercial solar PV adoptions include both purchasing/owning the solar PV and deployment of solar PV system through TPO contracts.

3) The median installed PV cost in California from 1998 to 2013³ of three PV size ranges: 0-10 kW-dc, 10-100 kW-dc, and 100-1000 kW-dc.

4) Commercial solar PV incentive application data includes incentive application dates, proposed solar PV system sizes, and rebates from the CSI program⁹.

B. Preprocess of the Datasets

1. Forecast the Commercial Solar PV Size of Potential Adopters

As mentioned in Section III A, incentive programs have different impacts on different size groups. Three Generalized Bass Models will be developed for customers with an estimated PV system size of 0-10 kW-dc, 10-100 kW-dc, and 100-1000 kW-dc respectively. The entire commercial customer population needs to be divided based on their forecasted PV system size, so that we can obtain M for each size group. We assume that customers of the same building type have similar preference in choosing the size of a solar PV system. Intuitively, customers who use more electricity are likely to adopt larger PV systems. However, it is difficult to find a deterministic relationship between the PV size and the annual electricity usage. For example, in Figure 4, there is a large variation in the PV system size for customers who have very similar annual electricity consumptions.

Nevertheless, given a potential customer's annual electricity usage and building type, we can still estimate the probability that the customer will install a solar PV system in a certain size range. For example, in Figure 4, for customers with an annual usage of 10^5 - 10^6 kWh, there are n_1 , n_2 , and n_3 adoption records in the three size groups. Then we can estimate that for any "education-primary" customer with an annual usage of 10^5 - 10^6 kWh, the probabilities to adopt a solar PV system of size 0-10 kW-dc, 10-100 kW-dc, and 100-1000 kW-dc are $n_1/(n_1 + n_2 + n_3)$, $n_2/(n_1 + n_2 + n_3)$, and $n_3/(n_1 + n_2 + n_3)$ correspondingly. The procedure to estimate these probabilities is carried out for each building type, and the detailed process is as follows:

Step 1: Divide the adoption records into four groups by their annual electricity usage: $<10^4$ kWh, 10^4 - 10^5 kWh, 10^5 - 10^6 kWh, and $\geq 10^6$ kWh. In each electricity usage group, further divide the records into three groups by the solar PV sizes: 0-10 kW-dc, 10-100 kW-dc, and 100-1000 kW-dc.

Step 2: In each electricity usage group, calculate probabilities that a customer will adopt a solar PV system in the three size groups.

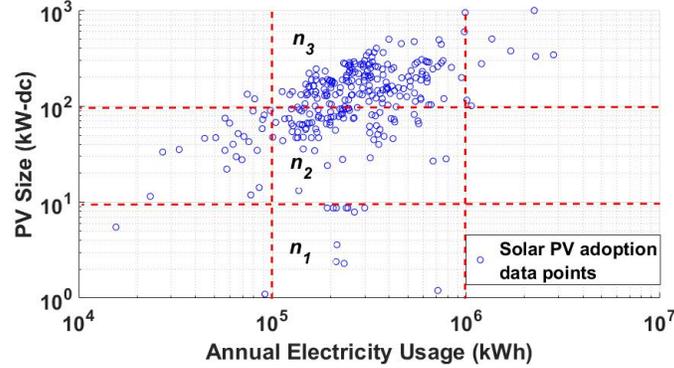


FIG. 4: Adoption records of 297 customers in the group “education-primary,” divided into different PV size groups and annual electricity usage groups.

Step 3: In each size group of each electricity usage group, calculate the average solar PV size. This is used to forecast the average solar PV size of potential adopters. If a building type has too few adoption records, we merge it with other similar building types.

In each building type, by multiplying the probability by the customer population in dataset 1 of the same electricity usage range, we can get the number of potential adopters in each size group. Assuming that customers’ electricity usage increases by 2% annually, we can repeatedly estimate M each year, and we replace the constant customer population M in (16) with $M(t)$. Figure 5 shows the estimated total customer population over time for each PV system size range. $M(t)$ changes slightly over time, since we assume customers’ electricity usage increases gradually on an annual basis.

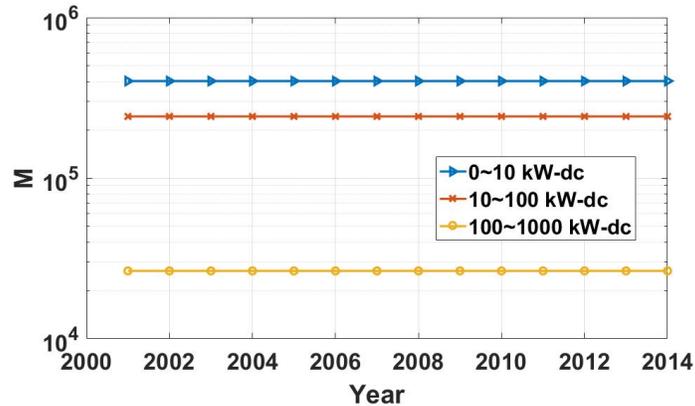


FIG. 5: M of different size groups.

2. Calculation of Incentive Savings

The incentives received by commercial customers from the CSI program are estimated by taking the average of each year’s cash rebates of the entire state of California, based on part 4) of the data set. This model is a simplification of the actual CSI incentive program, which has a 10-tier structure with available incentive funds decreasing over time. The federal level ITC has been in effect since 2006. According to the latest ITC amendment, the incentive credit for a solar PV system will be 30% of expenditures till 2019. This incentive credit rate is scheduled to decrease from 30% in 2019 to 10% in 2022 and beyond³⁶.

C. Estimation of Model Parameters and Standard Errors

Model parameter estimation is conducted by using 168 data points of monthly solar PV system adoption from January 2001 to December 2014. The RMSE of the estimated adoption is calculated for the same time range. The NLS problem is solved by the Nelder-Mead simplex algorithm²². The monthly installed PV system cost and incentive are calculated by linear interpolation, using the annual installed PV cost and incentives data.

Before model parameters are estimated, the monthly adoption data series is smoothed using moving average method with a window of 3, 5, and 7 months. The smoothing process mitigates the spikes in the historical monthly adoption data. As mentioned in Section III A, GBM with both incentives and costs is used for the 10-100 kW-dc and the 100-1000 kW-dc groups, and GBM with only costs is used for the 0-10 kW-dc group. However, for the size groups 0-10 kW-dc and 10-100 kW-dc, the asymptotic standard errors are larger than the parameter estimates of β_0 . This means β_0 is insignificant in these two cases. Therefore instead of GBM, BM is used in the 0-10 kW-dc group, and incentives are removed from the GBM for the 10-100 kW-dc group.

To validate the significance of estimated parameters, asymptotic standard errors are calculated as follows¹⁵. Assume N sample points are used in the estimation. Let $\theta = [c \ d \ a \ b \ \beta_0]'$ be the vector of parameters. Let K be the degree of θ . Based on (16), let $h(t_i, \theta) = Mc[F(t_i) - F(t_{i-1})]$. The variance of disturbance u_i is estimated as follows:

$$\hat{\sigma}^2 = \frac{1}{N - K} \sum_{i=1}^N [S_i - h(t_i, \hat{\theta})] \quad (17)$$

where $\hat{\theta}$ is the estimated parameters. Then

$$X^{0'} X^0 = \sum_{i=1}^N \left(\frac{\partial h(t_i, \theta_0)}{\partial \theta_0} \right) \left(\frac{\partial h(t_i, \theta_0)}{\partial \theta_0} \right)' \quad (18)$$

The estimated covariance matrix of θ is given by:

$$Est.Asy.Cov[\theta] = \hat{\sigma}^2 (X^{0'} X^0)^{-1} \quad (19)$$

The standard errors of p and q , as functions of a and b , can be estimated as follows³⁴. Let $g(\theta)$ be a function of the parameter vector θ , the standard error of g can be estimated by:

$$SE(g) = \left(\frac{\partial g(\hat{\theta})}{\partial \theta} \right)' Est.Asy.Cov[\theta] \left(\frac{\partial g(\hat{\theta})}{\partial \theta} \right) \quad (20)$$

By following the steps above, the estimated parameters and their asymptotic standard errors are calculated and shown in Tables I, II, and III. The fitted PV adoption curves with a smoothing window of 3 months are shown in Figures 6, 7, and 8.

TABLE I: Estimated parameter values and their standard errors (SE), using GBM with the incentives and cost, 100-1000 kW-dc

window		d	c	a	b	p	q	β_0	RMSE	BM RMSE
3	value	17	6.49E-02	2.10E+02	2.89E-02	1.37E-04	2.88E-02	-1.44E+01	2.52	2.89
	SE	5.78E-01	9.25E-03	7.01E+01	2.85E-03	3.38E-05	2.88E-03	3.22E+00	-	-
5	value	17	4.97E-02	7.01E+02	3.56E-02	5.07E-05	3.56E-02	-2.37E+01	1.86	2.43
	SE	2.85E-01	3.16E-03	2.13E+02	2.00E-03	1.28E-05	2.01E-03	2.86E+00	-	-
7	value	17	4.58E-02	1.21E+03	3.96E-02	3.26E-05	3.96E-02	-2.23E+01	1.60	2.16
	SE	2.67E-01	2.19E-03	3.42E+02	1.80E-03	7.88E-06	1.81E-03	2.49E+00	-	-

TABLE II: Estimated parameter values and their standard errors (SE), using GBM with cost, 10-100 kW-dc

window		d	c	a	b	p	q	β_0	RMSE	BM RMSE
3	value	9	8.28E-03	1.13E+02	2.45E-02	2.15E-04	2.43E-02	-7.15E+01	3.60	3.81
	SE	5.66E-01	5.34E-04	4.32E+01	3.53E-03	5.32E-05	3.57E-03	1.97E+01	-	-
5	value	11	7.49E-03	2.56E+02	3.16E-02	1.23E-04	3.15E-02	-5.16E+01	3.09	3.32
	SE	5.99E-01	3.50E-04	1.02E+02	3.74E-03	3.49E-05	3.77E-03	1.47E+01	-	-
7	value	11	8.26E-03	1.80E+02	3.03E-02	1.64E-04	3.01E-02	-3.82E+01	2.75	2.93
	SE	6.54E-01	4.04E-04	5.78E+01	3.02E-03	3.77E-05	3.05E-03	1.06E+01	-	-

TABLE III: Estimated parameter values and their standard errors (SE), using BM, 0-10 kW-dc

window		c	a	b	p	q	RMSE
3	value	3.28E-03	1.57E+03	5.31E-02	3.37E-05	5.30E-02	3.50
	SE	1.67E-04	6.94E+02	3.40E-03	1.27E-05	3.41E-03	-
5	value	3.25E-03	1.67E+03	5.36E-02	3.20E-05	5.36E-02	2.87
	SE	1.34E-04	6.08E+02	2.80E-03	9.98E-06	2.81E-03	-
7	value	3.24E-03	1.72E+03	5.39E-02	3.13E-05	5.39E-02	2.42
	SE	1.12E-04	5.29E+02	2.37E-03	8.27E-06	2.38E-03	-

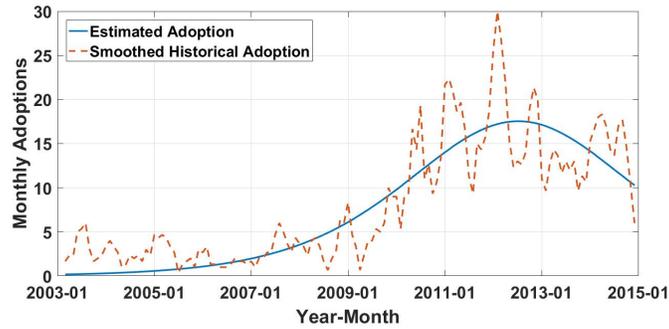


FIG. 6: Adoption curve fitting of 0-10 kW-dc

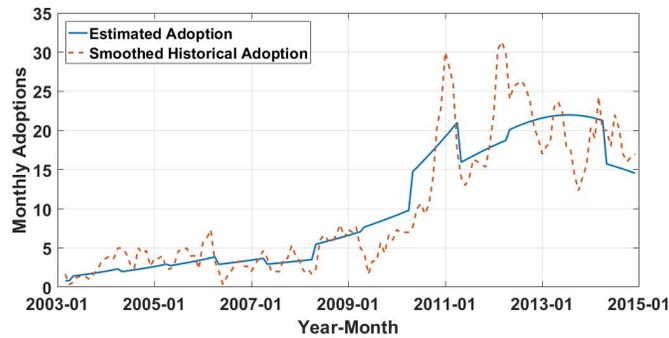


FIG. 7: Adoption curve fitting of 10-100 kW-dc

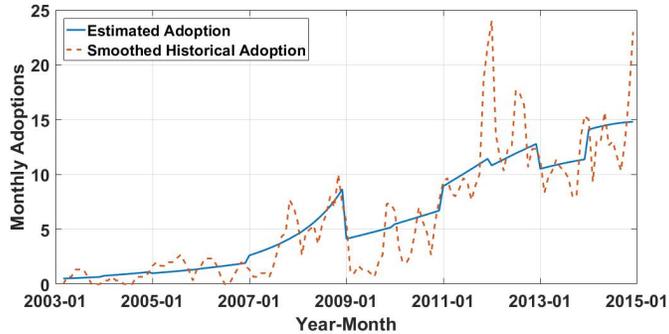


FIG. 8: Adoption curve fitting of 100-1000 kW-dc

D. Interpretations of Model Fitting Results

1. Validity of the Parameter Estimation and RMSE

As shown in Tables I, II, and III, the estimated parameters are stable across different smoothing windows, i.e., the estimated parameters under different smoothing windows are very similar. The estimated standard errors are much smaller than the parameter values. The explanatory variables in all three models are considered to be significant. In the 100-1000 kW-dc and the 10-100 kW-dc groups, the GBM have lower RMSE than the BM.

2. Interpretations of Parameter Estimates and Effective Decision Variables

As discussed in⁵, the innovation factor p represents the contribution to the new adoptions that do not depend on the number of previous adoptions. These adoptions are due to some influence outside the social system of the customers, and let's call it the external influence. On the other hand, the imitation factor q represents the contribution to the new adoptions that are due to the prior adoptions. The probability of these adoptions are proportional to the prior market penetration level. The new adoptions due to q can be interpreted as an effect of word-of-mouth from customers who are satisfied with the product. In the case of solar PV adoption, the imitation factor q represents the effect of solar PV information spread by prior adopters. From Tables I, II, and III, we can observe that the values of p in the 100-1000 kW-dc and the 10-100 kW-dc groups are larger than that in the 0-10 kW-dc group, while the values of q in the 100-1000 kW-dc and the 10-100 kW-dc groups are smaller than that in the 0-10 kW-dc group. This shows that larger-sized groups are more likely to be affected by external influence, compared with smaller-sized groups. The external influence includes advertisement and direct sales pitch from solar PV developers. This phenomena is called the small commercial solar gap¹⁷. In addition, small commercial solar projects often have varying contract terms, power purchasers without credit ratings, and site-specific project requirements. The customer procurement and transaction costs associated with smaller commercial projects are nearly the same as those for larger deals. These difficulties have often led developers to focus their attention on larger commercial projects.

As mentioned in Section III A and Section IV C, the final effective decision variables for the three size groups are different. For the 100-1000 kW-dc group, both the incentive and the cost have strong impacts on the solar PV adoption; for the 10-100 kW-dc group, the impact of the incentive is much weaker and the incentive is insignificant; for the 0-10 kW-dc group, even the cost is no longer a significant decision variable. These observations further corroborate the small commercial solar gap phenomena.

3. Forecasting Eventual Adoption Rate and Delay Effect

Note that the 100-1000 kW-dc group has the largest c and the 0-10 kW-dc group has the smallest c . This shows that the eventual solar PV system adoption rate is higher for customer groups that plan to install

larger solar PV systems. This observation can be explained intuitively as follows. With higher electricity costs, larger commercial customers are more motivated to install the solar PV system if it makes economic sense. In addition, with more building roof space, larger commercial customers typically have better solar PV mounting conditions than smaller customers. Finally, larger customers are more likely to be in better financial condition, which provides them easier access to solar PV system financing options.

Note that the eventual commercial solar PV adoption rate estimated in our model is much lower than the residential and/or commercial solar PV adoption rate estimated in other literatures^{1,2,14,21,23}. In the work of² and¹, the eventual adoption rate is simply assumed to be 30% for residential customers. In the work of²³, instead of eventual adoption rate, total roof area suitable for solar PV installation is estimated. It is concluded that 60%-65% of the roof area of commercial and industrial buildings, and 22%-27% of the roof area of residential buildings are suitable for solar PV installation. In the work of¹⁴, the eventual adoption rate is estimated to be 51% for residential customers and 52% for commercial customers. The results of both²³ and¹⁴ are based on analysis of the building roof space data. However, not all buildings suitable for solar PV installations will eventually adopt solar PV. The aforementioned references ignored the fact that the commercial customers may not be the owner of the building. This leads to the incentive splitting problem, where building owners pay for the solar PV system, but cannot easily recover savings from reduced electricity use that accrue to the tenants. Furthermore, if commercial building occupants only signed short-term leases, they will not have enough time to recoup the installation costs of solar PV systems¹⁸.

Another observation from the model fitting result is that the effect of time delay d is larger in the 100-1000 kW-dc group than the 10-100 kW-dc group. As larger solar PV projects require substantial capital and may have a significant impact on the distribution network, deciding to adopt the solar PV system, securing the electrical permit and installing the system all require longer lead time.

V. QUANTITATIVE EVALUATION AND FORECAST OF THE IMPACT OF INCENTIVES AND SOLAR PV COSTS ON THE ADOPTION

The solar PV adoption model is a useful tool for policy evaluations. Once the model parameters are estimated, the impact of government incentives and declining cost of solar PV systems on the adoption can be quantified and forecasted. The adoption forecasting model can provide useful feedback to government policy makers in developing future renewable energy policies. In this section, we first quantify the impact of federal and state solar incentive programs on the adoption. The assumptions regarding incentive programs and solar PV system costs are as follows. The incentive for the CSI has been in effect since 2007, and is assumed to be zero beyond 2015. The ITC program has been in effect since 2006, and its investment credit rate is assumed to decrease from 30% in 2019 to 10% in 2022 and beyond. It is assumed that in the next five years, the solar PV system cost will be declining at the same historical rate.

By setting the CSI and/or the ITC to zero, we simulated what would have happened to the commercial solar PV system adoption without the incentive programs. Let's treat the cumulative solar PV adoption capacity without both incentive programs as the benchmark. Figure 9 shows the percentage increase in cumulative PV adoption capacity due to one or both of the incentive programs.

Figure 9 demonstrates that in 2008 the provisioning of the CSI program increased the cumulative solar PV adoption by 14.9% compared to the benchmark case, and the ITC program increased the cumulative PV adoption by 16.6%. By implementing both incentive programs, the cumulative solar PV adoption increased by 43.55% compared the benchmark case.

Based on the forecasting results, the ITC program has a greater influence than the CSI program on the commercial solar PV adoption in California. This is because the ITC provides more rebates than the CSI. In 2007, the CSI's average rebate was about 27.5% of the installation cost, but the rate kept dropping, and was only 7.5% in 2014; on the other hand, the ITC has kept a tax credit rate of 30% of the installation cost since 2006.

Similarly, we can also quantify and forecast the impact of solar PV systems' cost on adoption. As mentioned in Section I, the federal and state governments have been supporting research and strengthening solar manufacturing capabilities to drive down the cost. Let's treat the cumulative solar PV adoption capacity where the cost of solar PV system always stayed at the level of year 2001 as the benchmark. Figure 10 illustrates the impact of reduction in solar PV system cost on the cumulative PV system adoption. Figure 10 shows that in 2012, when the solar PV cost declined at the historical rate, the cumulative PV adoption capacity is 25.1% higher than the benchmark case; and if the cost had declined half as fast as the historical

rate, the cumulative adoption is 9.9% higher than the benchmark case where the cost had stayed at the same level as year 2001.

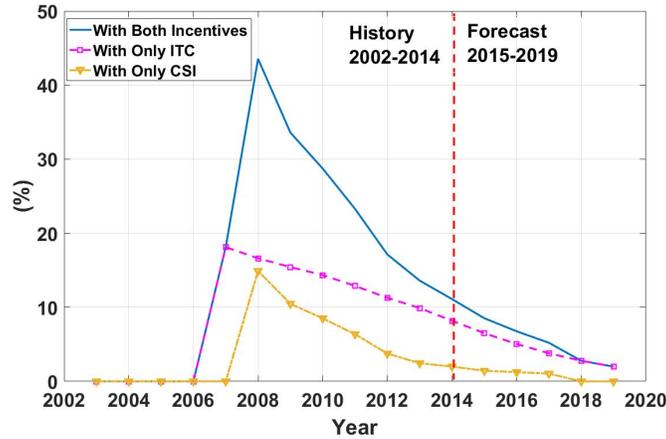


FIG. 9: Percentage increase of cumulative installed solar PV capacity under different incentive scenarios, 100-1000 kW-dc.

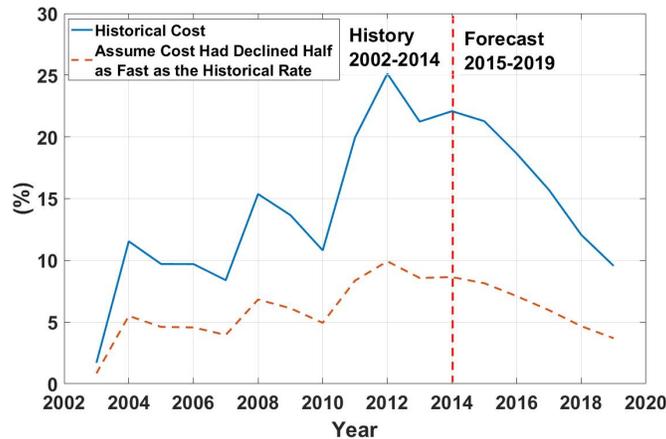


FIG. 10: Percentage increase of cumulative installed solar PV capacity under different cost assumptions, 100-1000 kW-dc.

VI. CONCLUSIONS AND FUTURE WORK

A commercial solar PV adoption forecasting model based on the Generalized Bass Model is developed in this paper. This model not only provides robust parameter estimates, but also yields lower estimation error than the Bass Model. In addition, the model is capable of not only forecasting the eventual adoption rate of commercial solar PV systems, but also estimating the time delay of impacts on adoption. The proposed commercial solar PV adoption model is a very useful tool to quantify and forecast the impact of government policies and solar PV system costs on the commercial solar PV adoption. The simulation results show that both direct government solar incentive programs and declining solar PV system costs had a significant impact on the adoption of commercial solar PV systems in Southern California. Moreover, we introduced a method to forecast the size of the solar PV system that a customer is likely to adopt. This forecast can provide a

valuable guidance to the power distribution system planners regarding optimal grid expansion and upgrade plans.

Based on the historical adoption data, the forecasted eventual adoption rate of commercial solar PV systems is much lower than that of residential systems. With a higher percentage of leased buildings in the commercial sector, the incentive splitting problem is more pronounced and has inhibited widespread adoption of commercial solar PV systems. Therefore, traditional government solar system incentive programs need to be complemented by policies that directly promote the adoption of solar PV system for non-owner-occupied commercial buildings. In the future, we would like to explore and evaluate the impact of third-party ownership on the adoption of commercial solar PV system.

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