



# Structuring financial incentives for residential solar electric systems



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## ABSTRACT

This paper introduces a simple methodology to aid in the decision of how to distribute financial incentive funding for residential solar electric systems in order to maximize demand. Incentive funding can be used more effectively if adjusted according to the decrease in price and the increase in demand of solar electric systems. The decision of how to reduce these incentives due to changing annual funds, while increasing or even maintaining the growth of solar electric system demand, is of great interest to policymakers and public benefit funded program administrators. In order to aid in this process, a three step methodology is described in this paper. The first step uses the concept of learning-by-doing to determine the relationship between historic pricing and demand. The second step employs discrete choice modeling with spatial analysis to determine the relationship between market, financial, and social factors with historic demand. The final step uses nonlinear programming to forecast incentive structuring for maximizing demand. Finally in order to validate the model the study uses solar market data from Portland, Oregon. The results show a decrease in incentives over the period of study from 2014 until 2020, except for 2017 and 2018 when federal and state tax credits expire respectively.

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## 1. Introduction

The adoption of residential solar electric systems has increased drastically over recent years. The decrease in the price of solar energy, the availability of incentives, and the increase in active and passive peer effects have had a positive impact on the rate of adoption of solar electric systems. A question that policymakers and public benefit funded program administrators commonly have is how to adjust incentives in order to maximize adoption. In order to answer this question, it would be beneficial to first understand what impact these incentives have previously had on consumers. However, there is limited research on the understanding of solar adopters and most of the focus has been on aggregated economic and social factors. In order to understand how incentives impact adoption of solar electric systems, it would be beneficial to understand how heterogeneous consumers respond to change. Without extensive field research and with the lack of available data on solar electric system adoption beyond general location, price, and incentives, the possibility of understanding the heterogeneity

of consumers is limited. This study therefore only considers the relationship between census data and adoption on a zip code basis to gain a basic understanding of consumer adoption of solar electric energy.

This study first reviews the current solar photovoltaic (PV) policies, actors, industry, market, and issues in order to bring them together into one conceptual model of positive and negative effects. Research on solar electric systems discusses different aspects of the impact of increasing solar adoption, but very few, if any, discuss them together. This study then reviews different technologies and diffusion models.

The overall objective of this study is to determine what incentives to offer in order to maximize demand of solar electric systems, while remaining within a public benefit funded program administrator's predefined budget. The methodology followed in this study consists of three steps. The first step uses the concept of learning-by-doing to determine the relationship between historic pricing and demand. The second step uses discrete choice modeling with spatial analysis to determine the relationship between economic and social factors with historic demand. The final step uses nonlinear programming to forecast incentive structuring for maximizing demand.

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