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Can adoption of rooftop solar panels trigger a utility death spiral? A tale of two U.S. cities

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A R T I C L E I N F O

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A B S T R A C T

The growing penetration of distributed energy generation (DEG) is causing major changes in the electricity market. One key concern is that existing tariffs incentivize 'free riding' behavior by households, leading to a cycle of rising electricity prices and DEG adoption, thereby eroding utility revenues and start a death spiral. We developed an agent based model using data from two cities in the U.S. to explore this issue. Our model shows worries about a utility 'death spiral' due to the adoption of rooftop solar, under current policies and prices in the U.S., are unfounded. We found, consistently for a number of scenarios, that, while the residential segment is impacted more heavily than the non-residential segment, the scale of PV penetration is minimal, in terms of overall demand reduction and subsequent tariff increases. Also, the rate of adoption would probably be smooth rather than sudden, giving the physical grid, the utility companies, and government policies enough time to adapt. Although our results suggest that fears of a utility death spiral from solar systems are premature, regulators should still monitor revenue losses and the distribution of losses from all forms of DEG. The concerns should lead to a more focus on tariff innovations.

1. Introduction

In this paper, we examine the extent to which solar photovoltaic (PV) penetration can erode utility revenues and undercut the traditional financial model of power companies, leading to a so-called 'death spiral' of the utility business. This question is important not only for the companies and their stakeholders, but also for policymakers who expect incumbent utilities to make significant investments to support the transition to a decarbonized electricity sector.

Ever since its inception, the electricity sector has been made up of large, central generating companies that operate very reliable equipment and distribute power to customers. New distributed generation technologies with low entry costs, however, have the potential to affect the physical and financial structure of the industry. Rooftop solar PV is one such small-scale technology that can be adopted by a large proportion of a utility company's customers.

The traditional pricing models permitted by U.S. regulators require utilities to cover most of the fixed costs of their investments and operations through charges based on the amount consumed, with a small, fixed, monthly charge for recovering the fixed costs plus a regulated profit. Consequently, any reduction in sales due to distributed power could lead to companies charging their remaining customers higher rates, which, in turn, could lead to more customers installing solar – or economizing in some way, a factor that is beyond the scope of our model. If this cycle of price increases and additional installations happens at a high enough rate, utilities could enter into what has been called a 'death spiral.' This loss of revenue and demand can have far reaching impacts as utilities still need to build and maintain transmission and distribution capacity to provide reliability, reliability that extends to homes with solar panels on the roof. Under existing pricing policies, PV owners do not pay utilities for this service for that part of their power demand that is met by PV.

Worries about a utility death spiral abound. *The Economist* argues that the electricity industry in Europe faces an existential threat.[1] The Edison Electric Institute, a U.S. industry association, warns that the electric industry faces 'disruptive challenges' comparable to the effect of mobile

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[1] Briefing: How to lose half a trillion euros, The Economist 12th October 2013, http://www.economist.com/news/briefing/21587782-europes-electricity-providers-face-existential-threat-how-lose-half-trillion-euros (last Accessed 12 December 2015).

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phones on wire-based technologies.[2] In Hawaii, the penetration of rooftop solar PV is one of the highest in the world, with approximately 12% of all households having solar panels [1]. This penetration has contributed significantly to a 21% decline in residential electricity sales since 2007 (See Appendix A of Supplementary material for more details). Over the past decade German utilities have written off substantial assets in what looks like a death spiral. An alternative view of the German situation [37], however, is that the write-offs are due more to the actions of generators than to the penetration of solar [38,39] (see Appendix B of Supplementary material for a summary of the argument).

This prospect of a 'death spiral,' raises two important issues: what is the scale of the effect resulting from the expansion of rooftop solar installations and what is the rate at which the effect will occur? In this paper, we investigate these two issues as well as the higher level issue, important for policymaking, of the robustness of the findings.

In order to address these questions, we develop an agent based model (ABM) in which building owners adopt rooftop PV panels depending on the perceived payback period for their investments, given rooftop PV costs and utility electricity prices. The perceived payback period is influenced by a contagion effect that depends on the number of panels installed in their geographical vicinity. This effect is applied only to residential customers. The measure is a rough proxy for attitudes toward either the early adoption of technology or environment, which are determinants of technological dispersion [2,3]. Our agent based model allows us to estimate not only the size of the effect, but also the rate at which customer adoption affects the revenues of the utilities. With sensitivity/post-solution analysis of the model we learn much about its robustness, our third main issue. Finally, the agent based model affords incorporation of imitation effects (influences from neighbors) and, in the future, other customer behavior.

We assess two locations in the U.S., Cambridge, Massachusetts, and Lancaster, California, under realistic market conditions. We track the installed capacity, solar generation, net demand, and rate impacts over a 20-year period and in 200 scenarios to reveal a range of potential outcomes. We find that, under realistic assumptions regarding rooftop PV adoption, the consequences for the electric transmission and distribution business are limited if the revenue from residential and non-residential segments are combined. Moreover, we find that change is smooth, rather than rapid, affording time for policy responses should predictions of the model prove significantly mistaken.

The main body of this paper is organized as follows. In the next section, we present some of the growing literature pertaining to the effects of DEG and of the adoption of solar PV. In the following section, we describe the important features of our two study cities, Cambridge, Massachusetts, and Lancaster, California, as they relate to adoption of rooftop PV. Section 4 provides an overview of our agent based model, including a description of its overall motivation and its detailed mechanics. The Setups subsection discusses the default scenarios for Cambridge and Lancaster, and describes their calibration to real data.

Section 5 presents the results of applying our model to two pricing scenarios, with runs simulating 20 years of activity. We then present our findings from an extensive and systematic robustness analysis of the modeling assumptions, anchored in the default scenarios. A clear picture emerges from these findings, which we explain in the Discussion section. The conclusion contains comments on the policy implications of our findings, assesses limitations of this study and points toward promising opportunities for future research.

2. Literature review

Much of the recent research on distributed PV market fits into three interconnected areas. The first focuses on the patterns of distributed PV adoption and potential market size. The second covers the implications for utilities and their business models. The third seeks to quantify the value of solar to the grid, in order to provide fair pricing mechanisms and market designs. This paper falls within the first two areas and touches on the value of solar in reducing net electricity demand.

A 2008 National Renewable Energy Laboratory (NREL) study undertaken by Navigant Consulting modeled the market penetration of rooftop PV in each of the 50 U.S. states, and in several scenarios [4]. The analysis first calculated the technical potential of rooftop PV by inventorying the usable roof space in the U. S., including the effects of shading, building orientation and roof structural soundness. A simple payback period for rooftop PV investments was calculated, so as to arrive at an economic potential. In the base case, the business as usual scenario, a total of 1566 MW and 57 MW of rooftop PV was projected to be installed in California and Massachusetts, respectively, by 2016.

A 2010 paper, also by NREL, used a similar approach to calculate rooftop PV adoption and identify the factors that have the greatest impact on PV penetration [5]. The analysis found that lower PV costs had the largest impact on increasing PV adoption, followed by policy options that improve the economics of PV, including net metering incentives and policies pricing carbon emissions of competing energy sources.

Several factors restrict the viability of rooftop PV. A 2015 NREL study identified the limiting factors for rooftop PV, as opposed to the larger opportunities presented by community solar installations [6]. The analysis found 81% of residential buildings in the U.S. have enough suitable space for a 1.5 KW PV installation. Assuming 63% of households consists of non-renters, the study estimates that 51% of households could install 1.5 KW PV systems.

Graziano and Gillingham [7] examined the spatial pattern of rooftop PV adoption in Connecticut. They found that higher density housing and a bigger share of renters decreases adoption. Interestingly, their research also found a 'neighbor effect' from recent nearby adoptions that increased the number of installations within 0.5 miles in the following year. They found this neighbor effect diminished over time and space.

Rai and Robinson [8] developed and attempted to empirically validate a spatial agent based model of rooftop PV adoption that incorporates economic as well as behavioral factors. In another study, Robinson and Rai [9] analyzed the adoption of residential photovoltaic technologies in Austin, Texas using a geographical information system integrated agent based model using data from 2004 to 2013. They found that financial aspects had well predicted the rate and scale of PV adoption, but the social interactions were critical to predict spatial and demographic patterns. They argued these results could be useful to design locationally target rebates and achieve cost effective results.

Utilities are facing the prospect of customers reducing their net electricity purchases as they adopt rooftop PV. Cai et al. [10] simulated the feedback of utility costs and lower sales in a California utility's territory to assess the implications of rooftop adoption. They found that the 'death spiral' feedback reduces the time it takes for PV capacity to reach 15% of peak demand only by a maximum of four months. By implementing a fixed connection charge for rooftop PV, the utility would delay the time needed for PV capacity to reach 15% of peak demand by two years. Overall, the authors found utilities could lose a significant portion of their high income customers, which increases risks to the utility, since low income customers are more sensitive to price increases. The logistic curve, which we use in the sequel, represents a starting point for representing consumer behavior.

Darghouth et al. [11], however, claimed that there is an overlooked feedback loop that can temper the death spiral argument: increased PV deployment leads to a shift in the timing of peak prices that could reduce bill savings received under net metering in a time varying rates context. They found that, for the US, the two feedback effects nearly offset one another and therefore produced modest net effects, a result

2US Energy: Off the grid, Financial Times 13th January 2015, http://www.ft.com/cms/s/0/b411852e-9b05-11e4-882d-00144feabdc0.html#axzz3uNxNbw72 (last Accessed 12 December 2015).

similar to the results in the current study, but that magnitude and directions vary by customer segment and by state. They concluded that high PV adoption is highly sensitive to tariff structure. Moving towards time-varying rates accelerates adoption in the near and medium term but slows deployment in the longer term.

A rich literature on consumer attitudes towards adoption of new energy technologies is developing. Stern [12] provides an overall framework for developing a deeper understanding of consumer behavior. Kastnera and Stern [13] survey the literature on the consumer thinking that underpins their decisions to invest in energy efficiency. Schelly [3] interviews residents of Wisconsin to understand the motivations of those who adopt renewables, finding that payback is important and environmental concerns are not enough. Gromet et al. [14] find that promoting the environment can have a negative impact on adopting energy efficiency measures. Bollinger and Gillingham [15] estimate the peer effects on purchases in neighborhoods. Andrews and Johnson [16] examine the organizational culture dimensions that influence energy use in corporations.

Ruester et al. [17] examine how the role of an operator of a distribution system will have to change to accommodate distributed generation. The European industry perspective can be seen in Hallberg [18]. Kind [19] outlined in an industry white paper the financial risks to utilities of customers adopting DEG, including solar PV.

3. Case study

Two cities illustrate the potential of solar and provide the case studies for our analysis. Lancaster, California, has had significant PV growth and is known as a solar hub. Located in the western Mojave Desert, this city has some of the best solar resources in the world and, as a result, is home to many utility-scale solar projects and rooftop installations. Local government strongly supports their development. Lancaster requires all new residential developments to install an average of between 0.5 kilowatts and 1.5 kW of solar capacity (maximum production, under ideal conditions) per home built, the first municipality to institute such a requirement [20]. The mayor once said, "*We want to be the first city that produces more electricity from solar energy than we consume on a daily basis*" [21]. If this city of 160,000 people is able to achieve that goal, it could damage the local sales and revenues of Southern California Edison, the utility that serves Lancaster.

Lancaster is situated in a state with significant solar activity resulting from a favorable investment environment, relatively high electricity prices and abundant sunshine in much of the state. With 4316 megawatts installed in 2014, California now has about 10,000 MW of solar capacity [22]. About 330,000 customers participate in the state's solar net metering program and 42,000 MWh (megawatt hours) of solar energy was sold back to the grid in 2014 [23]. This is a 142% increase since 2011 (see Appendix A of Supplementary material for more details).

Because the average solar radiation in Massachusetts is not as strong as in Lancaster due to its higher latitude and more frequent cloud cover, solar panels produce less electricity than do similarly-sized systems in Lancaster. This makes Cambridge, MA, a useful comparison with Lancaster in terms of the potential for residential solar. Massachusetts has made a strong push for solar power. The state has over 800 MW of solar capacity [22] and aims to have 1600 MW installed by 2020 [24]. With favorable net metering provisions and retail electricity prices of 17 cents per kWh, which is slightly higher than California's and 43% higher than the national average [25,26] solar is a potentially cost-effective option for Massachusetts consumers despite a lower rate of insolation.

The city of Cambridge, MA, differs from Lancaster in several ways, providing an opportunity to compare different regional conditions and potential utility impacts. Moreover, Massachusetts has extensive, publicly available data on rooftop capabilities for solar and a detailed solar mapping tool of the city, developed at MIT and other places [27]. In addition to different solar conditions, Cambridge has fewer people but is more urban, having a population density 10 times higher than Lancaster. The urban composition, along with a 35% homeownership rate, reduces the extent of PV adoption, because renters are unlikely to invest in a long-term assets such as rooftop PV [6].

Table 1
Demographic, solar resource and energy price characteristics.
Source: NREL [28], U.S. Census Bureau [29], EIA [26].

Category	Lancaster, CA	Cambridge, MA
Population, 2013	159,523	107,289
Housing Units, 2010	51,835	47,291
Homeownership rate, 2009–2013	60.1%	35.0%
Median household income, 2009–2013	$50,193	$72,529
Land area in square miles	94.28	6.39
People per square mile	1692	16,790
Average Annual Solar Radiation (kWh/m^2/day)	6.44	4.39
Average Retail Electricity Price from Utility (cents/kWh)	14.8	16.99

Demographic, housing, and solar resource characteristics and energy prices for Lancaster and Cambridge are summarized in Table 1.

For this table we sourced demographic, solar resource, and energy price characteristics for Lancaster, CA, and Cambridge, MA. demographic and housing statistics from the U.S. Census, solar radiation from NREL's PVWatts Calculator [28] and retail utility prices from EIA [30].

4. Model

We developed an agent-based model (ABM)[3] that simulates the adoption of rooftop PV panels. Agent-based modeling is a suitable methodology in the present instance for several reasons. It can aid in understanding consumer energy choices as it can improve understanding of scientific and applied aspects of the demand side which in turn could improve design better policies [31]. Also, ABMs are excellent at capturing dynamic aspects of the system modeled. Further, they afford representation of heterogeneous collections of agents. The model we describe in the present work avails itself of all of these advantages. In this model, the agents are building owners who decide each year whether or not to install PV. The probability that a customer will or will not adopt PV is a function of the perceived payback period and a logistic curve that reflects consumer choice behaviors [32,33]. The model is implemented in Python with ArcGIS visualization and is a template we designed to be modified as appropriate for other locations and data sets beyond Cambridge and Lancaster. The model comes in two versions: one uses a dynamic price model and the other uses a static price model. Here we consider the elements that are common to both versions. We discuss their differences when we present our results.

Key inputs to the model consist of the number of buildings, their corresponding rooftop areas and their locations. The size of buildings is used to determine both their electricity demand profiles and their ability to install PV panels. Their locations are used to determine contagion effects: residential agents with neighbors who already have PV are more likely to adopt PV. PV adoption in the model is a function of the economics of PV investments (we assume that PV systems as purchased and owned by customers), plus a neighborhood effect that is instrumented to be converted to PV cost reductions that lead to quicker paybacks. We represent the strength of the neighborhood effect through altering the shape of the logistic curve, which represents non-captured values embedded in consumer choices – such as attitudes toward the environment and the presence of early adopters – which are variables

[3] The model including source code, detailed results, and supplementary materials are available at https://github.com/KAPSARC/Utilities-of-the-Future/tree/master/2-Utility_Death_Spiral.

used in the literature to explain dispersion of new technologies as well as the general responsiveness of consumers making economic or utility enhancing decisions. It should be noted that the neighborhood effect is applied only to residential customers. PV adoption for non-residential customers is purely a function of the economics of PV investments.

The model treats each building as a single agent, with the logistic curve providing the probability that the building owner chooses to add solar, given electricity price, solar system cost, and neighborhood effect (for residential agents). Thus, the model is a stochastic simulation with specific real buildings randomly adding PV. The model increments time in discrete, annual steps over the course of a 20-year period. We choose this horizon because that is the conventional life span of a solar panel. A consumer makes a choice of adding solar or not in each year. We assume that once a building has installed rooftop PV it remains in place for the duration of the simulation and that no new installation is possible (See Appendix C of Supplementary material for illustrative flow charts).

4.1. Model mechanics

We use GIS data to calculate buildings' rooftop areas. Based on this value, we assign a probability distribution for each of the 19 types of buildings reported by the U.S. Department of Energy [34,35] considered in the model. These buildings are as follows: residential (small house, medium house, large house, midrise apartment), commercial (restaurant, fast-food restaurant, small hotel. Large hotel, small office, medium office, large office, stand-alone retail, strip-mall, supermarket, warehouse), and others (hospitals, outpatient facility, primary school, secondary school). Then we estimate candidate solar size from 13 different rooftop PV size for each building ranging from 2 kW to 12 kW for residential buildings and 2 kW–500 kW for non-residential buildings (See Appendix D of Supplementary material). Each building type has an hourly electricity demand profile for a typical meteorological year, which varies by city. Finally, the model permits us to constrain the percentage of buildings eligible to install PV solar panels. This is done through the model parameter L in expression (2). Feldman et al. [6], conclude that only 51% of buildings in the U.S. could install solar panels. The analysis, carried out for the U.S. National Renewable Energy Laboratory (NREL), noted that 81% of residential buildings in the U.S. have enough suitable space for a 1.5 KW PV or higher installation and that 61% of households are non-renters.

Adoption decisions proceed in two stages. First, buildings adopt PV panels depending on the payback period for a PV investment. The payback period incorporates both installation cost and an imputed benefit from the neighborhood effect. We calculate the payback period with the formula in (1) and we use a mirrored logistic function, similar to the methodology in Paidipati et al. [4], to determine the probability of solar adoption in a given year.

In (2) x is the payback period in years, L is the maximum probability (1, or 100%) or market share for solar, k determines the steepness of the curve and *nne* is the net neighborhood effect parameter. The reference mirrored logistic function used in this analysis is shown in Fig. 1. In this example, buildings would have an 18% probability of installing rooftop PV if the payback period is five years.

$$Payback\ \ Period(years) = x = \frac{PV\ \ installed\ \ cost*(1-nne)}{8760\text{hours}*PV\ \ capacity\ \ factor*retail\ \ electricity\ \ price} \quad (1)$$

$$f(x) = L^*\left(1 - \frac{1}{1+e^{-k*x}}\right) \quad (2)$$

Note that even with a negative payback not all residences install solar panels. This is because the payback calculation does not include the time cost to the building owner; risk aversion to new, expensive technology; and building owners with a short-term horizon.

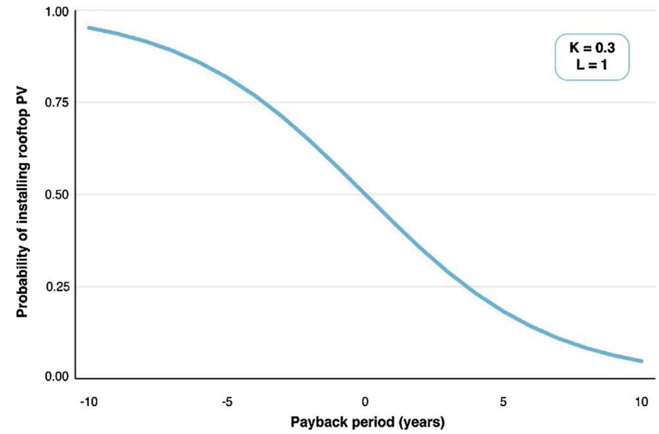

Fig. 1. Probability of installing rooftop PV.

Realistically, people take time to make important investment decisions.

We add to residential customers a contagion effect that depends on the number of panels installed in their geographical vicinity. The more installations nearby, the greater the likelihood that a homeowner installs panels. One explanation for this is that people's perceptions of the risks of solar and costs for gathering information are lower when they can talk to neighbors who already have PV installed. This measure of increased likelihood is a rough proxy for follower behavior during early adoption. In contrast to Graziano and Gillingham [7], where 'neighbor effect' is measured in units of PV panels adopted if a neighbor installs solar, we instrument the neighborhood effect as the net neighborhood effect (*nne*): the neighborhood effect (a model parameter) multiplied by the percentage of neighbors having solar, where the set of neighbors consists of the buildings within a radius of 90 ft. Later periods in the simulations of payback time reflect lower values of PV costs for agents with neighbors who have already installed solar panels.

The model simulates the effect on the utility as follows: First, we assume the utility has an annual revenue requirement, F, for recovery of fixed costs and allowed profits, denoted by F_O. It should be noted that the fixed cost assumption might not hold in the long term because of possible future investments to upgrade the grid. However for simplicity we assume a fixed cost throughout the 20-year-period. Then, we calculate the annual revenue requirement from an initial demand and an initial price of PrF_O. We have estimated the value of PrF_O, \$0.08 per kWh, from the electricity rates for the Cambridge/Boston area.[4] A sensitivity analysis around this value is briefly discussed in the Results section.

The electricity price in any single year is $F + V$, where V is the generation cost. Next, we assume that in year 0, at initialization, $F = F_O =$ total demand * *\$0.08* = total demand * PrF_O. This constitutes the revenue requirement in each year for the utility to avoid a death spiral, i.e. for the utility to continue to be able to earn its permitted return on investments. The retail price in a given year is $\text{PrF}_t + \text{PrV}$, with PrV set to be constant as $\text{PrV} = \textit{initial price} - PrF_O$. Solar additions decrease the sales of electricity by the amount of solar generation in each year. The model outputs include hourly electricity demand, the number of rooftop PV installations, PV capacity, PV electricity generation and net electricity demand.

4.2. Setup

We input the retail electricity price (\$/kWh). The reference price applied to the residential customers while non-residential costumers usually get lower price, assumed to be 9% lower. Another input is the

[4] Available at https://www.eversource.com/Content/docs/default-source/rates-tariffs/190.pdf?sfvrsn=10.

installed cost for rooftop PV ($/Watt peak). We assume that when the system size gets bigger the cost per Watt peak gets lower. We have included a cost discount rate proportional to the size of the system size. That is, the cost is calculated following Eq. (3):

$$\text{PV rooftop system cost} = \text{Reference cost (\$/kWp)} - \text{System size (kWp)} \quad (3)$$

For example, if a system reference cost is $3000/kWp, a small size system (1 kWp) would cost (3000–1 = $2999/kWp). While a bigger size of the same system (i.e., 500 kW) would cost (3000–500 = $2500/kWp). Two other inputs are the PV capacity factor (percentage of capacity delivered during a year) and a neighborhood effect (a percent discount of PV costs). Each PV option has an hourly electricity generation profile based on its characteristics and a typical meteorological year in the analyzed location. The generation profiles come from the NREL's PVWatts Calculator [28] as applied to the 19 different types of buildings represented in the model and matched to the buildings in Cambridge and Lancaster.

To explore the patterns of rooftop PV installations and their implications in Cambridge and Lancaster, we present a reference case and range of scenarios. The reference scenarios represent the best available data for the current conditions for rooftop PV and electricity in both cities (Table 2).

For our reference scenario assumptions and calculated PV payback periods for Lancaster, CA and Cambridge, MA, the assumptions for PV installed costs were taken from Feldman et al. [36], capacity factors were calculated with the PVWatts Calculator [28], and retail electricity prices are from the U.S. Energy Information Administration [30]. The figures for PV installed costs are used in the first year of our simulations. After that the model imposes an annual PV system cost reduction, we derived as an average of the figures reported by [36]. The annual reduction is estimated at 5.9% in the first three years followed by 0.95% in the next ten years and 0.67% in the last seven years.

The annual probabilities for rooftop PV adoption in the reference scenarios are 0.005 and 0.01 for Lancaster and Cambridge, respectively, ignoring neighborhood effects. The logistic curve K-factor, at 0.3, was subjectively assessed. We set the value of K as approximately a threshold between very fast increases in adoption rates – at K and above – and much slower increases. The effect is to bias the model slightly towards faster adoption rates and thus towards overestimating the difficulties for the utilities. We undertook extensive sensitivity analysis on K, and the results are not sensitive to modest departures from $K = 0.3$ (See Appendix E of Supplementary material for more details). In addition, we set the value L to restrict maximum penetration to a certain limit. The rationale behind that is not all buildings have the ability to install solar systems on their roof due to many reasons such as roofs not facing south, shaded roofs, roofs in poor conditions, and so on. We have conducted a sensitivity analysis on three different values of L (0.5, 0.75, 1) discussed in the Results section. We use L = 0.5 in the reference scenario.

Table 2
Reference scenario assumptions and calculated PV payback periods.

	Reference Scenario	
	Lancaster	Cambridge
PV Installed Costs ($/kWp) (reference)	$3000	$3000
PV Capacity Factor	18%	15%
Retail Electricity Price ($/KWh)	$0.15	$0.15
Neighborhood effect	0.15	0.15
Logistic Curve L-factor	0.5	0.5
Logistic Curve K-factor	0.3	0.3
Rooftop PV Payback (years)	12.5	15
Probability of PV Adoption	1.0%	0.51%

5. Results

We used a model with two versions: a dynamic version in which prices change annually to reflect solar PV adoption and recovery of fixed costs, and a static version in which prices remain constant but the utility company sees reduced profits from the reduced revenues. The static case is more of a theoretical exercise and might not exist in real settings.

We discuss the dynamic price version first, in which the utility maintains its total T & D revenue, and hence its allowed rate of return, by raising its price, PrF_t, to compensate for revenue loss from solar generation. For simplicity, the utility considers two types of customer: residential and non-residential. The utility should recover the decline in electricity sales from each type by raising the prices on each type independently. Expressed more precisely, there are two components to the electricity price charged by the utility: the T & D recovery price, PrT_f, initially set at $0.08/kWh in the model, and the generation charge, PrV, for variable cost of generating power, paid to the presumed deregulated suppliers. We assume that PrV for Cambridge is $0.09/kWh and $0.07/kWh for Lancaster. Of course, when prosumers – consumers who also produce energy – provide solar power, the conventional power generators lose revenue and profits. However, in a deregulated environment these can be neglected: we are only concerned with the effects on the regulated utility company and whether it does or does not face a death spiral.

In the dynamic model, we adjust PrF_t (the T & D price) over time, increasing it as solar reduces demand, and we leave PrV unaltered. (See Fig. 2, for a flowchart of the dynamic price model.)

Specifically, let RRTD, the required revenue for T & D, be $0.08*total demand (realized in period 0 and which we assume is fixed) = PrF_1*total demand. For Cambridge, RRTD equal to $10,595,046 (for residential) plus $130,292,850 (for non-residential), where PrF_t is the transmission and distribution (T & D) recovery price, $0.08 in the reference scenario (i.e., in year 0).

We then adjust PrF_t for each sector dynamically in order to keep RRTD constant. The approximation we use is this. At the end of year $t - 1$ we determine the net demand as the total demand – the solar supply, and we apply it as the demand for year t. So, PrF_1 = RRTD/(total demand − solar supply) = RRTD/(net demand year t).

The results of running the Cambridge and Lancaster reference scenarios for multiple runs each, using the dynamic price model, is shown in Table F2 in Appendix F of Supplementary material. For Cambridge, at the end of 20 years the total price has risen from $0.15/kWh to $0.1637/kWh and from $0.135/kWh to $0.1512/kWh for residential and non-residential customers respectively. For Lancaster, price has increased from $0.15/kWh to $0.219/kWh and from $0.135/kWh to $0.153/kWh for residential and non-residential customers respectively. By that time solar supply (in kWh per year) is approximately 43.8

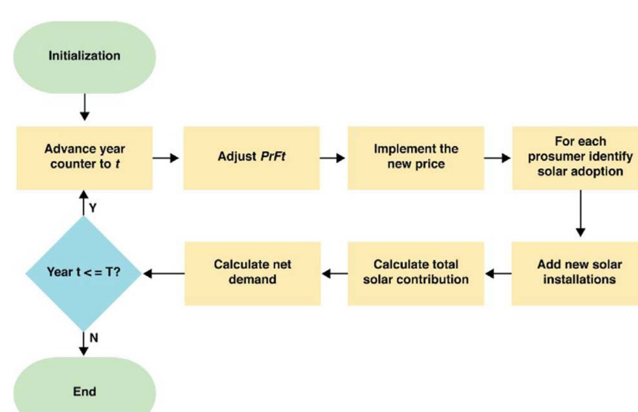

Fig. 2. Flowchart for the dynamic price model.

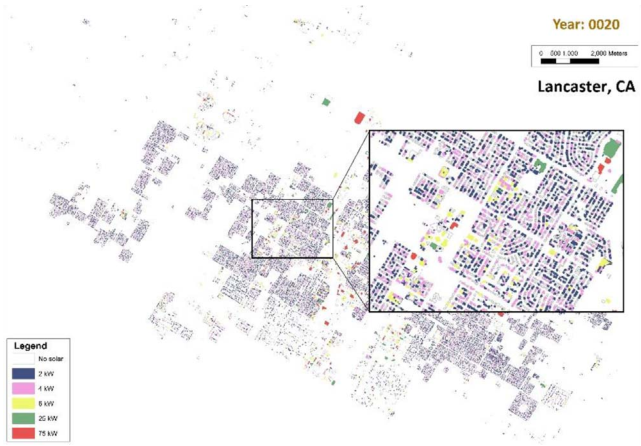

Fig. 3. A snapshot of a representative run of the simulation (year 20).

million in Cambridge and 323 million in Lancaster. Penetration levels – the percentage of buildings with installed PV – are on average 33% in Cambridge and 54% in Lancaster. Also, the speeds of adoption – the percentage of new installations per year – are 1.65% and 2.7% in Cambridge and Lancaster respectively (See Appendix F of Supplementary material for more result details). Fig. 3 is a snapshot from year 20 of a video showing how adoption unfolds in a single representative run over the 20-year period in Lancaster[5] (See Appendix H of Supplementary material for snapshots from years 0, 5, 10, and 15).

The reasons for the small price impact, despite the high penetration rates, are that all of this capacity generates only when the sun is out and the price increase affects just the T & D portion of a consumer's bill.

Examining the results from the static version of the model yields further insights. In this model the price for T & D, which includes revenue for the regulated profits of the utility, remains constant throughout the run. Because demand decreases with the adoption of solar PV and the T & D price does not rise, the utility's profits erode because the revenue shortfalls are taken from profits, not from scheduled payments to retire the capital investment. It should be noted that this part is more of a theoretical exercise to estimate the degree to which these profits decline. The static version might not exist in the real world. The version does, however, serve as a validation exercise for the model. It also shows that without tariff adjustments rooftop solar PV would indeed be materially detrimental to the utilities. Fig. 4 presents the high-level flow of control for the static price model.

As in the dynamic case, we completed 50 runs (replications) of the Cambridge and Lancaster reference scenarios. On average, solar PV meets about 14.5% of total residential demand and 1.5% of total non-residential demand in Cambridge after 20 years, while the figure is 46.5% and 3.7% for Lancaster. The numbers vary little among the 50 runs. The disparity in the numbers is credible, given that the capacity factor for relatively sunny Lancaster is 20% higher than that for Cambridge. This is echoed in the percentages of buildings with installed PV, which are on average 33% and 54%, respectively, for Cambridge and Lancaster (see Appendix F of Supplementary material for more result details). Fig. 5 provides an explanation for these differences: Lancaster has a much higher proportion of larger roofs.

To assess the cost to the utility (during year 20), we consider that the utility should receive $0.08 per kWh of demand supplied for recovering its transmission and distribution (T & D) costs. The static price model then enables us to calculate the loss of profits to the utility due to solar PV adoption, with the assumption that the price for T & D remains fixed.

Simply put, the Cambridge utility is granted annual T & D revenue of

[5] The full video is available from https://github.com/KAPSARC/Utilities-of-the-Future/tree/master/2-Utility_Death_Spiral.

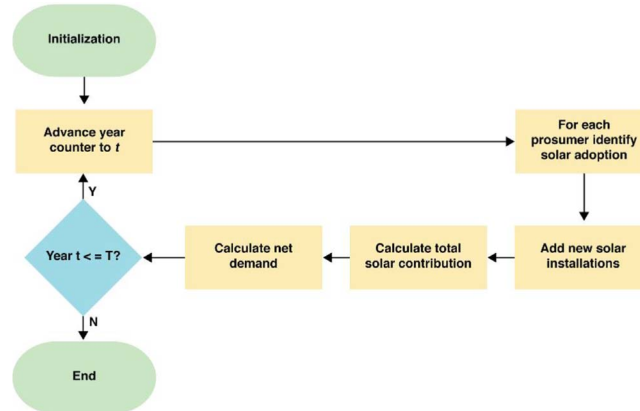

Fig. 4. Flowchart for the static price model.

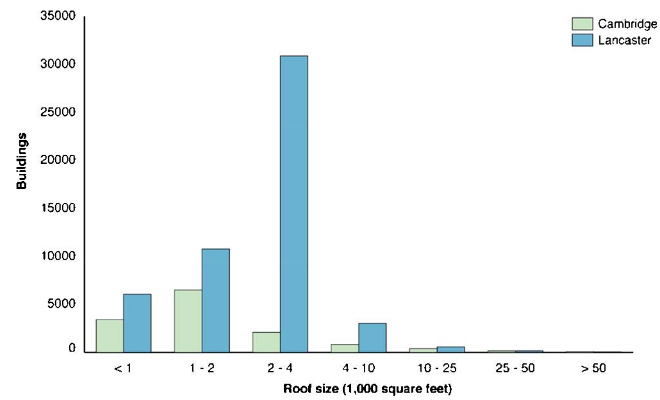

Fig. 5. Roof sizes in Cambridge and Lancaster.

$140,887,896 (= $0.08*total demand = $0.08*1.76E + 09). When solar generation is present, the net demand seen by the utility, for which T & D charges are assessed, is reduced by $0.08*solar supply (= $0.08*47,381,232 kWh). This nets out to a loss of T & D revenue to the utility of $3,790,498, which in turn represents a 27% profit reduction, on the assumption that 10% of the T & D revenue is allocated as profits to the utility. Similar calculations apply to the Lancaster data, yielding a 119% drop in profits.

Before we move to the main sensitivity analysis discussion of our model, we first briefly discuss the robustness of our model with respect to the value of PrF_0, the unit price required to recover the utility's fixed costs. We have run sensitivity analyses for different PrF_0 values (see Figs. I5 and I6 in Appendix I of Supplementary material). We see that the electricity price and the level of PV penetration gradually increase, in a more or less linear fashion, when PrF_0 varies from $0.04 to $014 per kWh.

We undertook extensive sensitivity/robustness analysis, related to the reference scenarios. We varied initial electricity price between $0.12 and $0.21 per kWh, solar installation cost between $1500 and $3500 per kW, and neighborhood effect between 0.1 and 0.2 (Table 3). This produced 250 scenarios (10 × 5 × 5) in all, each for Cambridge dynamic and Lancaster dynamic. The results are summarized in Figs. 6 and 7. We extend the sensitivity analysis by varying *L*-parameter from 0.5 to 1. We found that the L parameter is able to restrict the maximum penetration to the level considered to be reasonable. (See Figs. I7 & I8 in Appendix I of Supplementary material).

In Figs. 6 and 7—Sensitivity results for the dynamic model in the residential segment of Cambridge and Lancaster respectively—the neighborhood effect values vary between 0.1 and 0.2 (see Figs. I1 and I2 in Appendix I of Supplementary material for the non-residential segment). For both Cambridge and Lancaster, the results show that the increase in the electricity price over 20 years mainly depends on the

Table 3
Parameters used to create a range of scenarios.

Electricity Prices (cents/KWh)	12	13	14	15	16	17	18	19	20	21
PV Costs ($/kW)	1500	2000	2500	3000	3500	–	–	–	–	–
Neighborhood Effect	0.1	0.12	0.15	0.18	0.2	–	–	–	–	–
L-parameter	0.5	0.75	1	–	–	–	–	–	–	–
PrF_0	0.04	0.06	0.08	0.1	0.12	0.14				

anyone wishing to look beyond these, our model is available for modification as a starting point for further analysis.[6] In Lancaster, the price increases are significantly higher than Cambridge because of the higher capacity factor and the better economics in the residential segment, as seen in Fig. 7.

The broad findings regarding stability, robustness, coherence and smoothness remain valid. For Lancaster, the effect on profits for the utility is large if we don't increase prices. This is another insight from our results: the effect is small for the consumers, but large for the utilities, unless prices are raised accordingly. The price increases needed to restore the profitability of the utility, however, are not a major burden on consumers.

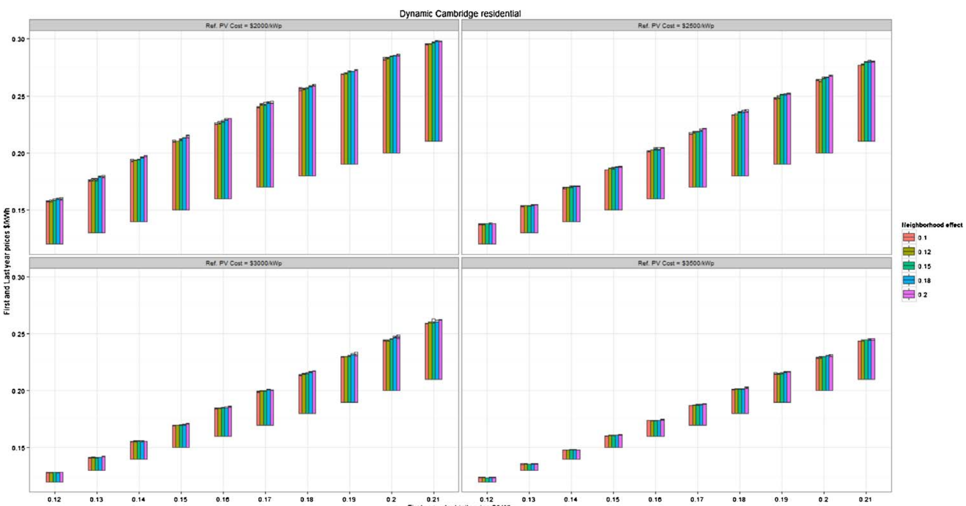

Fig. 6. Sensitivity results for Cambridge dynamic model (residential).

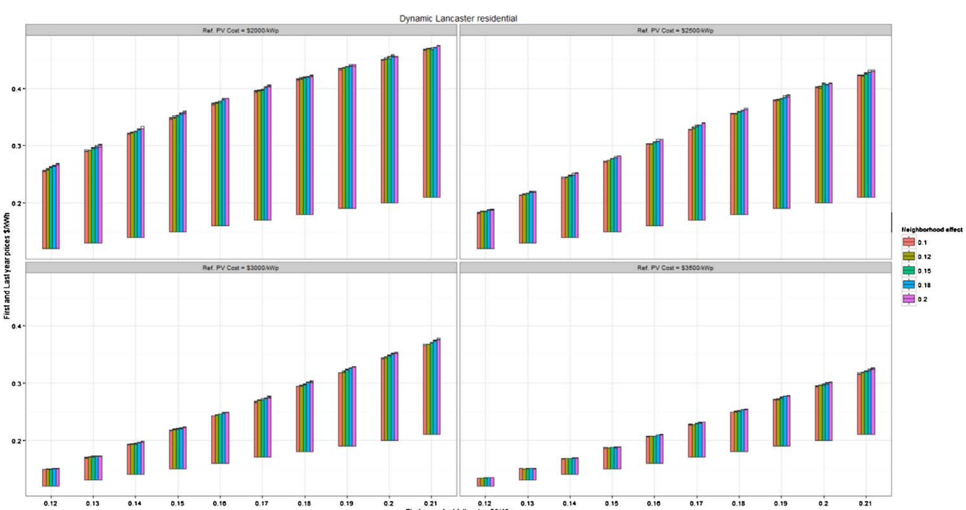

Fig. 7. Sensitivity results for Lancaster dynamic model (residential).

solar PV cost, and to a lesser extent on the starting electricity cost. Varying the neighborhood effect does not have a significant impact. We see that in our reference scenario, price increases by $0.02 per kWh (Cambridge) and $0.09 per kWh (Lancaster) at the end of 20 years (for the non-residential segment, we observe an increase of $0.001). In the worst case modeled, we see a price increase slightly above $0.1 per kWh (Cambridge) and $0.29 per kWh (Lancaster). In the non-residential segment (see Figs. I1 and I2) the price increases are $0.001 and $0.005 per kWh (Cambridge) and $0.001 and $0.006 per kWh (Lancaster) – for the reference and worst case scenarios respectively.

The higher level finding is: (1) the overall behavior of the model is coherent, (2) it is stable and (3) it indicates no sudden or threshold changes that would ambush either a utility or policy makers, since in fact price increases are smooth and slow. Of course, these findings are valid only for the scenarios examined and the factors modeled. For

In the sensitivity runs for the static cases, the same patterns are obtained. Moreover, we confirm that our conclusions are essentially unchanged when we consider the extreme, hypothetical case of 100% penetration and maximum solar PV capacity installed per rooftop. Our results show that the proportions of average residential electricity demand met by solar PV in the extreme case are 66.7% for Cambridge and 80.6% for Lancaster when we assume net metering. For non-residential customers, the average electricity demand met by solar is 7.2% for Cambridge and 8.1% for Lancaster, reflecting the fact that non-

[6] Model and data repository: https://github.com/KAPSARC/Utilities-of-the-Future/tree/master/2-Utility_Death_Spiral.

residential customers have limited roof size and much higher electricity demand than residential customers. Nevertheless, the combined residential and non-residential demand met by solar only amounts to 11.9% for Cambridge and 26.9% for Lancaster (See Appendix G of Supplementary material for more result details).

6. Discussion

The widely expressed worry about a utility death spiral sounds legitimate. Yet with the aid of our models we find little actual cause for concern. So what are these models reflecting that is absent in the anecdotal worry about a runaway process?

There are several factors at work, represented in our models, which prevent rooftop PV adoption from being a runaway process that can overwhelm the utilities. The first is that the maximum amount of rooftop PV is limited by the number of buildings and the rooftop areas they support. These factors are present as real data in our models, data derived from the actual buildings in Cambridge and Lancaster.

Second, our models recognize that PV adoption is not instantaneous. Instead it 'diffuses' much as do new technologies, so as to slow down adoption to a manageable pace. We quicken the pace by including a neighborhood effect, but find that various levels of speeding up matter very little to the results.

Third, it is entirely possible in principle that rooftop PV adoption could be limited, due, say, to factors one and two, but it still could overwhelm the utilities and their bases of business. Whether this will actually occur depends upon how much solar power is generated, compared to the overall demand. The extreme scenario we modeled indicates however that this is unlikely to happen. While the risk of lost revenues from the residential segment is high, this is mitigated by higher non-residential demand that is still relying on grid supply.

Fourth, we restrict the simulation period to 20 years. Because each year the model adds solar to a fraction of the remaining buildings that have not already added solar, with an infinite horizon all building owners would do so. This bias in the model would become important if the period covered extended well beyond the 20-year time limit, but is not significant with the short horizon used here. To the extent this bias is present, we overestimate the financial impact of solar.

Given these considerations, it is clear that even with quite substantial rooftop solar PV penetration, in terms of the percentage of buildings adopting rooftop PV, the total amount of power produced is small. Specifically, it is 2.5% for Cambridge and 14.9% for Lancaster compared with the total demand for electric power in our reference case, which in both cases is below the threshold of 15% that observers such as Cai et al. [10] worry about. Moreover, our finding on this is quite robust. For example, the model sizes PV installations based on the size of a building and its type, such as small house, office building, etc. These sizes are standard, starting from 2 kW for a small house, and so on. Thus, increasing the productivity of rooftop installations in any realistic manner – e.g., by enlarging them, by employing more efficient collectors – is unlikely to alter our general findings.

We should note that our model assumes full net metering and a flat rate structure for the electricity consumed by residential and non-residential customers. Alternative rate structures, ranging from fixed pricing (e.g. based on peak usage) to dynamic (time-of-use) pricing, would result in larger or smaller effects on utility revenues.

DEG potentially damages the electric utility business fundamentally in three ways. The first by loss of revenues for recovering fixed costs of electricity transmission and distribution networks. This potential threat, specific to distribution-only utilities that need to invest in and maintain network infrastructure, is the focus of the present study. To repeat, we found that the threat is minimal with regard to installation of rooftop solar PV. Of course, other forms of DEG could well result in significant damage in terms of lost revenues. For example, large scale adoption of community wind and/or solar PV, covering hectares of ground would be quite another matter.

The second potential source of damage to the utility business is loss of revenues for recovering fixed costs of electricity generation. Our study has eschewed this aspect of the problem because in a deregulated environment, common to both Massachusetts and California, electricity generation is undertaken by merchant providers and is not protected by regulation guaranteeing a rate of return. The matter is different in the case of regulated utilities, which have received approval for construction of generating plant and are entitled to a guaranteed rate of return. In this case the generators have the same status as the transmission and distribution networks and there is, at least potentially, a policy issue to be addressed. That issue is beyond the scope of the present study.

Finally, the third potential source of damage to the utility business is loss of profits from future regulated generation and/or transmission and distribution facilities. DEG in general and solar PV in particular may lead to reduced demand in the future for expansion of regulated facilities, given the assumptions that the utilities abstain from investing in solar PV themselves. In consequence, the facilities will not be built or will be postponed, resulting in a loss of new business (and regulated rates of return) to the utilities. Again, this is beyond the scope of the present study, and we certainly agree that this is fertile ground for future investigation. That said, we also note that the policy case for this third threat is different from the first two, and must generally be seen as much weaker, if not problematic.

7. Conclusion

Worries that a utility death spiral will result from increased adoption of rooftop PV are overdone. Absent new information, the threat appears to be minimal under a wide range of assumptions. The modeling exercise reported in this paper has shown that the scale of rooftop PV adoption is unlikely to threaten distribution utilities' basic business model. Also, the rate of rooftop PV adoption is likely to be smooth rather than sudden, so there is no immediate need for pre-emptive action. The modeling results are robust across a broad spectrum of credible scenarios.

This is not, of course, to say that such worries should be entirely abandoned. Continued monitoring, assisted by further model development, is certainly in order, as is examination of the effects of factors not modeled here, such as balancing costs – which are normally not charged as part of the fixed cost recovery funds – and the disruptive effects of new technologies.

Looking forward, at least two additional issues merit prompt attention. The first concerns tariff innovations. Even if the death spiral effect is not a genuine threat, the fact remains that the existing tariff incentives act to encourage the sort of 'free riding' by rooftop PV adopters that inspired the original worries. Because of efficiency and equity considerations, the challenge of instituting appropriate tariffs remains crucial, even if rooftop PV adoption does not by itself constitute a call for urgent policy changes. Given the role of the grid as a backup to shortfalls in solar, a simple policy correction could be to charge homeowners the insurance value of having the grid to cover shortfalls. The second issue relates to extending the agent based model to include a more articulated, wider range of prosumer behaviors. This might include such factors as entrepreneurial acquisition of much larger PV capacity, perhaps using land instead of rooftops and demand response regimes, coupled with mandatory participation in balancing by DEG producers. These last two issues are complex, unresolved and vital for the good operation of future distribution grids.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.erss.2017.06.041.

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