# DEMAND FOR RESIDENTIAL SOLAR PHOTOVOLTAIC SYSTEMS: EVIDENCE FROM NOVA SCOTIA

by

Mahmood Hasan

Submitted in partial fulfillment of the requirements
for the degree of Master of Arts

at

Dalhousie University
Halifax, Nova Scotia
April 2020

*To my father and mother.*

*Thank you for all your love and sacrifices.*

# Table of Contents

# List of Tables

# List of Figures

## Abstract

This thesis examines the demand for residential Solar Photovoltaic (SP) installations in Nova Scotia (NS) from 2016 to 2019. There has been no study that estimates the economic and demographic determinants of demand for SP systems in NS. Using a negative binomial logit hurdle model, I find that the installation cost of SP systems, provincial rebate rate available for homeowners, and median household income at the census dissemination area level have significant effects on the decision to install SP systems. The point estimate of the price elasticity demand for SP systems is -1.26, sufficiently high to suggest that the demand for the residential SP market is highly responsive to rebate and incentive policies.

## List of Abbreviations Used

| | |
|---|---|
| AC | alternating current |
| AIC | Akaike information criterion |
| BIC | Bayesian information criterion |
| CF | capacity factor |
| $CO_2$ | carbon dioxide |
| DA | dissemination area |
| DC | direct current |
| GHG | greenhouse gas |
| GWh | gigawatt-hour |
| kWh | kilowatt-hour |
| LCOE | levelized cost of energy/electricity |
| LPM | linear probability model |
| Mt | megatonne, 1,000,000 metric tons |
| MW | megawatt, 1,000,000 watts |
| NBLHM | negative binomial logit hurdle model |

| | |
|---|---|
| NBRM | negative binomial regression model |
| NS | Nova Scotia |
| OLS | ordinary least squares |
| PLHM | Poisson logit hurdle model |
| SP | Solar Photovoltaic |
| TNBREG | truncated negative binomial regression model |
| TWh | terawatt-hour |

## Acknowledgements

I would like to express my profound admiration and gratitude to my supervisor, Professor Talan İşcan. Thank you for believing in me and for your dedication, constructive feedback, new ideas and patience with my work. This work would not have been possible without your support. Also, I am honored to have been supervised by my other committee members, Professor Catherine Boulatoff and Professor Yulia Kotlyarova, who have shown immense interest in my work and provided productive comments and suggestions.

I would also like to thank Dr. Wayne Groszko and Dr. David Rapson for their valuable input during the early stages of this thesis. Their words of encouragement motivated me to carry out research on solar photovoltaic. I would like to thank the industry professionals in Nova Scotia who have always welcomed questions and provided insights into the solar industry, specifically, Brian McKay (Aztek Solar), Dave Corning (Efficiency Nova Scotia) and Tom Rendle (WattsUp Solar).

Thanks to the many colleagues at Dalhousie University for showing interest in my thesis and for the many discussions we had on solar energy. Your contributions brought clarity in a lot of the work I did. Thank you, Syeda Faisal, for proofreading my work and for continuously checking up on my progress. I would also like to acknowledge the feedback from Yury Rozhin and Maruf Hasan.

I have had an amazing time throughout my study period at the Department of Economics and it would not have been so fruitful and exciting without the faculty members and administrative staff. Thank you for all your efforts and support. To the friends in Halifax, thank you for being there for me, you all know who you are.

# Chapter 1

# Introduction

Climate change is one of the most pressing global issues. All scientific and policy proposals for arresting and reversing the human impact on the climate involve, among other things, dramatically changing how our societies generate electricity. According to Environment and Climate Change Canada (2019), Canada's total greenhouse gas (GHG) emissions in 2017 were 716 megatonnes (Mt) of carbon dioxide equivalent ($CO_2$ eq) and of these emissions 10% was due to electricity generation. Even though Nova Scotia (NS) had an average reduction of 0.79% per year in GHG emissions from 2005 to 2017, in 2017 NS still accounted for emissions of 2.23% of $CO_2$ eq,[1] with an increasing use of renewable sources like wind and biomass being responsible for the reduction in GHG emissions.

Energy sources like wind, hydro, and Solar Photovoltaic (SP) systems are currently praised as sustainable sources of energy (Lund, 2007). There are two major uses of solar technology in residential households: solar thermal and SP systems. While solar thermals are used for home heating, SP systems provide electricity to operate household appliances and recharge electric vehicles. Both solar thermal and SP market are part of the same goal of using alternative energy sources to meet household energy needs and thus similar factors such as price and incentive programs drive their demand. As part of a national strategy to reduce emissions, the federal government directed all provinces in 2016 to put a price on carbon pollution and NS uses a cap-and-trade program that came into effect in January 2019. The cap-and-trade covers

[1] With a population of slightly under 1 million people, this amounted to emission of 16 tons of $CO_2$ eq per person.

80% of total emissions and sets annual limits in the total amount of GHG emissions allowed in the province for the years 2019–2022. NS plans to reduce GHG emissions to 45-50% below the 2005 level by 2030.

GHG emission in NS due to the electricity sector in 2017 was 42% of the total, a much higher percentage compared to the rest of the country (Canada Energy Regulator, 2019d). This is because, while hydropower was the principal source of electricity generation in the country (60%), electricity generation in NS was mainly from coal (52%). There are policies in place to reduce GHG emissions in the electricity sector. The federal coal-fired electricity regulations (published in September 2012) set a limit to 420 tonnes of $CO_2$ per GWh (gigawatt-hour) from electricity generation using coal, coal derivatives or petroleum coke (Canada Energy Regulator, 2019a). Additionally, new regulations are in effect from January 2020 to December 2029 for the electricity market in NS. GHG emissions from the electricity sector are set to be a maximum of 7.5 Mt $CO_2$ eq in 2020, a maximum of 27.5 Mt $CO_2$ from 2021 to 2024 (average 6.8 Mt $CO_2$ eq per year), a maximum of 6 Mt $CO_2$ in 2025 and a maximum of 21.5 Mt $CO_2$ from 2026 to 2029 (Government of Canada, 2019).

In addition to restrictions in GHG emissions, alternative energy sources also have the potential to mitigate the effects of climate change and significantly reduce GHG emissions (Asaee et al., 2019). While the majority of the wind and hydro plants are used at an industrial scale to produce electricity, one advantage of residential SP is that it allows households to produce electricity for residential use.

Residential SP provides low maintenance, pollution-free and distributed alternative sources compared to the conventional electricity generation and distribution, with considerable potential for growth (Canadian Solar Industries Association, 2019). From 2007 to 2015, only about 130 SP systems were installed in NS, but by the end of 2018, total installations rose to 530 systems with an annual capacity of 3.4 megawatts (MW). Part of the reason explaining this increase in SP system installations stems from the fact that from 2012 to 2018 the cost to install SP systems has decreased 42%. This was at least partially made possible by incentives given by the government (Wayne, Christie, and Sarah, 2018).

Along with subsidies and promotion campaigns, investment in education and training is available in NS to assist in the diffusion of residential SP system installations. These policies are typically undertaken by the provincial and municipal governments and are currently available in Calgary, British Columbia, Prince Edward Island and Nova Scotia (Canadian Solar Institute, 2020).

The purpose of this study is to examine the factors that affect residential SP system installations in NS and analyze the effectiveness of the rebate program on the number of installed SP systems. I develop a demand model to evaluate the effectiveness of rebate policies implemented in NS. The model identifies the key economic variables that influence the demand for residential SP systems. It also identifies several policy adjustments introduced to increase the participation of more households in the market.

I use data from two sources: WattsUp Solar Ltd and 2016 Canadian Census. I collect installations data of SP systems from WattsUp Solar Ltd. I compute the cost of each installed SP system and estimates of rebate. From Statistics Canada (2017), I obtain census data containing demographic and economic variables such as population density and median household income from 2016 to 2019. Finally, I merge installed SP systems data, cost of each SP system and rebate with the census data at the dissemination area (DA) level and create a panel dataset.

The main dependent variable of interest, SP system installations, is a count variable. I use count data econometric techniques to model the installations. In the literature several methodologies are employed to analyze count data (Cameron and Trivedi, 2013; Cragg, 1971; Winkelmann, 2008; Yen and Huang, 1996; Weaver et al., 2015; Chapados, 2014; Englin and Shonkwiler, 1995; Greene et al., 2007; Chin and

Quddus, 2003). To model the demand for SP systems, Gillingham and Tsvetanov (2019) use a Poisson hurdle model. Other count data models include the Poisson regression model (PRM) and the negative binomial regression model (NBRM). PRM fails to address the overdispersion of data and NBRM does not consider the zero counts to be generated from a different process than the positive counts, which is crucial in analyzing count data dependent variable with too many zeroes (Cameron and Trivedi, 2013). In my dataset 95.6% of the installations data are zeroes, and as such a hurdle model better accommodates these excess zeros. Based on the Akaike information criterion (AIC), the negative binomial logit hurdle model (NBLHM) is the preferred methodology compared to the PRM and NBRM.

One of the key driving forces of residential SP in NS is government incentives (rebate), which started in 2018. The number of installations in the dataset increases over time, and this coincides with a gradually reduced rebate rate toward the end of the study period. I estimate a price elasticity of demand of -1.26 suggesting that the demand for residential SP systems is highly responsive to rebate and incentive policies. Simulation results suggest that since its inception in 2018 and until 2021, the provincial rebate program will have likely incentivize 1,911 SP systems with a capacity of about 17.8MW, which is about 96% of the capacity targeted by the program. The provincial rebate program is expected to continue at least until 2022 (Corning, 2019), and simulation results suggest that in 2022 an additional 671 new SP systems with a capacity of about 6.2MW will be installed under this program. An important dimension of incentive programs is the rebate pass-through which is the percentage of rebate that is passed on to the consumers. I find a 49% rebate pass-through. A low pass-through rate indicates that the supply schedule of SP systems is inelastic.

There are only a few studies that estimate the price elasticity of demand for residential SP but there are no notable estimates using Canadian data. Results vary greatly. Using Connecticut solar market data and a fixed effect Poisson hurdle model, Gillingham and Tsvetanov (2019) find a price elasticity of demand of -0.65. Using the same dataset and a reduced-form approach, Rogers and Sexton (2014) and Hughes and Podolefsky (2015) find a rebate elasticity of -0.4 and -1.2, respectively.

Consumers perceive an innovative technology as a new product in the market (Shama, 1982). Research on durable and innovative technologies finds that employment status, household income and education are directly correlated with their adoption (Im et al., 2003; Martinez et al., 1998; Olli et al., 2001). This is particularly important in the context of this study, as the use of solar technology in NS is still at its early stages and can be viewed as innovative technology.

There is an extensive body of literature on the diffusion of SP (Zhang et al., 2012; Dewald and Truffer, 2011; Duan et al., 2018). A number of them identify the barriers to SP installations. For example, Burke et al. (2019), Rai and Beck (2017) and Curtius (2018) find that socio-technical, management, economic and policy barriers hinder SP installations in both low and high-income countries. Zhai and Williams (2012) also find that, in the areas in China that are connected to the grid, socio-technical factors, such as lack of knowledge of SP by the adopters to carry on maintenance of the rooftop SP systems, are negatively correlated with the decision to install.

Economic barriers also account for the lack of rooftop SP dissemination. The high initial cost to install (average system cost of $20,000 in Canada) is a major investment with an uncertain rate of return. Paidipati et al. (2008) present a model of market penetration of rooftop SP in each of the 50 states in the United States. Their model takes into account the technical potential of rooftop SP and payback period for investments. They find that a higher payback period leads to a decrease in market penetration of SP in Massachusetts, New Jersey and Tennessee. By contrast, consumer SP awareness programs, incentives, and net metering tend to increase installations even with longer payback periods.

Barriers also exist in the form of a lack of knowledge on the environmental benefits of renewable energy sources and available incentive programs. Islam and Meade (2013) find that, in Austria and the United States, a lack of trust in the available information and proper training reduces the diffusion of SP, and educating the public and suppliers about solar technology is suggested as a possible solution. They also suggest that education campaigns should be extensively used to educate the suppliers on SP policies, SP's environmental consequences and feed-in-tariff programs to increase SP diffusion. Nova Scotia Community College in partnership with the Nova Scotia Department of Energy and Mines, organizes free training programs to educate the public on solar technologies and the techniques of installing and maintaining SP systems.

Social interactions and peer effects can positively affect installation of SP systems (Rai and Beck, 2017; Noll et al., 2014). Bollinger and Gillingham (2012) find that in California, an additional installation in a zip code increases the probability of an SP system installation in the same zip code by 0.78 percentage points. Population density tends to increase the probability of installations, possibly by reducing the cost of social interactions. Bollinger and Gillingham (2012) view population density as an indicator of social interactions and a clustering of SP systems in regions as an indicator of peer effects.

Similarly, (Graziano and Gillingham, 2015) model the demand for SP by analyzing spatial patterns of diffusion in Connecticut and find that the grid cost of electricity and SP marketing campaigns play a significant role in adoption. The authors also find that the installation of an additional SP system within a 0.5 miles radius in the previous 6 months period, increases expected future installations by 0.44. Moreover, McEachern and Hanson (2008) model the demand for SP using installed SP systems data in 120 villages in Sri Lanka that are not connected to the electricity grid. The authors find that decision of villages to install SP systems are governed by expectations of whether the villages will be connected to the grid.

A durable investment good like a SP system has close substitutes, especially given that substitutes like the conventional electricity generated from fossil fuels or nuclear energy have already incurred sunk and fixed costs. Lower cost of substitutes, thus, is a major contending factor and incentives can significantly reduce the cost associated with SP. Groote and Verboven (2016) estimate the decision to install residential SP systems using data on the Flanders SP market where they consider both static and dynamic specifications. The static model does not take into consideration the consumer expectations of the future. The dynamic model uses a discrete choice model that considers the valuation by the households of the future benefits of SP investment and their likeliness to wait for better future investment opportunities. The authors find that using the dynamic model increases the cost coefficient of SP by 40% compared to the static model. Similarly, Burr (2014) uses a dynamic discrete choice model for residential SP system demand, assuming that the residential consumers can perfectly predict the future changes in a subsidy program and decide whether to install or wait.

Chen and Wei (2018) use a Stackelberg game to analyze the SP market in China and study socially optimum incentive policies. Gerarden (2017) considers a dynamic model of demand for and supply of SP and addresses the effects of subsidy programs on consumer decisions to install and the innovation of firms. The author concludes that not only does a subsidy increase SP installations, it also increases firms' revenues, eventually increasing technical efficiency and lowering the cost of production. In this study, I consider a static demand analysis, and leave dynamic modeling to future work.

Lobel and Perakis (2011) develop a discrete choice model for the adoption of SP by residential consumers using data from Germany for the period 1991-2007. They argue that policymakers in Germany should give strong subsidies at the beginning and continue with a phase-out over time. Initially, when adoptions are low, a high subsidy helps disseminate information about rooftop SP and reduce costs through learning by doing. However, as adoption rates increase, it becomes more expensive to provide high subsidies. Efficiency NS is decreasing the rebate rate since its inception on June 25, 2018, which could be due to the positive externality induced by subsidies. Initially, subsidies help display and showcase installations that invite demand. However, over time, as SP installation costs rise, solar panel prices decline, and electricity prices rise, the need for subsidy could gradually disappear due to the familiarity of the product among potential customers and gain in experience by the solar panel installers.

The rest of the thesis is organized as follows. Chapter 2 begins with a discussion of electricity production using SP systems, describes the electricity market, and SP landscape in NS. Chapter 3 provides information about data sources, variables and descriptive statistics. Chapter 4 overviews several count data models and justifies selecting the negative binomial logit hurdle model (NBLHM) to analyze the installation of SP systems in NS. Chapter 5 presents the estimation results and predictions using a linear probability model (LPM), PRM, NBRM and NBLHM, policy simulations, robustness checks and the remaining limitations of the study. Chapter 6 concludes.

# Chapter 2

# Background

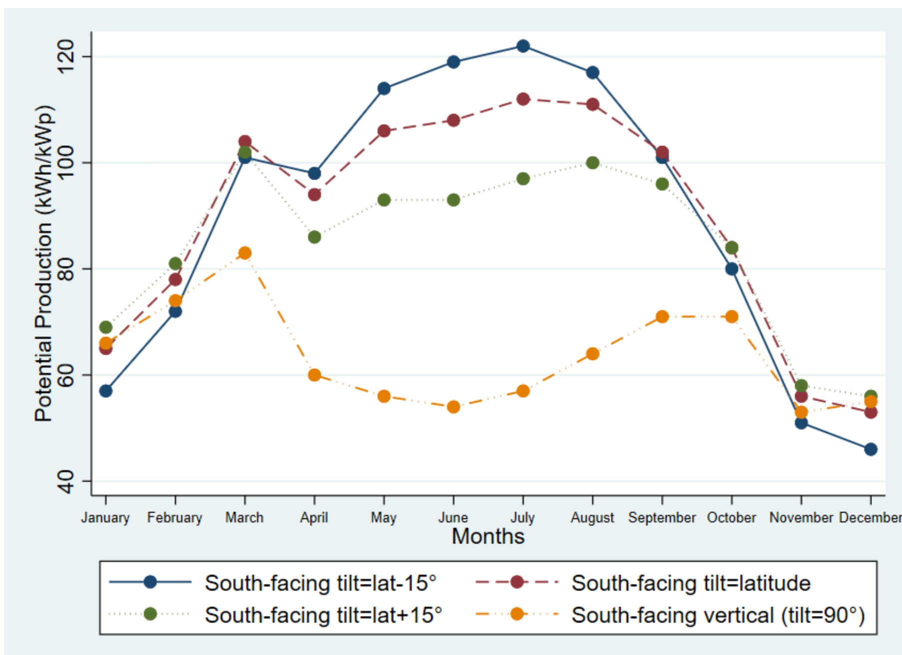
## 2.1 Solar Panel Technology

The amount of energy that reaches the earth from the sun in one hour is sufficient to provide total energy consumed by humans in one year ($4.6 \times 10^{20}$joules). Solar panels can be used to capture the energy (photons) from the sun using solar cells and in turn produce electricity (Gil, 2008). Solar panels are usually made of silicon which is a semiconductor and its electrical property to be conductive in one direction and insulating in the opposite direction enables electricity production. When photons from the sun hit the surface of a solar panel, electrons are knocked off the silicon atoms in the panels and the negatively charged electrons are driven to one side of the cells which are then passed through wires in the solar panels (Energy Sage, 2018). These moving electrons result in direct current (DC) and are converted to alternating current (AC) using inverters as appliances need AC to operate. The AC then flows through performance monitoring (optional), main electric panel, and meter. Finally, the electricity produced can be used by appliances and unused electricity is dispersed to the main grid or stored using batteries if available (Crabtree and Lewis, 2007).

The amount of electricity produced by a solar panel depends largely on the efficiency of solar panels, as well as several other factors like insolation and the direction at which panels are mounted in relation to the sun (Energy Sage, 2017). Here, efficiency refers to the percentage of energy from the sun that is converted to electricity by a solar panel. An LG solar panel, for example, has efficiency in the range of 18.4%

to 21.7% depending on the type of materials used, wiring and amount of light (photon) that solar panels reflect away instead of absorbing. In NS, the majority of the solar panels in use have an efficiency of 15% to 20%.

The size of a panel is measured in Watts and the electrical energy produced is measured in kWh (kilowatt-hour). For example, 10 units of 400 Watt panels each amounts to an installed capacity of 4 kilowatts of power and can produce approximately 4,060 kWh of electrical energy (Natural Resources Canada, 2017).




Source: Natural Resources Canada (2017)

Figure 2.1.1: Electricity Production by Solar Panels in NS

Figure 2.1.1 shows the different amounts of electricity produced in kWh per kilowatt peak when solar panels are mounted across different directions in Halifax, NS. There is a sharp decrease in electricity production with SP systems in October through February, and then in April because of a natural decline in insolation. However, after April electricity production increases. According to Natural Resources Canada (2017), on average, insolation decreases from 15.1 Mega Joules/squared meter

($MJ/m^2$) in March to 13.5 $MJ/m^2$ in April and increases to 14.3 $MJ/m^2$ in May. The direction of mounting affects the amount of solar radiation absorbed by solar panels. Panels mounted with a south-facing tilt and latitude$-15°$ produce more electrical energy than other positions.[1] Even though this is the optimal position, structure of the residential units and obstructions from surroundings (trees or other houses and buildings) can prevent installation at this position.

## 2.2 Electricity Market

In the year 2018, the energy sector in Canada accounted for 11.1% ($230 billion CAD) of the GDP and electricity production contributed to 1.7% of GDP. In 2018, 80% of total electricity generation came from non-GHG emitting sources and 67% from renewable sources with only 0.5% from SP. The installed capacity of SP systems was 3,113 MW in Canada compared to 49,692 MW in the United States and 45,930 MW in Germany (Whiteman et al., 2019).

In Canada, total electricity generation in 2017 was 652 terawatt-hours (TWh), among which hydro accounted for 60%, non-hydro renewables 7%, coal 9%, nuclear 15%, and gas/oil/others 10%. Canada is also a net exporter of electricity and from 2007 to 2018, net exports of electricity (only to the United States) increased to 42 TWh by approximately 31% compared to 32 TWh in 2007 (Natural Resources Canada, 2020).

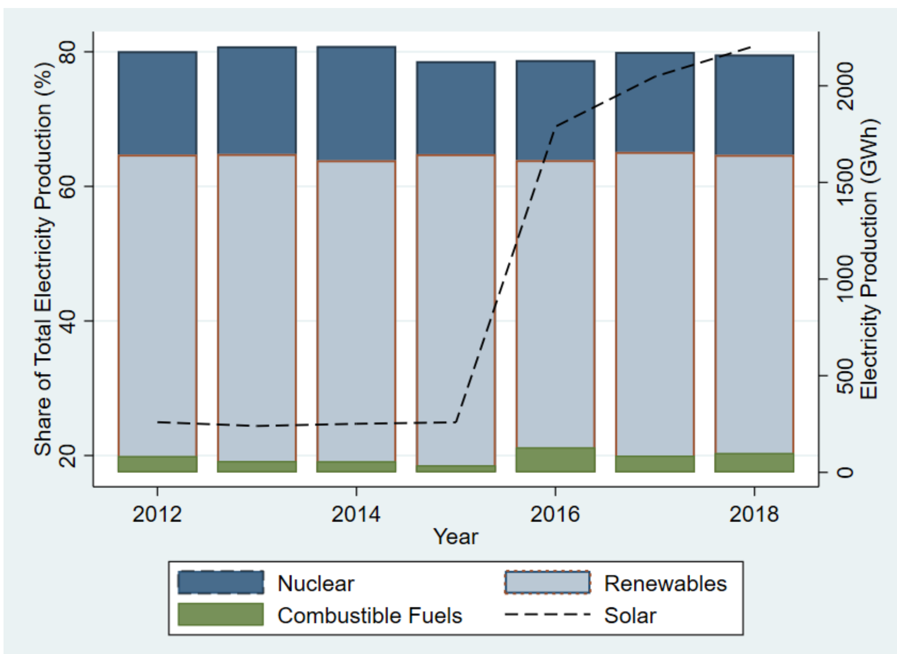
Figure 2.2.1 shows the change in percentage contribution of nuclear, renewables and combustible fuels[2] to the total electricity production along with total electricity produced by SP systems (secondary axis) in several provinces in Canada from 2012 to 2018.[3] Total electricity generation in 2012 and 2015 was 595 TWh and 593 TWh,

[1] The latitude of Halifax, NS, Canada is 44.651070.

[2] Renewable sources include hydro, solar tidal and wind in Canada. Combustible fuels include fossil fuels.

[3] Data for solar electricity production is only available for Alberta, British Columbia, Northwest Territories, Ontario, Prince Edward Island, and Quebec.

respectively, a 0.3% decrease. During this period both total and percentage of electricity generation using combustible fuels decreased, while total electricity production using non-GHG emitting sources increased from 463 TWh to 483 TWh, a 6% increase. Yet, from 2015 to 2018, total electricity generation increased by 8.2% and so did the use of combustible fuels (19%) and non-GHG emitting sources (5.7%). However, from 2015 to 2018 electricity production using solar increased by 752%, starting from a low base. Even though there was a huge deployment of SP in Canada, the share of electricity produced from solar compared to electricity produced from all other sources is still low.




Note: Solar electricity production includes data from Alberta, British Columbia, Northwest Territories, Ontario, Prince Edward Island and Quebec.
Source: Statistics Canada (2019).

Figure 2.2.1: Share of Resources to Produce Electricity and Total Electricity Production by Solar Panels in Canada

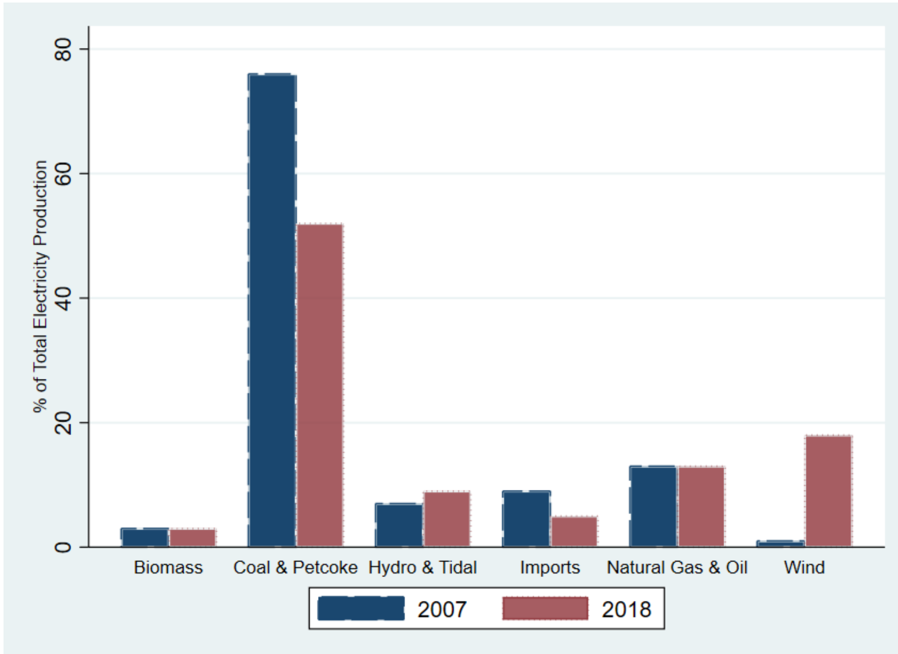
While hydropower is extensively used to produce electricity in Canada, NS produces the majority of its electricity from coal, petcoke and natural gas with wind producing more electricity than hydro. Also, nuclear facilities to produce energy is not available in NS and there are currently no plans to do so (Canada Energy Regulator, 2019c).

The size of the energy sector in the Atlantic region was \$10.20 billion: 29,642 petajoules of primary energy[4] were produced in 2017, among which 32% was from crude oil, 29% from uranium, 24% from natural gas, 3% from natural gas liquids, 5% from hydro, and only 5% from other renewables including SP systems. In 2010, NS introduced a legislative standard (Renewable Electricity Plan), to produce 25% by the year 2015 and 40% by the year 2040 of the total electricity in the province using renewable energy.

In the year 2015, 24% (2,659 GWh) of the total electricity generation in NS was from renewable sources where hydro constituted 9%, wind 9%, and biomass 6% (Canada Energy Regulator, 2019b). Nova Scotia Power (2019) states that by the end of 2018, 30% of total electricity generation in NS was by Renewable Sources.[5] Figure 2.2.2 shows electricity production by different sources in NS in the years 2007 and 2018. Majority of the change in resources use were due to an increase in wind along with a reduction in the use of coal and petcoke.

Several programs were introduced to reach a target of 40% renewable sources by 2020 in NS, including Competitively-Sourced Commercial Renewables projects (CSCR), Community Feed-in Tariffs (COMFIT), and net metering. Nova Scotia Power CSCR is a policy to allow independent power producers to supply electricity using renewable sources. In 2010, 600 GWh of large-scale renewable energy production was undertaken by the NS government under the renewable electricity plan, where 50% was to be produced with projects implemented by the independent power producers and the rest from NS power projects. Similarly, the Electricity Reform Act (2013) enables consumers to select retailers of their choice and electricity sold through

[4]Primary energy is the energy contained in raw fuels such as crude oil, natural gas, and renewables.
[5]Electricity production by SP systems is not included.

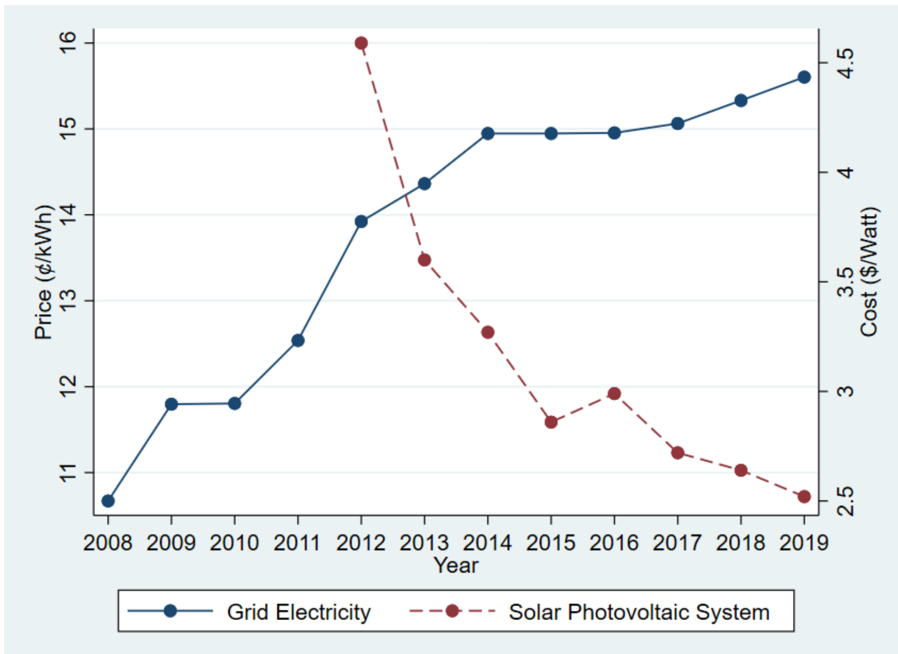



Electricity production using SP systems is not included.
Source: Nova Scotia Power (2019).

Figure 2.2.2: Nova Scotia Electricity Production from Different Sources

these retailers is sourced from low-impact renewables like solar wind and tidal.

The COMFIT program, although currently not accepting new applications, aims to promote investment in renewable energy in NS by local small-scale investors (Department of Energy and Mines, 2019). As part of the 2010 renewable electricity plan, the program guarantees to qualified investors a "feed-in-tariff" (rate) per kilowatt-hour for a certain period regardless of market and economic conditions. Energy produced by these small-scale producers is fed into the grid as denoted by "feed-in". Community development investment funds, First Nations, co-operatives, universities, non-profits and municipalities qualify for the program. Feed-in-tariff is a tool used in many countries, like the United States and Germany, and other provinces, like Ontario and Saskatchewan, to attract local investments. In total COMFIT resulted in $135 million investment in NS with a targeted production of 100MW of renewable electricity by 2020. As of May 2019, under COMFIT, renewable projects were generating 157MW of electricity, with 30MW of additional approved capacity. Also, Developmental Tidal Feed-in Tariff Program, like COMFIT, is used to produce electricity from tidal energy (Department of Energy and Mines, 2013).




Notes: The left axis shows the rise in electricity price in NS from 2008 to 2019. The right axis shows the decline in the cost of installed SP systems in NS. Dollar values are in 2019 dollar.
Source: Nova Scotia Power (2018) and WattsUp Solar Ltd.

Figure 2.2.3: Price of Electricity and Cost of Solar Photovoltaic Systems

Figure 2.2.3 shows the price of electricity supplied by the grid and the cost of SP systems in $/Watt, from 2008 to 2019. The price of electricity has increased by 46% over this period. At the same time, the cost of SP systems per Watt decreased by 45% from 2012 to 2019. Residential electricity prices are to increase by 1.2% on average each year from 2020 to 2023. According to Nova Scotia Power (2018), the increase in the price of electricity provided by the grid is in part due to higher costs associated with electricity generation using renewable energy sources used to meet renewable energy targets. While renewable sources indeed decrease the wholesale cost of electricity (Mills et al., 2019), the unreliable nature of renewable sources (e.g., bad weather) adds up to the cost. For example, wind necessitates the use of instant backup power using fossil fuels or batteries, which, when used, drives up the price of electricity.

Table 2.2.1: SP System Installations in Nova Scotia

| Years | WattsUp Solar | Province Total |
|---|---|---|
| 2016 | 17 | 83 |
| 2017 | 33 | 127 |
| 2018 | 78 | 200 |
| 2019 | 107 | 500 |

Notes: SP stands for Solar Photovoltaic.
Source: WattsUp Solar, Denty and Jacques (2018) and Corning (2019).

While between 2016 and 2019, on average the cost of SP in NS declined from \$3.78/Watt to \$2.53/Watt, the number of SP installations increased. Table 2.2.1 shows the number of SP systems installed by WattsUp Solar and total installations in the province. The number of newly installed SP systems in NS increased from 83 in 2016 to 500 in 2019. Unfortunately, there is no comprehensive documentation of the total number of installations nor the installed capacity of residential SP systems in NS. The province total numbers reported in Table 2.2.1 are from a report by Denty and Jacques (2018) and Corning (2019), and not meant to be definitive.

## 2.3 Incentive Programs

The most crucial instrument to stimulate residential SP adoption in NS is a rebate administered by Efficiency Nova Scotia[6] under the Solar Homes program; Table 2.3.1. Currently, there are around 50 authorized installers actively working with the HRM (Efficiency Nova Scotia, 2020).

[6]Efficiency Nova Scotia is an efficiency utility company that works with more than 200 local partners in NS to conduct energy efficiency projects.

Table 2.3.1: Rebate Rates for SP System Installations in Nova Scotia

| Amount | Date Effective |
| --- | --- |
| $1/Watt (installed DC capacity) up to 35% of eligible system costs (excluding HST) or $10,000, whichever is less | June 25,2018 |
| $0.85/Watt (installed DC capacity) up to 30% of eligible system costs (excluding HST) or $8,500, whichever is less | March 26, 2019 |
| $0.60/Watt (installed DC capacity) up to 25% of eligible system costs (excluding HST) or $6,000, whichever is less | November 1, 2019 |

Notes: SP stands for Solar Photovoltaic.
Source: Corning (2019).

According to Corning (2019), with an adoption quota of 200 SP systems, 800 applications were received while $1/Watt rebate was available. The installers were notified about the rebate reduction to $0.85/Watt, 4 days prior to its announcement date and 400 among the 1,100 applications were received in 4 days. Total applications received until November 2019 was 1,900. The total value of the projects is CAD $47.5 million and the total rebate to be disbursed is CAD$11.8 million. Moreover, total projects completed are 700 with a capacity of 6.5MW, and the rebate amount CAD$5.6 million has already been paid. More applications are expected to be received even though the rebate amount is decreasing in steps.

The second element of SP incentive programs is net metering. This program allows NS Power customers, who have installed solar electricity generation equipment on their premises, to sell excess electricity back into the grid at a price. NS power credits total electricity supplied by any consumer at the same price consumers pay for the electricity they buy from the grid, even if the price increases.

Another crucial instrument used to stimulate SP system installations, coupled with the Solar Homes program, is the Solar City program (Halifax Regional Municipality, 2020b) which has been an important instrument in the dissemination of SP in NS. It was introduced on May 15, 2016 for three years, and is funded by the Property Assessed Clean Energy Program (PACE) (Clean Foundation, 2020). PACE is a loan program that allows homeowners to implement energy efficiency upgrades such as insulation for ceilings and heat pumps.

The Solar City program is administered by the Halifax Regional Municipality, which provides financing at a fixed rate of 4.75% over 10 years to eligible property owners across Halifax regional municipality (HRM) only. Eligible property owners include residential households, not-for-profits, places of worship, cooperatives, and charities. SP, solar hot air, and solar hot water systems can also be financed using the program. Financing is only applied to the property and is transferable if the owner of the property changes. Credit checks are not required but owners need to be in good financial standing with respect to local improvement charges, property taxes, and any other municipal charges. Under the program, interested property owners can seek guidance from a Solar City officer to better analyze their energy needs and determine possible solar energy systems that can be used.

Similar programs are adopted to finance energy efficiency and renewable energy projects by several other NS municipalities, including Towns of Bridgewater, Berwick, and Municipality of the District of Shelburne (Denty and Jacques, 2018). SP system installations increased after the introduction of the financing option and from May 2015 to September 2018, 216 systems were installed under the program. The first phase ended on May 15, 2019, and additional 3 years were approved for this program. The Solar City program has not only assisted organizations and residential customers to adopt the new technology of SP systems, but also resulted in local SP system installation businesses to expand. Unfortunately, the data used in this study do not contain information on Solar City program participation, and hence I am not able to assess its impact on residential SP system installations. Denty and Jacques (2018) report that in 2017, SP systems with capacity 319.5 kW were installed within HRM, among which 161.2 kW were under the Solar City program. By the end of 2017, \$39,710.88 were paid out by net metering with total connections amounting to 453. (Unfortunately no data are available for 2018 and later years.)

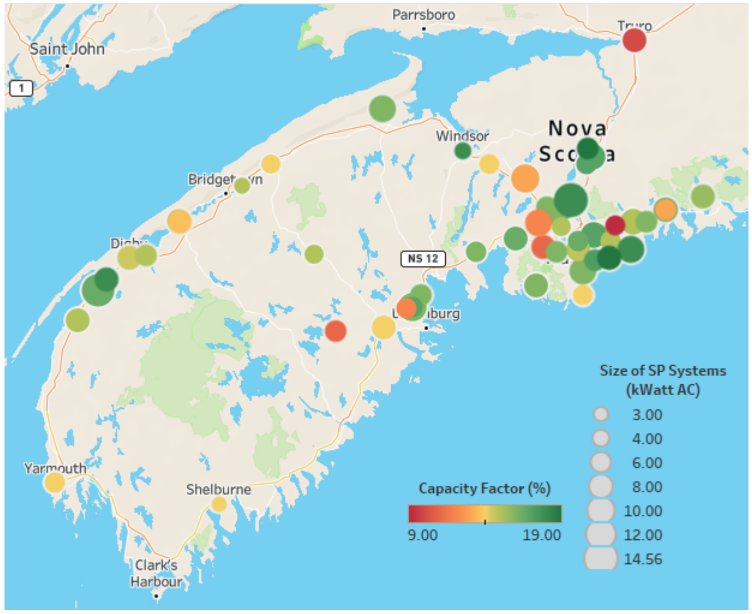
## 2.4 Capacity Factor and Levelized Cost of Energy

WattsUp Solar is one of the 50 companies operating in 10 of the 18 counties in NS. WattsUp Solar provides data on electricity generated by more than 300 SP systems over 4 years from 2016 to 2018. The electricity generation data can be used to investigate SP efficiency and cost in NS in terms of capacity factor (CF) and levelized cost of electricity (LCOE), respectively. In total, one SP system in 2016, 13 SP systems in 2017, 39 SP systems and 110 SP systems in 2019 have year-round electricity generation data and I use these SP systems to calculate annual CF and LCOE.

CF is defined as the actual electricity produced by an energy system over the total capacity of the system for a given period. CF can be calculated for any electricity generation sources using both AC and DC sizes and is used as a metric to analyze the efficiency of different energy systems (International Renewable Energy Agency, 2019). Annual CF can be calculated using

$$\text{Capacity Factor} = \frac{\text{Actual Output Produced}}{\text{Total Capacity}}, \tag{2.1}$$

where Total Capacity = size of SP system × 365 days × 24 hours. For example, a 3.25 kW system, situated in Paradise NS, generated 4,349 kWh of electricity in the year 2016. Total capacity is 3.25 × 365 × 24 = 28,470 kWh. Thus dividing 4,349 by 28,470 gives a capacity factor of 0.15 or 15%. The variation in CF is brought by different factors such as region, inverter used, angle at which SP system is mounted and shading.



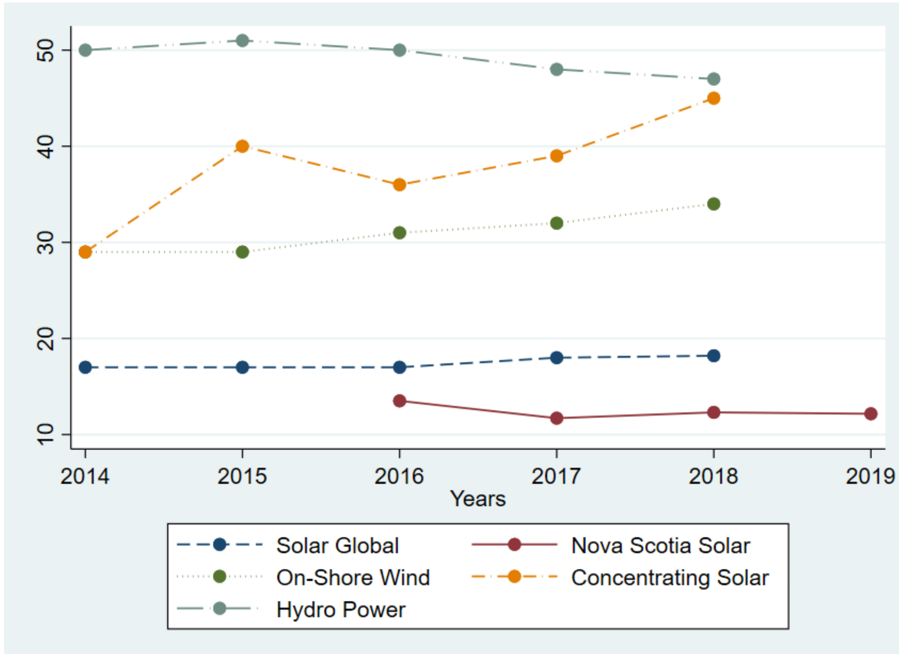

Notes: SP is Solar Photovoltaic. SP systems (AC sized) installed in various regions as shown by circles. 110 residential SP systems operational throughout 2019 are mapped. Capacity factor expressed as an annual average for each SP system for both residential and commercial SP systems. Map made with software Tableau.
Source: WattsUp Solar.

Figure 2.4.1: Capacity Factor by SP System Size in Nova Scotia

Figure 2.4.1 shows the variation in CF for different SP system sizes in different regions of NS in 2019.[7] On average, larger SP systems have a higher CF. SP system installations in Digby, Yarmouth, Shelburne and Colchester counties are relatively smaller compared to Halifax county and CF is also lower.

Figure 2.4.2 presents the yearly change in CF for SP systems in Nova Scotia and global weighted average CF for other renewable energy sources. Hydropower has the highest CF but a decreasing trend since 2016. One reason for the decline can be the slowing down of the development of hydropower in developed countries due to the lack of new sites for its generation (Boccard, 2009). CF of SP systems in NS and on average in the world shows a moderate increasing trend compared to 2014 values. More importantly, the CF of SP systems in NS is lower compared to the

[7] Both commercial and residential SP systems are used for calculation.




Notes: For all renewable sources except Nova Scotia Solar, capacity factor is in global weighted average. Concentrating solar produces electricity by converting thermal energy from sun to electricity. Solar includes both commercial and residential SP systems (DC size).
Source: International Renewable Energy Agency (2019) and WattsUp Solar.

Figure 2.4.2: Capacity Factors for Renewable Energy Sources

global weighted average. In 2018, CF of an SP system in NS was 12.3%, compared to the global weighted average of 18.2%.

Additionally, on-shore wind has a higher CF than residential and commercial SP but lower than concentrating SP. Concentrating SP converts energy from sunlight into thermal energy which is then used to generate electricity, generally by using a steam or gas turbines (Müller-Steinhagen, 2013). The global weighted CF of concentrating SP systems in 2018 increased by 55% compared to 2014 and this high CF of concentrating SP systems can be a result of the widespread use of this technology around the world (Whiteman et al., 2019). Djebbar et al. (2014) studied the potential of concentrating SP systems in Alberta, British Columbia, Saskatchewan, Manitoba and Ontario. At the end of 2014, the first concentrating SP system started operating in Medicine Hat, Alberta (Green Energy Futures, 2014). However concentrating SP systems are yet to be used in NS to produce electricity.

Levelized cost of electricity (LCOE), on the other hand, compares the cost of different sources of energy production. The absolute cost to produce electricity by different sources cannot be compared as the cost varies by region, project, capital cost, maintenance cost, and many other variables. LCOE takes into consideration all the different factors that affect electricity price and normalizes it to a comparable value in \$/kWh.

To compare LCOE (\$/kWh) values of SP systems in NS with previous study by International Renewable Energy Agency (2019), I use similar assumptions to calculate LCOE. I assume an economic life of an SP system to be 25 years, operations and maintenance expenditures of CAD\$25 per kWatt with annual inflation of 2%, energy produced by an SP system to decrease by 0.6% every year and a discount rate of 6% per year.[8] Table 2.4.1 shows the average cost of an SP system in NS, rebate and average electricity produced by an SP system from 2014 to 2019, as used for LCOE calculation. LCOE is calculated using

$$\mathrm{LCOE} = \frac{\sum_{t=1}^{25} \frac{I_t + M_t + F_t}{(1+r)^t}}{\sum_{t=1}^{25} \frac{E_t}{(1+r)^t}}, \tag{2.2}$$

where $I$ is investment on an SP system or the total cost per kWatt, $M$ is operations and maintenance expenditures, $F$ is fuel cost (which in case of SP is zero), $r$ discount rate and $E$ is energy produced by the SP system. I calculate LCOE of installed SP systems with actual average electricity production in kWh/kWatt DC in NS. I also use the average cost of installations in the data for each year to find investment or total cost of an SP system in a given year.

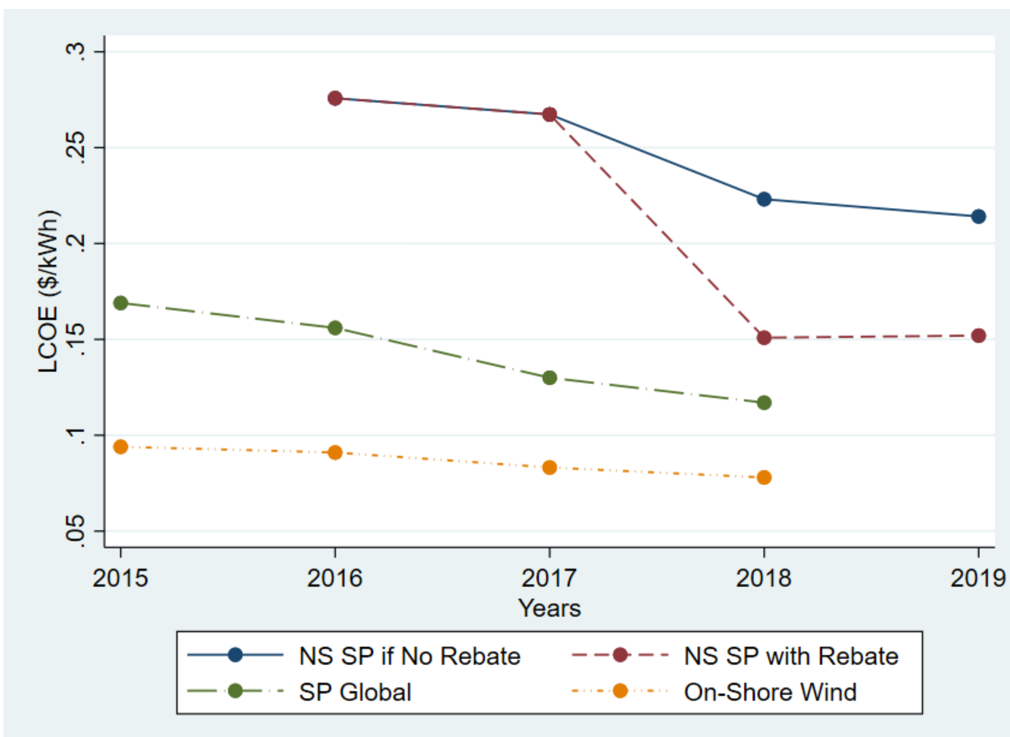
Figure 2.4.3 shows the change in LCOE (\$/kWh) of on-shore wind and SP systems in the world and NS. LCOE has been decreasing for all renewable energy sources

[8] Under the Solar City program discount rate is 4.75% per year over 10-years

Table 2.4.1: Data Used for LCOE Calculations

| Variables | Values |
|---|---|
| Total cost of an SP system in 2016 | 3,780 |
| Total cost of an SP system in 2017 | 3,110 |
| Total cost of an SP system in 2018 | 2,680 |
| Total cost of an SP system in 2019 | 2,520 |
| Rebate in 2018 | 1.02 |
| Rebate in 2019 | 0.85 |
| Electricity produced in 2016 | 1,183 |
| Electricity produced in 2017 | 1,025 |
| Electricity produced in 2018 | 1,078 |
| Electricity produced in 2019 | 1,065 |

Notes: SP is Solar Photovoltaic. Total cost is in \$/kWatt. Rebate is in \$/Watt. Electricity production is in kWh/kWatt direct current (DC). All dollar values are in 2019 dollars. Cost of installation is for both residential and commercial SP systems.




Notes: SP is solar photovoltaic. LCOE is levelized cost of energy/electricity. NS is Nova Scotia. Global SP LCOE is in global weighted average. SP LCOE is calculated with DC sized SP systems. SP includes both commercial and residential SP systems. Dollar values are in 2019 Canadian dollars. Source: International Renewable Energy Agency (2019) and WattsUp Solar.

Figure 2.4.3: Levelized Cost of Electricity for Different Renewable Sources

with on-shore wind incurring the lowest cost to produce a kWh of electricity. The SP systems in NS that benefited from a \$1/Watt rebate in 2018, the LCOE is 0.151 \$/kWh which is a 44% decrease compared to SP systems installed in 2017.

Given a rebate of \$0.85/Watt, the cost to produce electricity by installed SP systems in 2019 was \$0.152/kWh which is less than the grid electricity rate of \$0.156/kWh. Therefore, rebate structure in 2019 enabled SP system installers to reach grid parity and it was cheaper to produce electricity with SP systems than to use grid electricity. On the other hand, LCOE of SP systems in NS is more than the LCOE of the global weighted average of SP systems and on-shore wind, even if rebate is applied. Moreover, if rebate is phased out, LCOE of SP systems is likely to increase in NS as total costs to be paid by the installers will increase. This also means that it will be difficult to reach grid parity by SP systems if rebate is no longer available. While the calculation of LOCE varies by each system installed, location and other factors, the analysis of LCOE in NS illustrates the importance of rebate to reach grid parity.

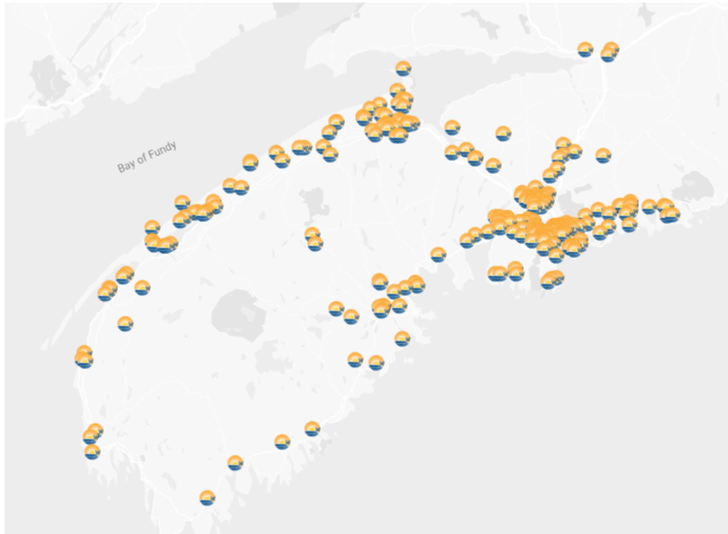
# Chapter 3

# Data

## 3.1 Sources

I use data from two sources: WattsUp Solar Ltd and 2016 Canadian Census. Solar Photovoltaic (SP) system installations data are obtained from the website of WattsUp Solar. Data were accessed on October 10, 2019 from: https://wattsupsolar.ca. Each installed SP system is mapped to a geographic location (Figure 3.1.1) and each observation contains installation information including the date of operation, installed capacity in both DC and AC sizes, number of panels used, location, and inverter use. The total number of installed residential SP systems from 2016 to 2019 is 235. The SP system installations data is geocoded at the DA level using ArcGIS Pro and merged with the census data at the DA level.

The cost of an individual installed SP system is not provided by WattsUp Solar, but their website has a user-friendly tool to calculate the cost in 2019 dollar values. Variation in cost comes from several factors: the make of solar panels installed (e.g., LG), type of inverter used (e.g., IQ6+), number of panels installed, size in Watt of each panel, an approximate total service fee (e.g., administrative cost), and the total size of the installed SP system. For example, using LG solar panels, IQ6+ inverter, 27 solar panels with a size of 400 Watt per solar panels, CAD$3,000 service fee, a 10.8 kWatt DC sized SP system installation costs, CAD$2.48 per watt in 2019. Similarly, using Silfab solar panels, M250 inverter, 36 solar panels with a size of 285 Watt per solar panels, CAD$3000 service fee, a 10.26 kWatt DC sized SP system installation costs CAD$3.19 per watt in 2019.




Note: Each point on the map represents an individual SP system installation.
Source: WattsUp Solar website, https://quote.wattsupsolar.ca/systems.

Figure 3.1.1: Solar Photovoltaic System Installations in Nova Scotia

I calculated the cost of these 235 installed SP systems using the web-based tool. Some DAs have more than one installation. In those cases, I use a cost averaged over all installations in that DA. This results in 200 distinct DAs with installation and cost data. Thus, for a variable $x$, my unit of observation is $x_{it}$ where $i$ is a DA and $t$ is year. Specifically, if $x_{it}$ is the cost of installation in a DA, I use the average cost of all the installations in DA $i$ during year $t$.

The amount of rebate that was applied to each installed SP system is not available. However, rebate can be computed using Table 2.3.1. I have data on the date at which each installed SP system started operating, but not when the installation was approved for a rebate, if it was at all. Rebate is determined based on the date of the application to install an SP system. I assume an average 4-month period of project implementation to estimate the date of application and I set rebate equal to what was available 4 months prior to the date of operation. Several DAs have multiple installations and an average value of total rebate applied to all the installations is taken.

In the WattsUp data, 95% of the DAs in NS have zero installation. The corresponding shadow price and rebate for these DAs are recorded as follows: rebate is set equal to the maximum amount that was available during a specific year. For example, all DAs that had zero installations in 2016 and 2018 are assigned a rebate of 0 $/Watts and 1$/Watts, respectively. The shadow price (cost of installation) variable needs to be handled with care. In studying the Connecticut solar market, Gillingham and Tsvetanov (2019) use the average cost of installation in the same municipality, and, if this is not possible, they use average within-county cost of installation. In this study, I use the average cost of installation for Nova Scotia by WattsUp in a specific year to determine the corresponding shadow prices. Additionally, I deduct rebate from the cost of an SP system to calculate cost-after-rebate for each DA-year pair.

Canadian Census 2016 (Statistics Canada, 2017) provides demographic and economic characteristics of 1,721 DAs for NS. The control variables obtained from this source are average age, population density, education at three levels (no certificate or degree, secondary education completed, and post-secondary education completed), owner-occupied households, and median household income. I remove 96 DAs due to missing information. I extrapolate the census data to an annual basis from 2016 to 2019, by applying average annual or quarterly changes, whichever is available from Statistics Canada. There is little variation over time in age, education and household ownership variables. Overall, the panel data consists of 1,625 DAs and 6,500 observations that include demographic and economic variables, along with rebate and cost data for each DA.

Several issues need to be mentioned and that will matter for the interpretation of the results. First, a considerable number of counties do not have installations and this can bias the results. Second, since the installation costs for these counties are imputed using the provincial average, there will be measurement error. Moreover, the cost estimates for installations prior to 2019 are not based on historical quotes

Table 3.1.1: Summary Statistics

| | Mean | SD | Min | Max |
|---|---|---|---|---|
| a) All DA-year pairs (N=4,560) | | | | |
| Installations | 0.05 | 0.27 | 0 | 7 |
| Cost of installations ($/Watt) | 2.99 | 0.48 | 2.24 | 4.42 |
| Rebate ($/Watt installed) | 0.46 | 0.47 | 0 | 1.02 |
| Cost-after-rebate ($/Watt) | 2.56 | 0.92 | 1.24 | 4.42 |
| Median income ($) | 67,250 | 25,150 | 17,344 | 2,20,519 |
| Population density | 1,621 | 3,065 | 0.40 | 62,525 |
| % of no education | 19.70 | 9.77 | 0 | 61.96 |
| % of secondary education | 25.30 | 6.07 | 0 | 51.38 |
| % of post-secondary education | 54.99 | 11.41 | 19.57 | 87.16 |
| Average age, in years | 43.27 | 5.34 | 23.80 | 65.60 |
| Owner-occupied households | 175.09 | 97.24 | 0 | 1,160 |
| b) DAs With At Least One Installation | | | | |
| Installations | 1.18 | 0.61 | 1 | 7 |
| Cost of installations ($/Watt) | 2.77 | 0.43 | 2.24 | 4.42 |
| Rebate ($/Watt installed) | 0.54 | 0.48 | 0 | 1.02 |
| Cost-after-rebate ($/Watt) | 2.23 | 0.80 | 1.24 | 4.42 |
| Median income ($) | 76,667 | 26,730 | 31,714 | 2,17,169 |
| Population density | 952 | 1528 | 1.04 | 6,974 |
| % of no education | 18.21 | 8.27 | 4.05 | 45.45 |
| % of secondary education | 24.60 | 5.45 | 7.27 | 41.67 |
| % of post-secondary education | 57.20 | 10.22 | 28.00 | 78.18 |
| Average age, in years | 43.32 | 5.30 | 30 | 57 |
| Owner-occupied households | 229.65 | 125.65 | 45 | 680 |

Notes: The unit of observations is a DA in a year. N is the number of observations. Installations is a count variable with counts ranging from 0-7. Cost-after-rebate = Cost of installations − Rebate for each DA-year pair. % of no education is total number of people with no certificate, diploma or degree expressed as a percentage of total population. Population density: number of people per square kilometer. Owner-occupied household is the number of households occupied by owner. SD is standard deviation. All dollar values are in 2019 dollars.

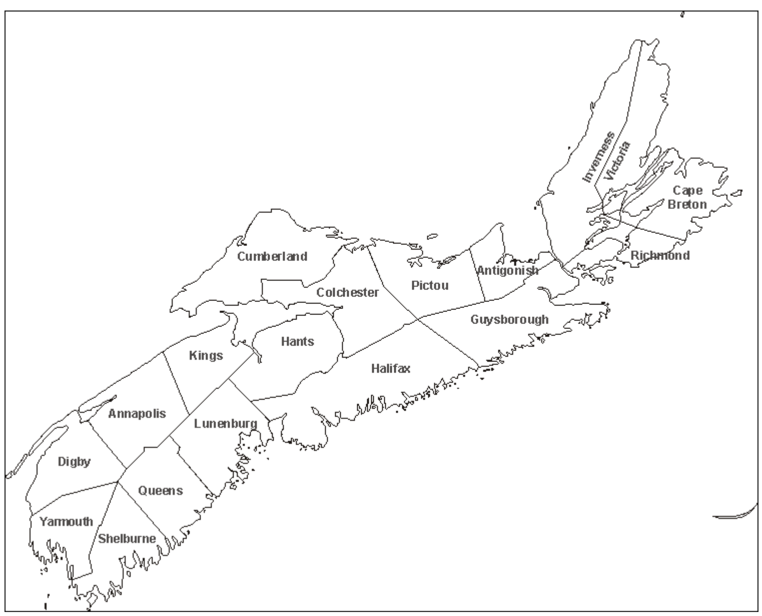
received by customers, but rather based on a hypothetical quote they would have received in 2019 had they installed the same system. As such, the cost estimates are likely to understate the change in cost of installations over the years.[1] Third,

[1] One major component of cost is the make and size of solar panels. In the dataset, in 2016 and 2017, the majority of the solar panels were Silfab and the average size of panels was 293W, whereas, in 2018 and 2019, almost all the panels installed were LG and the average size of panels was 353W. These changes in make and size are in respond to changes in relative prices and efficiency. If substitution bias is present, for instance, web-tool based costs estimates would imply a smaller decrease in average cost of installations.

WattsUp Solar does not install in eight out of 18 counties,[2] and these areas are removed from the dataset. Thus, following Gillingham and Tsvetanov (2019) and Hughes and Podolefsky (2015), counties with no installations are not considered for analysis. Taking everything into account, I have a balanced panel dataset of 1,140 DAs (4,560 observations) over 4 years.

Table 3.1.2: Frequency of Installations

| Installations | Frequency | Percent | Cumulative |
|---|---|---|---|
| 0 | 4,360 | 95.61 | 95.61 |
| 1 | 177 | 3.88 | 99.50 |
| 2 | 16 | 0.35 | 99.85 |
| 3 | 5 | 0.11 | 99.96 |
| 4 | 1 | 0.02 | 99.98 |
| 7 | 1 | 0.02 | 100.00 |
| Observations | 4,560 | | |




Source: Academic (2019).

Figure 3.1.2: County Map of Nova Scotia

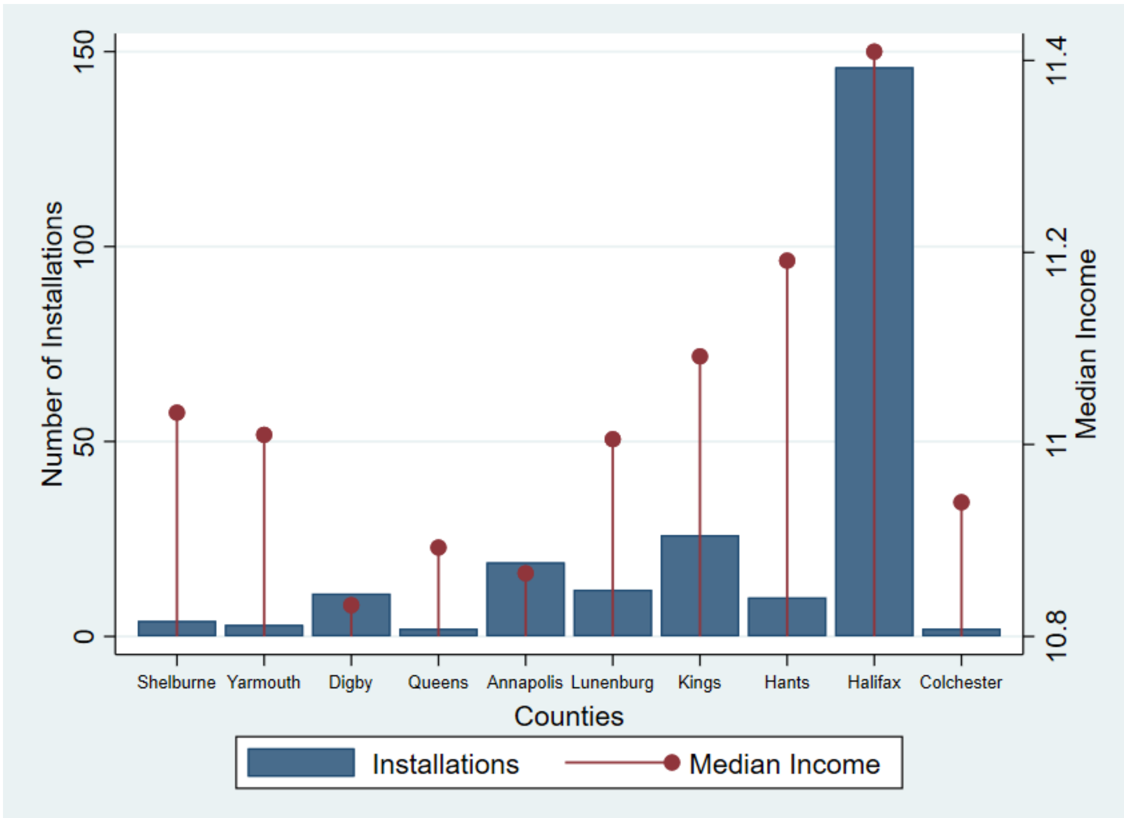
[2]The counties that are not serviced by WattsUp Solar are Antigonish, Cape Breton, Cumberland, Guysborough, Inverness, Pictou, Richmond, Victoria (Efficiency Nova Scotia, 2020).

Table 3.1.1, panel a, presents summary statistics for all DA-year pairs (full sample). Table 3.1.1, panel b, by contrast, shows the summary statistics for all DA-year pairs with at least one installation (subsample). The low mean of 0.05 in the full sample reflects the total SP systems installation of 228 in 4,560 DA-year pairs. Installations is a count variable with counts ranging from 0 to 7. Table 3.1.2 shows the frequency distribution of the installation variable that has 95.6% of zero counts.

The cost of installation ($/Watt) and cost-after-rebate values are higher in the full sample. This is because the shadow prices are calculated using the average cost of installations, and the average cost of installations in 2016 and 2017 were $3.87/Watt and $3.11/Watt, respectively, which drives up the mean value in the full sample. Also, the mean of owner-occupied households, which is the number of households occupied by owners in a DA, is higher in the subsample. This highlights that DAs that have more owner-occupied households are more likely to have SP system installations.

Additionally, the mean of median income is higher in the subsample with at least one installation than in the full sample. The population density in the full sample is much higher than that of the subsample. Densely populated DAs are mainly in the Halifax city centers where owner-occupied households are fewer.

Figure 3.1.3 shows the number of installed SP systems and median household income by county. During the period from 2016 to 2019, while Digby with a low median income had only 11 installations, Halifax with the highest median income had 146 SP system installations. However, in other counties, the relationship is mixed. For example, the median income in Kings county is lower than that of Hants county, but Kings county had more SP systems installed. The number of installations in Shelburne, Yarmouth, Queens, and Colchester is comparatively lower than other counties. Given that data are from a single installer, one reason can be the presence of many competitors of the company in those counties. For example, Shelburne and Colchester have 29 and 32 competitors and these companies can potentially be successful in these regions in drawing customers away from WhatsUp Solar Ltd.

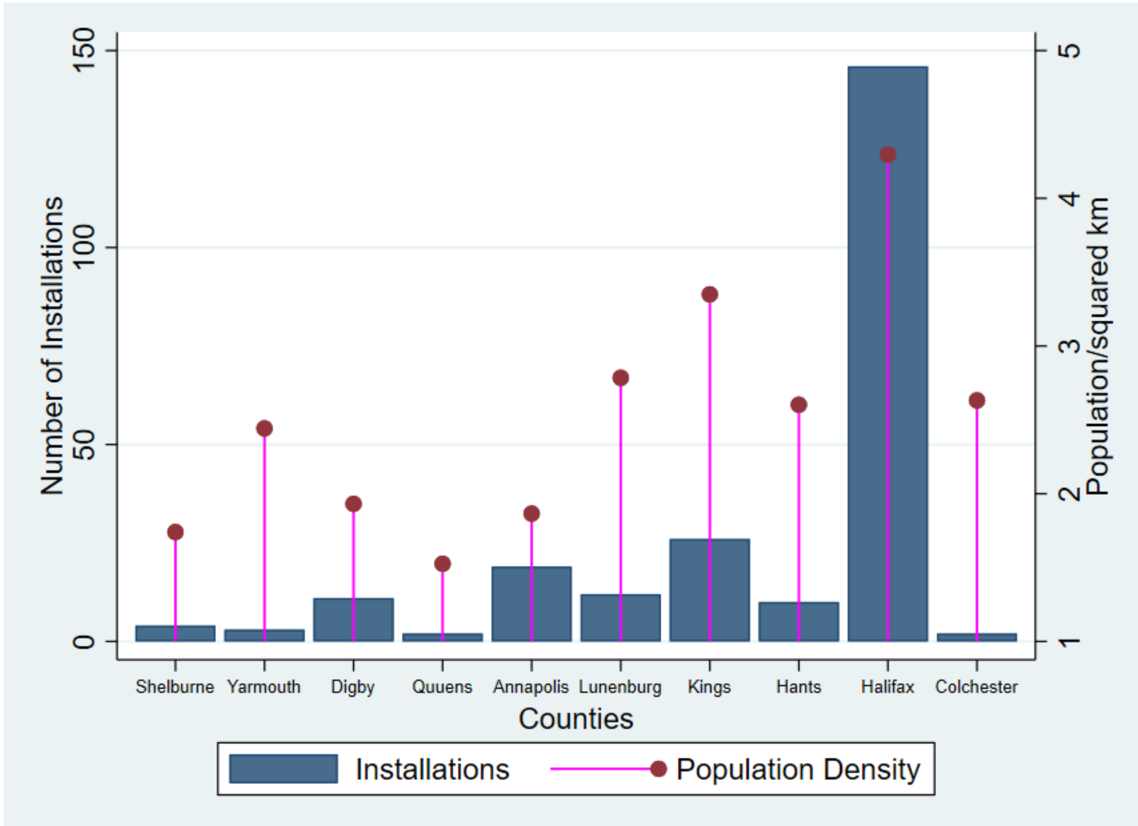



Note: Median Income is median household income in logarithms

Figure 3.1.3: Median Income and SP System Installations by County

While Halifax county with the highest population density has the maximum number of SP system installations among all counties (Figure 3.1.4), Queens, with the lowest population density, has the lowest number of SP system installations. However, the same positive relationship is not present if Colchester county is compared with Annapolis county. Overall, these figures suggest that to estimate the demand for residential SP systems, one should control for population density and median household income as these provide distinct information.

Figure 3.1.5 depicts the number of SP system installations in NS from 2016 to 2019. I use the same average cost curve of SP systems as in Figure 2.2.3 to analyze the relationship between the cost of and demand for residential SP systems and find an

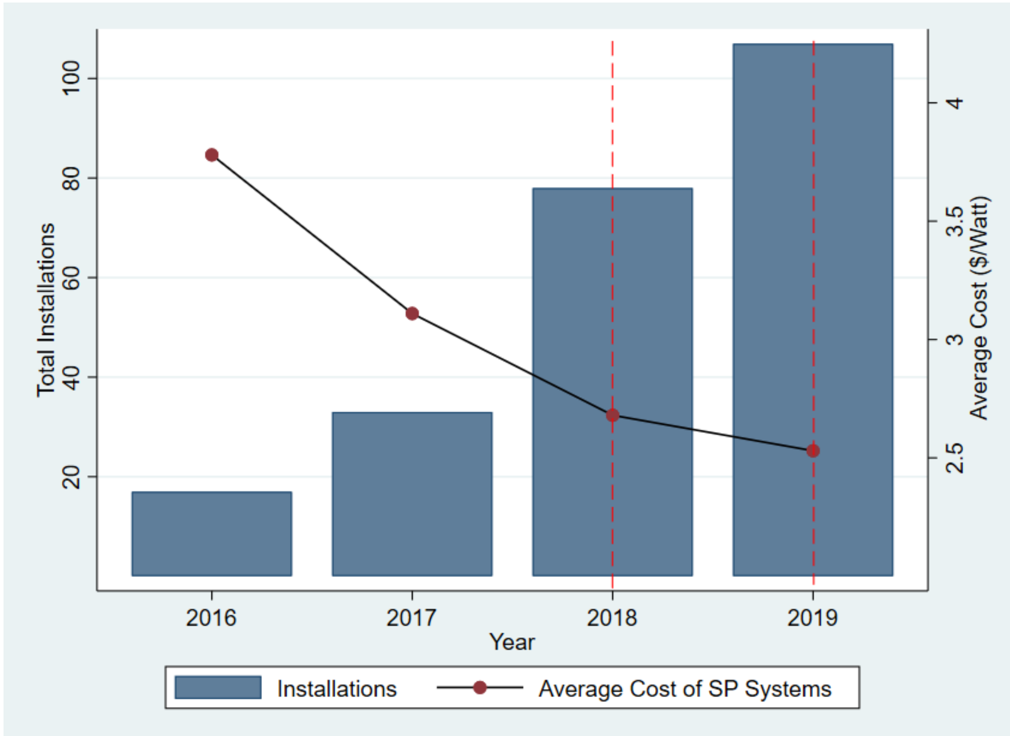



Note: Population Density is in logarithms.

Figure 3.1.4: Population Density and Solar Photovoltaic Installations by County

inverse relationship. Rebate of $1/Watt was introduced in 2018 and the total number of installations in 2018 was 78 compared to 33 in 2017. While rebate decreased to $0.85/Watt on March 26, 2019, the total number of installations increased.

Moreover, the 94% increase in installations from 2016 to 2017 reflects rising grid price and decreasing SP system cost effect. From 2017 to 2018, the number of installations increased by 136% and during this time the grid cost per kWh increased by 1.77% while residential SP systems cost per Watt decreased by 3.03%. The rising cost of grid electricity cost and decreasing installation costs, coupled with a $1/Watt rebate increased the number of installations by 136% between 2017 and 2018. On the other hand, the decrease in the growth rate of installations from 2018 to 2019 is likely to be due to a combination of the reduction of rebate and the cost decreasing




Note: The vertical red lines represent the introduction of rebate on June 25, 2018 of 1$/Watt and a decrease in rebate to 0.85$/Watt on March 26, 2019.

Figure 3.1.5: SP System Installations and Cost of SP Systems from 2016 to 2019

by 5.56% compared to 13.86% in the previous year.

While using data from a single installer is a major concern, alternative data sources, are not suitable for this study. Halifax Regional Municipality (2020a) provides solar electric generation data at 5-minute intervals for about 100 SP systems installed through the Halifax Solar City program. Similarly, a report by Denty and Jacques (2018) includes data on around 300 residential installations in 2016 and 2017 in NS. Unfortunately, however, none of these data sources can be linked to cost data required to estimate the price elasticity of demand.

Installing a SP system is an investment that bears a high initial cost and DAs with higher median income are expected to exhibit higher numbers of installations. The average cost of SP including rebate in 2019 in NS was $1.57/Watt. Given the average DC size of an SP system in NS in 2019 was 9.3 kWatt, this amounts to a total cost of CAD$14,508.

Additionally, one major concern with SP is that electricity production from SP depends on shading factor. Also, consumers are unable to rely entirely on electricity produced by their SP systems even if they install large units, unless they use battery storage. However, storage adds further costs to an already substantial capital investment. Unfortunately, I do not have location-specific shading factor and storage data.

### 3.2 Endogeneity

The cost of an SP system is a crucial variable in the demand for SP, and if the cost is endogenous, this may bias the estimates. Gillingham and Tsvetanov (2019) study Connecticut, which is a big market for SP and pursue an instrumental variable approach. As instruments they use wage and state incentives for SP systems which are marginal cost shifters. However, SP in NS is a relatively small market and most of the supplies (like panels, inverters) are sourced from an internationally competitive market (mainly China and Canada), and individual contractors do not have enough market power nor size to obtain discounts from the suppliers. Moreover, the regulating agencies and NS Power do not place onerous certification requirements on installers, above and beyond the requirement that the contractor works with certified electricians. As a result, there are around 50 certified solar panel installers in the province (Efficiency Nova Scotia, 2020). Since there are no major certification hurdles to enter into the installations market, I assume that the residential SP systems market is competitive and thus treat the installation cost as an exogenous variable with all changes in the cost of installation driven by unit labor costs and cost of equipment and not by the number of installations.

# Chapter 4

# Methodology

The dependent variable is the number of SP system installations (count variable) at the DA level and my objective is to estimate the impact of economic factors on the decision to install SP in NS. To model the demand for SP, I build on the work of Cameron and Trivedi (2013) who use count data models and Gillingham and Tsvetanov (2019) who use a Poisson hurdle model to analyze demand for SP systems in Connecticut. Count data are often modeled as a Poisson process. There are at least three estimation techniques: linear, Poisson regression model (PRM) and negative binomial regression model (NBRM). Below, I discuss these models and offer a list of their limitations. Later in the chapter I introduce negative binomial logit hurdle model (NBLHM) and present several criteria that will help assess whether to use NBLHM or other count data models.

I start with a general representation of the demand for SP. Let $Q_{it}$ be the number of SP systems installed in DA $i$ at time $t$, $X_{it}$ be a matrix of independent variables such as cost of installations and rebate, and $\beta$ be a vector of parameters. The demand function is

$$Q_{it} = D(X_{it}, \beta). \tag{4.1}$$

In the data, the count variable ranges from 0 to 7. I use the cost of installations (\$/Watt), rebate (\$), and other economic and demographic variables as explanatory variables. Median income is the median household income in logarithm, population density is the population density in logarithm, age is the average household age and

$\text{age}^2$ is squared average household age. I also control for the percentage of the population who has a post-secondary degree. Owner-occupied households is the number of owner-occupied homes in a DA.

## 4.1 Linear Model

Assuming a linear demand system, the demand for SP can be expressed as

$$Q_{it} = X_{it}'\beta + \epsilon_{it}, \tag{4.2}$$

where $\epsilon_{it}$ is idiosyncratic errors, and $\beta$ is a vector of parameters to be estimated. The linear model can be estimated by ordinary least squares (or maximum likelihood). However, OLS treats the dependent variable as continuous and misspecifies the data generating process of count data leading to predicted non-integer and negative outcomes; see (Wooldridge, 2010) and (King, 1988). While logit and probit regression models would deliver consistent estimates, they result in a significant loss of information as the range of the count variable is reduced to 0 or 1; see Gardner, Mulvey, and Shaw (1995).

## 4.2 Poisson Regression Model

Modeling the data generating process of count data as a Poisson process is standard, given that the Poisson distribution handles the presence of non-linearity and non-negative integer values in the data (Cameron and Trivedi, 2013). The probability distribution of count data using Poisson distribution is

$$P(Q_{it} = Q|\lambda_{it}) = \frac{e^{(-\lambda_{it})}\lambda_{it}^{Q}}{Q!}, \tag{4.3}$$

where $Q = 0, 1, 2, 3, ...$ is a Poisson random variable with

$$E[Q_{it}|\lambda_{it}] = \text{Var}[Q_{it}|\lambda_{it}] = \lambda_{it}, \tag{4.4}$$

so that the conditional mean and variance of the Poisson random variable are equal, with $\lambda_{it} = e^{(x'_{it}\beta)}$.

In a panel data setting, the conditional expectation of equation 4.1 using the Poisson regression model (PRM) is

$$E[Q_{it}|X_{it}, \beta] = \lambda_{it} = e^{(X'_{it}\beta)}. \tag{4.5}$$

The PRM has drawbacks. First, PRM does not take into account unobserved heterogeneity. While equation (4.4) assumes equidispersion, often the data are overdispersed, which means conditional variance is larger than the conditional mean (as in the case of installed SP systems used in this study).[1] Using PRM to estimate overdispersed data understates the standard error, which lowers p-values and might lead to an erroneous conclusion that the coefficient estimate on a variable is significant when it is not. Second, when the dependent variable has many zeros (95.61% in the data), the observations are not represented well by a Poisson distribution unless the sample mean is small. Problems of overdispersion and excess zeros can be addressed if the data generating process is such that the dependent variable has a negative binomial distribution, an extension to the Poisson distribution which is discussed next.

## 4.3 Negative Binomial Regression

The PRM fails to fit a model when overdispersion is present, as it only models observed heterogeneity by specifying that $\lambda_{it}$ is a function of observed $X_{it}$'s. The negative binomial regression model (NBRM) is an extension of the PRM. Given $\lambda_{it} = e^{(X'_{it}\beta)}$, the NBRM introduces an additional parameter $\alpha$ to address unobserved heterogeneity and overdispersion (Cameron and Trivedi, 2013). It modifies

[1] Several studies address the case of underdispersion using the gamma model (Winkelmann, 2008, p. 180) and the generalized event-count model (King, 1989).

equation (4.3) by introducing $\epsilon_{it}$ which are assumed to be uncorrelated with $X'_{it}s$:

$$\tilde{\lambda}_{it} = e^{(X'_{it}\beta + \epsilon_{it})}. \tag{4.6}$$

Taking $e^{\epsilon} = \delta$ where density of $\delta$ is a function of the NBRM overdispersion parameter $\alpha$,

$$\tilde{\lambda}_{it} = e^{(X'_{it}\beta)}\delta_{it}. \tag{4.7}$$

To estimate the model, set E$[e^{\epsilon_{it}}] = 1$ which results in E$[\tilde{\lambda}_{it}] = \lambda_{it}E[\delta] = \lambda_{it}$. Thus, the PRM and the NBRM have the same mean structure. The distribution of observations conditional on $X_{it}$'s and $\epsilon_{it}$'s is still Poisson:

$$P(Q|\lambda_{it}, \epsilon_{it}) = P(Q|x_{it}, \epsilon_{it}) = \frac{e^{(-\tilde{\lambda}_{it})}\tilde{\lambda}_{it}^{Q}}{Q!}. \tag{4.8}$$

However, $\epsilon_{it}$ is unknown and Long (1997) uses a gamma distribution for $e^{\epsilon_{it}}$ and this gives the negative binomial distribution

$$P(Q|x) = \frac{\Gamma(Q + \alpha^{-1})}{Q!\Gamma(\alpha^{-1})} \left(\frac{\alpha^{-1}}{\alpha^{-1} + \lambda}\right)^{\alpha^{-1}} \left(\frac{\lambda}{\alpha^{-1} + \lambda}\right)^{Q}, \tag{4.9}$$

where $\Gamma$ is the gamma function and $\alpha$ is a measure of the degree of dispersion. The PRM is characterized only by its mean $\lambda$, but the NBRM is a function of mean and the overdispersion parameter $\alpha$, and the conditional variance equates to $\lambda(1 + \alpha\lambda)$ (Cameron and Trivedi, 2013). As $\alpha \to 0$, the distribution in equation (4.9) converges to the Poisson distribution. Thus, the NBRM controls for overdispersion and corrects the standard errors. While NBRM can be used for this study, it does not distinguish between zero installations and a positive number of installations.

It is reasonable to think that there are several 'hurdles' (like fixed costs) that need to be passed before a decision to install an SP system can be made. Once the hurdle is passed, the number of installations may be determined by a host of novel factors. Distinguishing these two distinct characteristics of a count data with excess zeros is crucial in estimating the parameters of the model, an issue addressed by the hurdle model. A hurdle model can accommodate excess zeros and allows for the analysis of the two distinct data generating process. The dataset I use is a panel data at the DA level. While the hurdle model works best if data are available at the individual consumer level, for this thesis it is interpreted as an informational hurdle model applicable at the DA level.

## 4.4 Negative Binomial Logit Hurdle Model

Hurdle model was introduced by Mullahy (1986) to analyze count data where the zero counts and the nonzero counts are treated as two different processes. This two-part structure of the hurdle model has the following probability distribution:

$$P(Q_i = j) = \begin{cases} f_1(0) & \text{if } j = 0, \\ \frac{1-f_1(0)}{1-f_2(0)} f_2(j) & \text{if } j > 0. \end{cases} \tag{4.10}$$

The hurdle model combines a binary model to predict the 0's and a zero-truncated Poisson or zero truncated negative binomial to predict nonzero counts. In reference to this study, let $d_i = 1$ if a household does not install SP in a given period, i.e., $d_i = 1 - \min(1, Q)$. Then the probability function is given by

$$f(Q_i) = f_{1i}^{d_i}[(1 - f_{1i}) f_T(Q_i|Q_i > 0)]^{1-d_i}, \tag{4.11}$$

where independence is assumed between the hurdle and nonzero part with $f_{1i} =$ P$(d_i = 1)$ and $f_T(Q_i|Q_i > 0) = f_2(Q_i)/[1 - f_{2i}(0)]$. The log-likelihood is given by two parts:

$$\ln L = \sum_i \left(d_i \ln f_{1i} + (1 - d_i) \ln(1 - f_{1i})\right) + \sum_{d_i=0} \left(\ln f_2(Q_i) - \ln(1 - f_{2i}(0))\right). \tag{4.12}$$

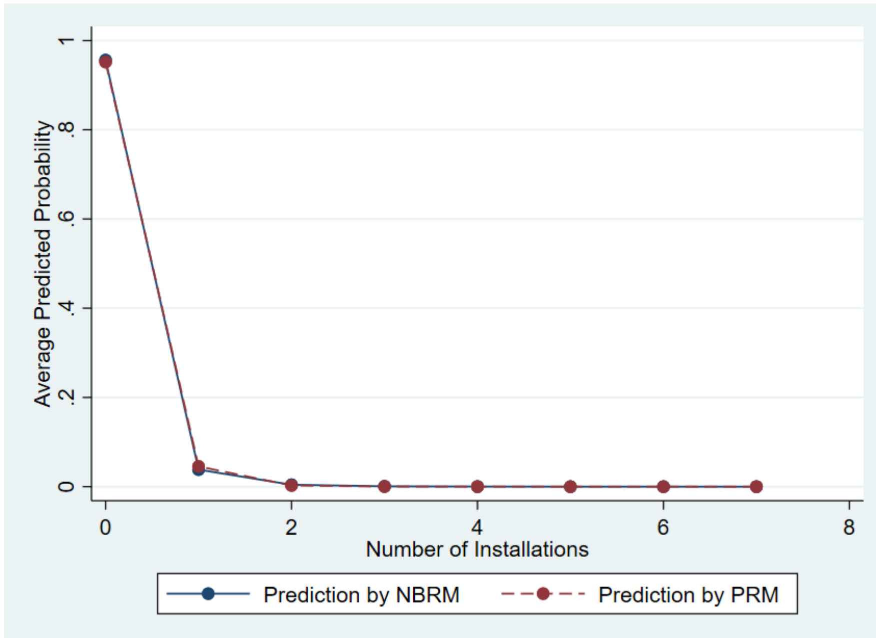
Excess zeros or too few zeros are both incorporated into the hurdle model by $f_1(0) > f_2(0)$ and $f_1(0) < f_2(0)$, respectively. The density function $f_1$ (hurdle or selection part) can be estimated using logit, probit, Poisson or negative binomial regression model. The density function $f_2$ is a count density with nonzero counts and can be estimated using truncated Poisson, truncated negative binomial or truncated Poisson log-normal regression model.

Equation 4.12 can be estimated using negative binomial logit hurdle model (NBLHM), in which case the hurdle or selection part density function $f_1$ will be estimated using a logit model, with the understanding that the number of SP systems (the dependent variable) is 0 if no installation takes place in a DA and 1 otherwise. The outcome part density function $f_2$ will be estimated using a truncated negative binomial regression model (TNBREG). TNBREG only uses those DAs where there is at least one installation. Justification of using NBLHM is discussed next.

## 4.5 Model Selection

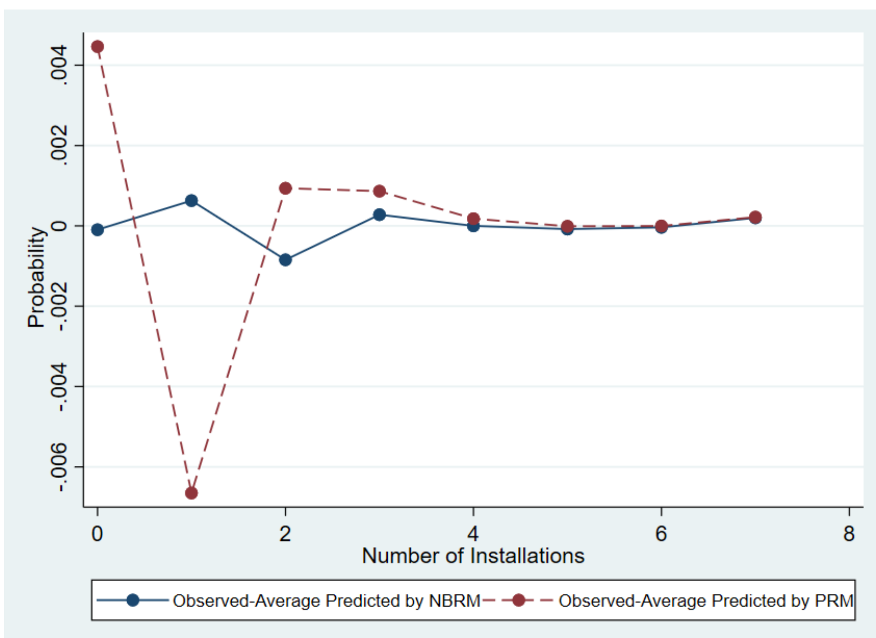
Figure 4.5.1 shows that the predictions of the number of installations from PRM and NBRM coincide. However, Figure 4.5.2 shows that the difference between observed and predicted installations is smaller for the NBRM, suggesting NBRM is a better model compared to PRM.

The reason both PRM and NBRM predict the number of installations well is because the available data have few DAs with installations greater than zero. As the mean $\lambda$ of a Poisson distribution increases, the distribution approaches a normal and the probability of zero counts decreases rapidly (Figure 4.5.3). The plot for $\lambda = 0.05$ is of importance as $\lambda$, the mean number of installations by DA in the dataset, is also 0.05. Given the data has a low mean value of installations, the Poisson distribution and distribution of the data are similar (Figure 4.5.1). Therefore, even though data are overdispersed with excess zeros, both PRM and NBRM fit the data well. In sum, either PRM or NBRM can be used judiciously, if one is prepared to assume that zeros and positive installations are determined by the same process.




Notes: NBRM is negative binomial regression model, PRM is Poisson regression model.

Figure 4.5.1: Observed and Predicted Installations, PRM and NBRM




Notes: NBRM is negative binomial regression model, PRM is Poisson regression model.

Figure 4.5.2: Difference in Actual and Predicted Installations, PRM and NBRM

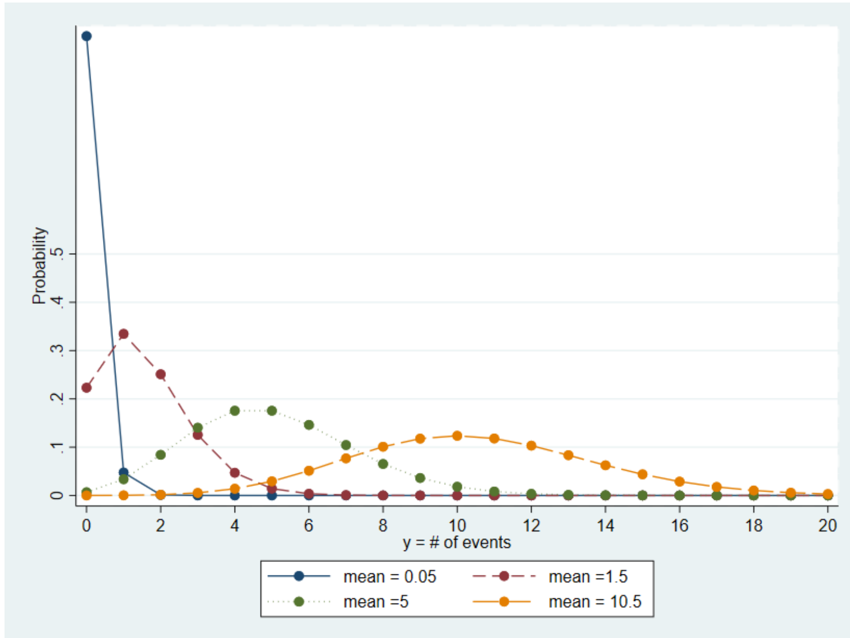



Figure 4.5.3: Poisson Distribution for Different Means

NBLHM, by contrast, accommodates the possibility that zeros and positive counts arise from two distinct processes. The Poisson logit hurdle model (PLHM) is an alternative to NBLHM where the selection part is estimated using a logit model, and the outcome part is estimated using a truncated Poisson regression model. Using the Akaike information criterion (AIC) and Bayesian information criterion (BIC) one can test whether PRM, NBRM, PLHM or NBLHM should be used. The results are presented in Table 4.5.1 for two specifications: when cost and rebate are controlled for separately (specification 1), and when only cost minus rebate is controlled for (specification 2).[2]

Both AIC and BIC are penalized-likelihood criteria and the model with the lowest value is suggested as the best model. Even though NBRM has the lowest BIC for both specifications, NBLHM has the lowest AIC value and is the preferred methodology. AIC suggests specification 1 but the number of parameters is greater in specification

[2]Further research is needed to understand whether these two specifications perform significantly differently at the selection and outcome stages.

1 compared to specification 2. I choose specification 2 as the preferred specification, given that the estimated coefficients are statistically significant and compared to specification 1 the results are more consistent with economic theory.

Table 4.5.1: Selection Criteria

| | Methodology | ll | df | AIC | BIC |
|---|---|---|---|---|---|
| Specification 1 | PRM | -847.72 | 9 | 1,713.44 | 1,771.27 |
| | NBRM | -832.02 | 10 | 1,684.03 | 1,748.28 |
| | PLHM | -814.27 | 18 | 1,664.54 | 1,780.19 |
| | NBLHM | -807.17 | 19 | 1,652.33 | 1,774.41 |
| Specification 2 | PRM | -895.53 | 8 | 1,807.07 | 1,858.47 |
| | NBRM | -864.16 | 9 | 1,746.32 | 1,804.15 |
| | PLHM | -863.08 | 16 | 1,758.15 | 1,860.95 |
| | NBLHM | -855.96 | 17 | 1,745.91 | 1,855.14 |

Notes: In specification 1, the cost of installation and rebate are controlled for separately. In specification 2, I combine the cost of installation and rebate to get cost-after-rebate. ll is log-likelihood, df is degrees of freedom, AIC is Akaike information criterion, BIC is Bayesian information criterion, PRM is Poisson regression model, NBRM is negative binomial regression model, PLHM is Poisson logit hurdle model, NBLHM is negative binomial logit hurdle model. The number of observations is 4,560.

## 4.6 Empirical Model of Demand for SP Systems

Cost of installations, rebate and median income are economic factors that are expected to be important drivers of demand for SP. Other factors such as population density, age, education and ownership of the house are also likely to be critical in the decision-making process to install SP systems.

The cost to install an SP system is expected to be negatively related in both the selection and outcome parts of the model. A decrease in cost increases demand, and even if one installation takes place, and the hurdle is crossed, a reduction in the cost of SP should increase demand for subsequent installations. One of the major estimates of interest is the price elasticity of demand estimate. While the SP market in NS is emerging, the price elasticity of demand is likely to be elastic with consumers being responsive to cost given that SP has close substitutes.

Rebate directly lowers the cost of SP systems, and once rebate was introduced at the end of June 2018, SP systems installation in NS increased. At the same time, with an increasing number of SP systems installation, policy makers tend to lower rebates at a rate that depends on their adoption targets. For example, in NS the adoption target between 2018 and 2020 is 2,000 SP systems and there have already been two levels of rebate reduction. These reductions are meant to increase the cost-effectiveness of rebate and at the same time increase SP adoption. Both the selection and the outcome models are expected to find a significant positive relationship between rebate and SP systems installation. This will imply that, whether a DA has zero installations or positive installations, rebate plays a significant role in SP adoption.

In specification 2, I use cost-after-rebate instead of using rebate and cost as separate variables. Consumers are usually given the quote of a cost of SP system installation after rebate is applied. This is crucial because, while rebate and cost can individually bring in variation and explain the data, the net cost may be a better predictor of demand. Keeping other variables constant, median household income plays an important role in the decision to install an SP and the selection part of the models is expected to give a positive relationship between median income and SP system installations.

Owner-occupied households variable measures the number of owner-occupied households in DA and only owner-occupied households qualify for residential SP. This variable is likely to be positively related to SP system installation as the greater the number of owner-occupied households, the higher is the likelihood of installations. More importantly, owner-occupied households give key insights on the effect of population density on SP systems installation.

Population density aids in the diffusion of technology through knowledge sharing and can increase exposure to SP. In such a case one can expect population density to increase the growth of the number of SP system installations in DAs with zero or

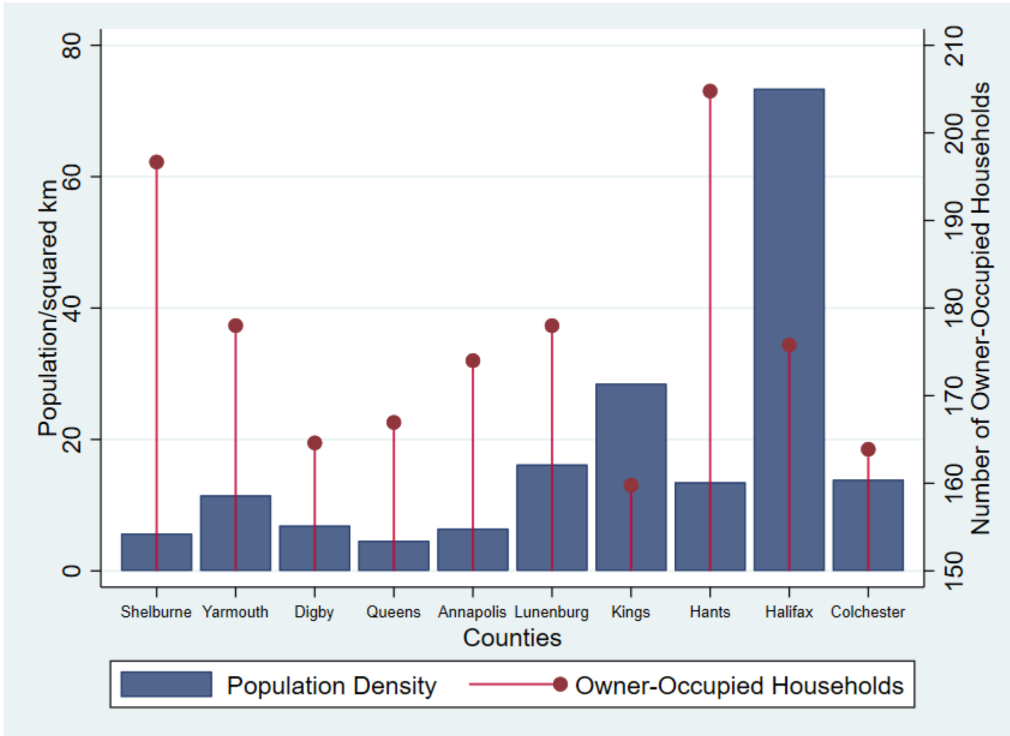



Figure 4.6.1: Population Density and Owner-Occupied Households by County

positive installations. However, a high population density also means fewer owner-occupied households are available in a DA (Figure 4.6.1). As a result, the likelihood of an installation can decrease if the number of households that are eligible, also decreases. At the same time, urban residents may be more likely to install SP systems.

Following the literature, I hypothesize education to be positively correlated with SP adoption (Qureshi, Ullah, and Arentsen, 2017). New technology and environmental benefits of SP may be more apparent and prevalent among younger generations, which would suggest a negative relationship between age and SP adoption. However, both education and age variables do not vary across years in the panel data setting.

To sum up, NBLHM estimates a selection model that explains the hurdles that need to be crossed and estimates the outcome model which explains the number of SP system installations, once the hurdle is crossed. While the selection model may find an explanatory variable to be significantly related to the dependent variable, the outcome model may find it insignificant, pointing to the existence of two decision-making processes. However, the key variables are expected to be significant in both the selection and outcome parts.

# Chapter 5

# Estimation Results

## 5.1 Parameter Estimates

I consider two aspects of the data generating process and model them using NBLHM. First, the hurdle that needs to be crossed as determined by the binary part (selection model) and the decision-making process once the hurdle is crossed as determined by the truncated negative binomial regression (outcome model). Installation cost, rebate, and median income are taken as key economic factors determining both the hurdle process and the decision-making process for positive counts.

I consider two model specifications. Specification 1 includes cost and rebate as separate variables, but specification 2 uses cost minus rebate as a cost-after-rebate explanatory variable. I begin the analysis with the linear probability model (LPM). Next, I present and discuss the results from PRM, NBRM and NBLHM for both specifications separately.

In the LPM, the dependent variable is a dummy variable with value one if any SP system installation took place in a DA and zero if no installation took place. Table 5.1.1 shows the estimated coefficients using LPM. According to the LPM estimates a \$0.01/Watt increase in the cost-before-rebate decreases the probability of SP systems installation by 0.11 percentage points (specification 1) and a \$0.01/Watt increase in the cost-after-rebate decreases the probability of installations by 0.017 percentage points. The LPM estimates of coefficients on median income, population density and education are insignificant in both specifications at the 5% significance level..

Also, for specification 1, LPM estimates a negative relationship between rebate

Table 5.1.1: LPM Estimates for Specifications 1 and 2

| | Specification 1<br>LPM | Specification 2<br>LPM |
|---|---|---|
| Cost-before-rebate | -0.110*** | |
| | (0.016) | |
| Cost-after-rebate | | -0.017*** |
| | | (0.003) |
| Rebate | -0.079*** | |
| | (0.017) | |
| Median income | 0.016 | 0.017* |
| | (0.010) | (0.010) |
| Population density | -0.002 | -0.002 |
| | (0.002) | (0.002) |
| Age | -0.009 | -0.009 |
| | (0.006) | (0.006) |
| Age squared | 0.000 | 0.000 |
| | (0.000) | (0.000) |
| % Post-secondary education | 0.000 | 0.000 |
| | (0.000) | (0.000) |
| Owner-occupied households | 0.000*** | 0.000*** |
| | (0.000) | (0.000) |
| Constant | 0.382** | 0.044 |
| | (0.171) | (0.164) |

Notes: Dependent variable is the number of residential SP installations by WattsUp Solar. LPM is linear probability model. The number of observations is 4,560.
Cost-after-rebate = cost of installations before rebate − rebate for each DA-year pair.
Clustered standard errors at the dissemination area level in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

do not indicate multicollinearity (Appendix A).

Table 5.1.2 presents the estimation results using PRM, NBRM and NBLHM for specification 1. A positive value for a coefficient indicates a positive correlation between a variable and SP system installation, while a negative coefficient indicates a

Table 5.1.2: PRM, NBRM and NBLHM Estimates for Specification 1

| | | | Hurdle Model | |
|---|---|---|---|---|
| | PRM | NBRM | Logit | TNBREG |
| Cost-before-rebate | -3.381*** | -2.923*** | -3.744*** | -0.654 |
| | (0.488) | (0.540) | (0.709) | (0.591) |
| Rebate | -1.733*** | -1.432*** | -2.191*** | 1.383** |
| | (0.287) | (0.356) | (0.418) | (0.653) |
| Median income | 0.671*** | 0.594** | 0.788*** | -2.089 |
| | (0.226) | (0.246) | (0.252) | (1.301) |
| Population density | -0.071* | -0.061 | -0.080** | -0.017 |
| | (0.038) | (0.042) | (0.037) | (0.115) |
| Age | -0.037 | 0.022 | -0.099 | 0.991 |
| | (0.133) | (0.156) | (0.123) | (0.622) |
| Age squared | 0.001 | 0.000 | 0.001 | -0.011 |
| | (0.001) | (0.002) | (0.001) | (0.007) |
| % Post-secondary education | 0.016* | 0.018* | 0.011 | 0.092** |
| | (0.010) | (0.010) | (0.009) | (0.042) |
| Owner-occupied households | 0.003*** | 0.003*** | 0.003*** | 0.008*** |
| | (0.001) | (0.001) | (0.001) | (0.003) |
| Constant | -0.522 | -2.749 | 1.092 | -26.44 |
| | (3.921) | (4.811) | (4.234) | (16.48) |
| $\alpha$ | | 0.590 | | 21.13*** |
| | | (0.659) | | (1.230) |
| Observations | 4,560 | 4,560 | 4,560 | 200 |

Notes: Dependent variable is the number of residential SP installations by WattsUP.
PRM is Poisson regression model. NBRM is negative binomial regression model. TNBREG is truncated negative binomial regression model.
Clustered standard errors at the dissemination area level in parentheses.
$\alpha$ is overdispersion parameter used in NBRM and TNBREG.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

negative relationship. According to the PRM and NBRM, cost and rebate are negatively related to the number of SP systems installation and the opposite is true for median household income, % post-secondary education and owner-occupied households variables.

NBRM estimates that a 0.01$/Watt increase in cost-before-rebate and rebate approximately decreases the expected number of installations by 2.9% and 1.4%, respectively. Also, as estimated by NBRM, a one percent increase in median household income increases SP systems installation by 0.6%. Moreover, both PRM and NBRM estimates age to be an insignificant factor in the decision-making process. Similar results are estimated by the PR. Both NBRM and PRM estimates population density to be insignificant at the 5% significance level.

The preferred model to analyze the data is NBLHM and it is characterized by two parts: logit (selection model) and TNBREG (outcome model). Estimated coefficients are presented in Table 5.1.2 under the Hurdle Model column. As estimated by the logit model, cost-before-rebate and population density are negatively related to SP systems installation and the increase in median income and the number of owner-occupied households increases the number of SP system installations. Importantly, this suggests that in DAs with zero SP system installation, a lower installation cost reduces the hurdle and thus the probability of installing SP systems increases.

The estimated coefficients of the selection model can be interpreted using average marginal effects which can be used to measure, on average, the amount of change in the probability of installations due to a unit change in the independent variable. The results are presented in Appendix B.0.1. According to the selection model, a 0.01$/Watt increase in cost-before-rebate and rebate decreases the probability of installing SP systems by 0.148 percentage points and 0.087 percentage points, respectively .

The selection model also predicts that as median household income and the number of owner-occupied households increase, the probability of SP systems installation increases. Specifically, a 1% increase in median income increases the probability of SP systems installation by 0.031 percentage points. Moreover, if population density increases by 1% the likelihood of SP systems installation decreases by 0.003 percentage points as estimated by the selection model.

On the other hand, in the outcome model, once the hurdle is crossed, in DAs where there is at least one SP system installation, the response of SP systems installation is more sensitive to rebate than to cost. Even in the regions where an installation takes place, rebate remains a cost-reducing element. According to the TNBREG, a 0.01\$/Watt increase in rebate increases the number of SP system installations by 1.4

Like the LPM, PRM and NBRM, NBLHM estimates of the selection model give a negative relationship between rebate and the likelihood of installing SP systems. The estimated negative relationship between rebate and SP systems installation and the insignificant coefficient of the cost variable in the outcome model require further considerations.

To examine whether the variables cost-after-rebate and rebate separately bring a statistically significant improvement in the fit of the model, I use Wald and likelihood ratio test, and conclude that this is indeed the case. One interpretation is that, as the number of SP systems installation increase in NS, the average household becomes more aware of the benefits of SP. A decreasing rebate might encourage consumers to install SP before the rebate program is discontinued. The decision to purchase SP systems by a consumer is considered as a "buy-or-wait" decision and it is important that a demand model can take into consideration this dynamic nature of consumer behavior (Rogers and Sexton, 2014). However, NBLHM is a static model that does not take dynamic consumer behaviors into consideration, and this means that the model can result in inconsistent results compared to the theory.

In specification 1, I use cost and rebate as a separate variable. While both cost and rebate jointly determine the decision to install, cost-after-rebate is the net installation cost a customer needs to pay to install SP systems. Thus, I consider specification 2, where I combine rebate and installation cost to get the after-rebate cost where cost-after-rebate = cost of installations before rebate − rebate calculated for each

DA-year pair.

Table 5.1.3: PRM, NBRM and NBLHM Estimates for Specification 2

| | | | Hurdle Model | |
|---|---|---|---|---|
| | PRM | NBRM | Logit | TNBREG |
| Cost-after-rebate | -0.512*** | -0.513*** | -0.446*** | -1.111*** |
| | (0.084) | (0.086) | (0.081) | (0.348) |
| Median income | 0.760*** | 0.664*** | 0.853*** | -2.107 |
| | (0.237) | (0.254) | (0.258) | (1.341) |
| Population density | -0.084** | -0.066 | -0.087** | -0.017 |
| | (0.040) | (0.040) | (0.037) | (0.114) |
| Age | -0.060 | 0.034 | -0.106 | 0.971 |
| | (0.144) | (0.151) | (0.126) | (0.616) |
| Age squared | 0.001 | -0.000 | 0.001 | -0.011 |
| | (0.002) | (0.002) | (0.001) | (0.007) |
| % Post-secondary education | 0.017* | 0.018* | 0.011 | 0.093** |
| | (0.010) | (0.010) | (0.009) | (0.042) |
| Owner-occupied households | 0.003*** | 0.004*** | 0.003*** | 0.008*** |
| | (0.001) | (0.001) | (0.001) | (0.003) |
| Constant | -10.33*** | -11.78*** | -10.26*** | -21.90 |
| | (3.965) | (4.177) | (3.874) | (17.22) |
| $\alpha$ | | 1.266*** | | 18.61*** |
| | | (0.373) | | (1.219) |
| Observations | 4,560 | 4,560 | 4,560 | 200 |

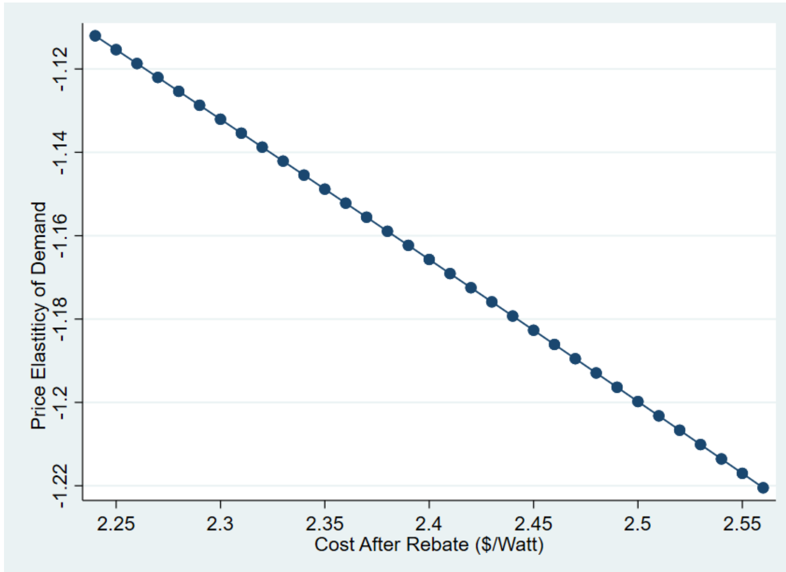
Notes: Dependent variable is the number of residential SP installations by WattsUp Solar.
PRM is Poisson regression model. NBRM is negative binomial regression model. TNBREG is truncated negative binomial regression model.
Cost-after-rebate = cost of installations before rebate− rebate for each DA-year pair. Clustered standard errors at the dissemination area level in parentheses.
$\alpha$ is overdispersion parameter used in NBRM and TNBREG.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5.1.3 present estimated coefficients by PRM, NBRM and NBLHM for specification 2. In contrast to specification 1, using specification 2, both the selection and the outcome model identify the cost to be a significant factor in determining SP systems installation. Except for the cost variable, both specifications estimate all the other variables to have a similar magnitude and significance on installing SP systems.

According to the estimates from PRM and NBRM, a 0.01$/Watt increase in cost-after-rebate decreases expected SP systems installation by approximately 0.51% and 0.51%, in both cases. Similarly, PRM and NBRM estimate that a 1% increase in median income increases expected SP systems installation by 0.76% and 0.66%, respectively. Moreover, PRM and NBRM estimate that, compared to non post-secondary educations, a one percentage point increase in population with post-secondary education leads to 1.7% and 1.8% increase in the number of SP system installations, respectively, only at the 10% significance level.

Similar to specification 1, I again use average marginal effects to interpret the logit estimates for specification 2 (Appendix B.0.1). I find that a 0.01$/Watt increase in cost decreases the probability of installations by 0.018 percentage points. Also, a 1% increase in median income increases the probability of SP systems installation by 0.035 percentage points. On the other hand, TNBREG estimates that a 0.01$/Watt increase in cost-after-rebate decreasesestimated number of SP systems by 1.1%. Additionally, compared to non post-secondary education, TNBREG estimates that a one percentage point increase in population with post-secondary education increases the number of installations by 9.7%.

I consider specification 2 as the preferred specification and discuss the price elasticity estimates from NBLHM. Elasticity of the cost-after-rebate variable can be calculated using both the logit and TNBREG estimates to get an overall effect of cost-after-rebate on the number of installations. However, price elasticity of demand estimates varies depending on the values at which it is calculated. This is shown in Figure 5.1.1. The price elasticity of demand at different values of cost-after-rebate (in 2019 prices) increases, holding other variables at their mean values. The figure shows that the demand for SP system installations is more elastic if evaluated at higher




Notes: Except for the cost-after-rebate, all other variables, such as median income and population density are held at their mean values. Estimates are from specification 2.

Figure 5.1.1: Price Elasticity of Demand

cost-after-rebate.

The average value of cost-after-rebate for the full sample and subsample with positive installations is \$2.56/Watt and \$2.23/Watt, respectively. Using cost-after-rebate of \$2.56/Watt, I find the price elasticity of demand for SP systems to be -1.26. The elastic nature of SP systems in NS means that consumers are price sensitive.

## 5.2 Policy Analysis

In the dataset total number SP system installations in 2018 and 2019 are 78 and 107, respectively. However, 200 SP systems were approved for installation in 2018 and 500 for 2019 (Corning, 2019). Thus, the WattsUp Solar dataset represents 39% and 21% of the actual number of SP systems installation for the years 2018 and 2019, respectively. For the policy simulations, I extrapolate the estimates specific to WattsUp to the rest of the installers, assuming that WattsUp Solar is a representative SP system installers in NS.

I present two sets of policy simulations that can assist policy makers to evaluate the effect of rebate on the number of SP systems installation and make policy adjustments to reach a certain target. First, I consider what would have happened if no rebate was offered in 2018, if the rebate of \$0.85/Watt in 2019 was continued up until 2021 and if the reduction of rebate to \$0.60/Watt is continued until 2021. Second, based on a rebate of \$0.60/Watt, I forecast the number of SP system installations from 2020 to 2022. These out-of-sample forecasts help assess the impact of declining rebates on the number of installations.

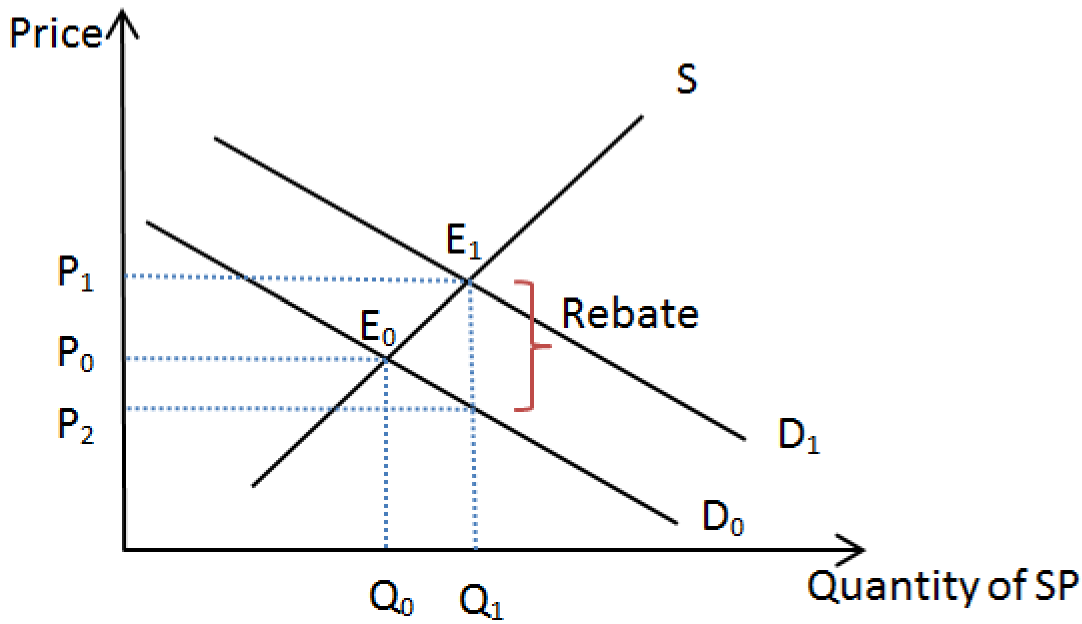
### 5.2.1 Rebate Pass-Through

In this section I discuss the concept of rebate pass-through which is an important input into the policy simulations. Incentive pass-through measures whether, and if so by how much, financial incentives pass-through from businesses to consumers. I now provide estimates of the portion of incentives that the households that install SP systems actually receive.

Table 5.2.1: OLS Estimates of Rebate Pass-Through

| | OLS |
|---|---|
| Rebate | -0.510$^{***}$ |
| | (0.056) |
| Median income | -0.145$^{**}$ |
| | (0.067) |
| Population density | -0.007 |
| | (0.012) |
| Constant | 4.708$^{***}$ |
| | (0.770) |
| Observations | 200 |

Notes: Dependent variable is cost of SP systems before rebate.
OLS is ordinary least squares. Standard errors in parentheses.
$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.




Notes: SP is Solar Photovoltaic, S is supply, D is demand, Price is the cost of an SP system installation, Q is quantity, and E is Equilibrium.

Figure 5.2.1: Rebate Pass-Through

Figure 5.2.1 illustrates an incentive or rebate pass-through under the assumption that the supply of SP does not shift. $E_0$ is the initial equilibrium in the SP system market with price $P_0$ and quantity $Q_0$. As rebate is introduced, the demand for SP systems increases and demand curve shifts to the right, from $D_0$ to $D_1$. New quantity demanded is $Q_1$, but instead of reaching $E_1$ with a price of $P_1$, consumers pay $P_2$ for the same quantity $Q_1$. This is because, the new price to be paid by the consumers, $P_2$ is $P_1 - \text{Rebate}$. Thus, new price is $P_2$ and the old price is $P_0$. Rebate pass-through is $((P_2 - P_0)/\text{Rebate}) \times 100$ and a value of 100% means that the total value of the rebate is captured by the consumers.

Several studies using SP systems installation data of the California solar market find different values of incentive pass-through rate. Dong et al. (2014) find that the pass-through rate in different counties in California ranges from 68% to 122% using the reduced-form regression method but the range varies, if the structural modeling method is used. Following Sallee (2011), I regress cost-before-rebate on rebate and control for median income and population density (Table 5.2.1).

The pass-through rate is given by the coefficient of the rebate variable, where a value of 1 means zero pass-through or that the rebate is captured by the suppliers of SP and a coefficient of zero means a 100% pass-through (Gillingham and Tsvetanov, 2019). The estimated coefficient on rebate is 0.51, which implies a pass-through rate of 49%.

This pass-through rate is not uncommon in an SP market. Podolefsky (2013) used data from California and found a 17% pass-through rate and Dong et al. (2014) found some counties with less than 70% pass-through rate. A low pass-through rate indicates an inelastic supply schedule for SP system installations.

### 5.2.2 Policy Simulations

Table 5.2.2 shows the required values used in the simulations. I assume SP cost decreases by 3% in 2020 and by 4% in 2021. Table 5.2.3 shows policy simulations for a no rebate scenario, a rebate reduction to \$0.85/Watt, and a rebate reduction to \$0.60/Watt in 2019 which comes into effect in 2020. I compare the 2018 and 2019 simulation results for each rebate change with observed installations in 2018 and 2019.

As an example, to simulate SP systems installation in 2018 assuming that no rebate was available, first I find the percentage increase in cost-after-rebate in 2018. Cost-after-rebate in 2018 was \$1.70/Watt but with no rebate, cost would have been \$2.72/Watt. This means an increase in cost of 60%. After adjusting for rebate pass-through, I use price elasticity of demand to get the percent decrease in the number of installations to be 37% or 74 fewer SP system installations in 2018 out of 200 observed installations.

Without a rebate, there would have been 187 fewer installations in 2019 (out of

Table 5.2.2: Values Used in Policy Simulations

| Variable | Value |
|---|---|
| Decrease in cost of installation in 2020 (%) | 3 |
| Decrease in cost of installation in 2021(%) | 4 |
| Average cost-after-rebate in 2018 ($/Watt) | 1.70 |
| Average cost-after-rebate in in 2019 ($/Watt) | 1.68 |
| Rebate increase from 2017 to 2018 ($/Watt) | 1.02 |
| Rebate decrease from 2018 to 2019 ($/Watt) | 0.85 |
| Price elasticity of demand (%) | -1.26 |
| Rebate pass-through (%) | 0.49 |
| Average installed residential SP capacity (kWatt DC) | 9.30 |

Notes: All dollar values are in 2019 dollars.

Table 5.2.3: Policy Simulations

| | 2018 | 2019 | 2020 | 2021 | Total added Capacity (MW) |
|---|---|---|---|---|---|
| Observed installations | 200 | 500 | | | |
| No rebate | 126 | 313 | | | |
| Rebate of $0.85/Watt | | | 607 | 742 | 12.54 |
| Rebate decreased to $0.60/Watt | | | 575 | 666 | 11.54 |

Notes: Simulation of 2020 is based on observed 200 installations in 2019. Total added capacity is measured in DC given that the average installed size of SP in NS in 2019 was 9.30 kWatt DC. All dollar values are in 2019 dollars.

500 actual). In 2019 rebate decreased from $1/Watt to $0.85/Watt. I use observed SP systems installation in 2019 to forecast results for the years 2020 and 2021. If this reduced rate of $0.85/Watt was continued, the number of new SP system installations would have increased to 607 in 2020 and to 742 in 2021, with an installed capacity of 12.54MW by 2021. On November 1, 2019, rebate was further reduced to $0.60/Watt and its effect can only be seen in 2020 and 2021. I find that, if rebate in the years 2020 and 2021 remains at $0.60/Watt, the number of new installations will increase to 575 and 666, respectively, with an installed capacity of 11.54 MW by 2021.

I also forecast SP system installations for the years 2020, 2021 and 2022 if rebate is further reduced from $0.60/Watt using three distinct scenarios. Applicable rebate in

2020 is \$0.60/Watt for all the scenarios. In scenario 1, I consider rebate to decrease by \$0.20/Watt each year from \$0.60/Watt. In scenario 2, I consider a decrease of \$0.15 every year. Finally, in scenario 3, I consider a decrease of \$0.10/Watt every year. I assume SP cost decreases by 3% from 2019 to 2020 and 4% each year in 2021 and 2022.

Table 5.2.4: Additional Policy Simulations

| | 2019 | 2020 | 2021 | 2022 | Total added Capacity (MW) |
|---|---|---|---|---|---|
| Rebate of \$0.85/Watt | 500 | | | | 4.65 |
| Scenario 1 | | 575 | 636 | 671 | 17.50 |
| Scenario 2 | | 575 | 643 | 696 | 17.81 |
| Scenario 3 | | 575 | 651 | 722 | 18.12 |

Notes: In scenario 1, rebate decreases by \$0.20/Watt each year from \$0.60/Watt. In scenario 2, rebate decreases by \$0.15/Watt every year. Finally in scenario 3, rebate decreases by \$0.10/Watt every year. Simulations are based on SP systems installation of 500 in 2019. Total added capacity is measured in DC given average installed size of an SP system in NS in 2018 and 2019 was 9.30 kWatt DC. All dollar values are in 2019 dollars.

The policy simulations in Table 5.2.4 suggest that a rebate of \$0.60/Watt in 2020 is expected to increase the number of SP system installations in 2020 to 575, from 500 installations in 2019. Given that there were 500 installations in 2019, scenario 3 gives an additional capacity of 22.77 MW from 2019 to 2022. Assuming all installations receive the applicable rebate, this measures to \$12.78 million of rebate to be paid from 2019 to 2022. Using electricity production data of 104 residential SP systems in NS in 2019, I find that a one kWatt DC system in NS on average produced 1,065 kWh/kWatt of electricity in 2019. Therefore, using scenario 3, this results in the production of 24,250 MWh of electricity over 4 years. According to Environmental Protection Agency (2020), this amounts to a reduction in GHG emissions of 17,176 metric tons $CO_2$ equivalent or GHG emissions from 3,146 households' electricity use in one year.[1] Efficiency NS aims to install 2000 SP systems from 2018 to 2021. With

[1]In 2017 average household electricity use in NS was 11,222 kWh, which amounts to GHG emissions of 5.46 metric tons $CO_2$/household equivalent (Canada Energy Regulator, 2020; Environmental Protection Agency, 2020).

700 SP systems already installed in the years 2018 and 2019, scenario 3 suggests that by the end of 2021, total SP systems installation over the four years period will be 1,926.

In the aforementioned simulations, two important factors are not taken into consideration. First, the increasing grid cost of electricity can be a crucial factor in policy simulations but is ignored for simplicity. Second, the simulations do not take dynamic consumer behavior into consideration. Nevertheless, the simulations attest that the rebate program will continue to stimulate SP growth in NS. Moreover, the gradual decrease in rebate have a moderate effect on the number of installations.

### 5.3 Robustness

In the data, only 200 DAs have SP system installations with corresponding price and rebate data. To fill in 95.6% of the missing price data, I use a shadow price, calculated using the average cost of installations in NS in a year. Also, I do not have information on the date of rebate application. So far, I calculated rebate using an average four-month period of project implementation to identify the data of application and consequently applied rebate that was available four months prior to the date of operation, assuming it on average takes four months for an SP to start operating since an application to install is made. In this section I undertake robustness check for specification 1 and specification 2 using NBLHM with a different shadow price along with a 3 and 5-month project implementation period to calculate the rebate.

To impute the shadow price Gillingham and Tsvetanov (2019) use average annual value for the same municipality and if this is not possible, they use average within county cost of installation. As a robustness check, I use the average shadow price within a county in a specific year to determine the corresponding shadow price. For example, all DAs with zero installation in Shelburne county in the year 2016 has the same average cost calculated using installed SP in Shelburne in 2016. However, there were no installations in 2018 and in such cases average cost of installations using cost data of available years in a county is used. Appendix C presents the parameters estimated by PRM, NBRM and NBLHM for each of the specifications.

Table 5.3.1: Elasticity Estimates Under Different Specifications

| | | Baseline | County Price | 3-month | 5-month |
|---|---|---|---|---|---|
| Specification 1 | Cost-before-rebate | -8.20 | -4.89 | -8.32 | -8.86 |
| | Rebate | -1.03 | -0.41 | -1.05 | -1.17 |
| Specification 2 | Cost-after-rebate | -1.26 | -1.19 | -1.26 | -1.17 |

Notes: Specification 1 includes cost-before-rebate and rebate as a separate variable. Specification 2 combines the cost-before-rebate and rebate where cost-after-rebate = cost of installations before rebate − rebate for each DA-year pair. In baseline, the rebate is calculated using a 4-month project implementation period and missing cost replaced with the average cost of SP system installations in NS in a year. 3-month corresponds to rebate calculation using a three-months project implementation period. 5-month corresponds to rebate calculation using a five-months project implementation period. County price corresponds to the missing cost of installations replaced with average cost at the county level. For specification 1, elasticity estimates are calculated at cost-before-rebate = 3, rebate = 0.85 and other variables at their mean values. For specification 2, elasticity estimates are calculated at cost-after-rebate = 2.56 and other variables at their mean values.

Tables C.0.1 shows the estimation results for specification 1 if the shadow price is calculated using the average cost of SP systems within a county. The estimated coefficients of cost-before-rebate are -2.070 and -0.911, respectively, which is much lower than -3.744 and 2.191, respectively, as estimated by the baseline specification. However, estimated coefficients of other variables are similar to the baseline specification estimates. The PRM and NBRM also estimate different effects of cost-before-rebate and rebate compared to the baseline specification. Table 5.3.1 shows that price elasticity of demand is -4.89 if the county price is used compared to price elasticity of demand of -8.20 when the baseline specification is used. Therefore, for specification 1, calculating the shadow price using a different method significantly changes results.

On the other hand, the estimation results for specification 2 remain much similar to the baseline specification estimates, even if I calculate shadow price using the average cost of SP systems within a county. The results are shown in Table C.0.4. Similarly, as shown in Table 5.3.1, compared to the baseline specification estimate of

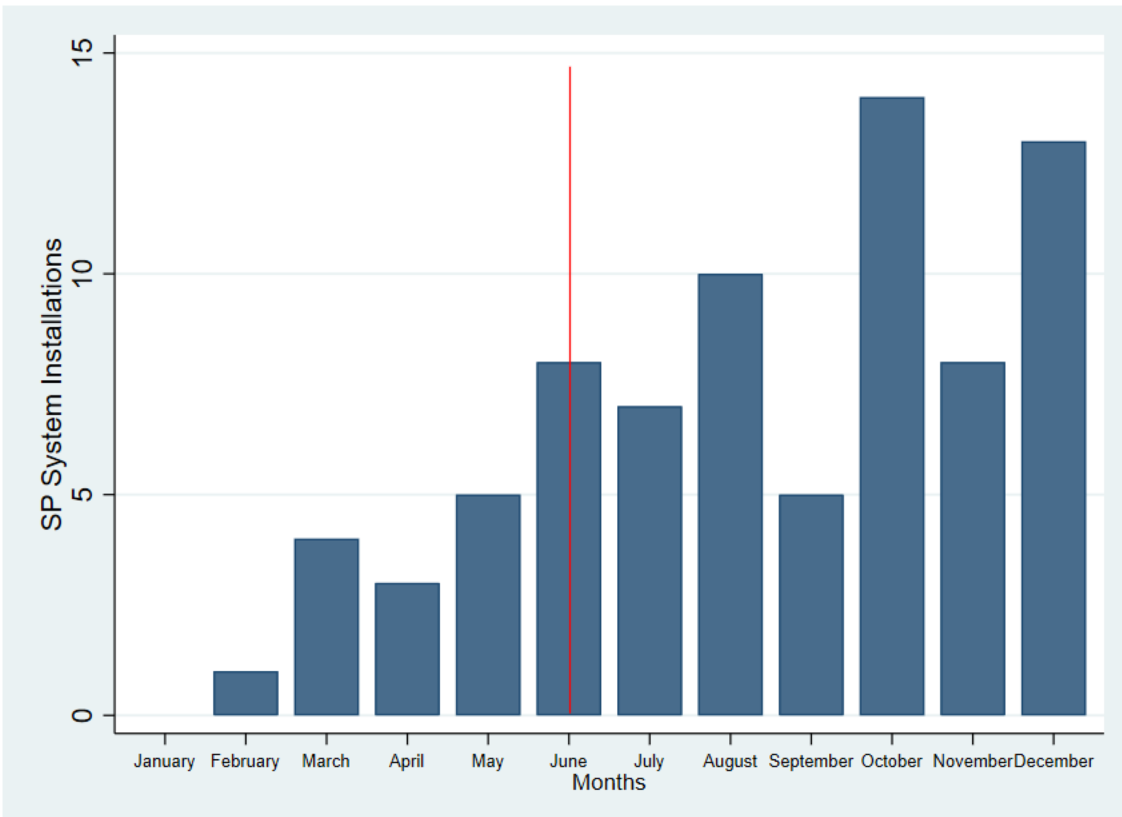
-1.26, the price elasticity of demand is -1.19 if the county price is used to calculate the shadow price. Thus, for specification 2, the estimates of the logit model and essentially NBLHM are not significantly affected if I use the average annual cost of SP systems installation in NS in a year to calculate the shadow price.

Alternatively, using three-month and five-month project implementation period give similar results compared to the baseline specifications. Tables C.0.2, C.0.3, C.0.5 and C.0.6 show parameter estimates when 3-month and 5-month project implementation periods are assumed. Table 5.3.1 presents the corresponding price elasticity of demand estimates for both the specifications. I find a similar price elasticity of demand estimates for both specifications.

Finally, I conduct a sensitivity test using the NBLHM with a specification without age and education controls (Tables D.0.1 and D.0.2). Price elasticity estimates for specification 1 and specification 2 are -8.24 and -1.30, respectively, which are similar to the baseline specification. Age and education variables vary little in the data and the estimated coefficients for the new specification is similar to the estimates from baseline specification.

## 5.4 Limitations

There are several limitations in this study that could be addressed in future studies. First, I consider a static model to estimate the demand for SP systems. Consumer dynamics in terms of "buy-or-wait" decisions and the existence of bunching in NS is not incorporated into the model. Figure 5.4.1 shows the number of SP system installations in NS before and after the introduction of rebate on June 25, 2018. It is evident that SP system installations took off after the rebate was introduced and there is "bunching". Therefore, rebate had a positive effect on the number of SP systems installation through both the selection and outcome models. However, specification 1 estimates rebate to have a negative relationship with the likelihood of SP systems installation. This can occur due to measurement errors in how I assigned rebate to the SP system installations. Specifically, many installations that occurred after the reduction in the rebate might have already been signed up for, and I assigned them to a reduced-rebate regime.




Notes: SP is Solar Photovoltaic. Vertical line represents introduction of rebate on June 25, 2018.

Figure 5.4.1: Bunching of SP System Installations in Nova Scotia

Second, the data used does not represent the actual number of residential SP systems installation during the period from 2016 to 2019 and the actual cost of each installed SP system is not available, rather calculated. Moreover, some counties are removed from the data as WhatsUp Solar does not install in those counties. This eliminates the possibility of installations to take place in those regions, which in reality may not be the case.

Third, several incentive programs and government policies are in effect in NS to facilitate installations. These include the Solar City program administered by Halifax Regional Municipality, marketing and training sessions. The Solar City Program can play an important role in the decision-making process by lowering the burden of initial capital investment. However, data on this variable was not available. Additionally, the grid cost of electricity can positively affect SP systems installation. I have data on annual changes in the grid cost of electricity in NS but it is highly correlated with the cost-before-rebate and rebate variables. Thus I could not account for the grid cost of electricity, but future studies can incorporate such an effect.

Fourth, there are DAs, included in the data, where no SP system installations can take place due to nature of geographic location. For example, DAs with forest cover where ample sunlight does not reach will always have zero installations. Including these DAs can bias the estimated coefficients and hence the price elasticity of demand estimates. In the literature, zero-inflated models are available that can address this issue.

Finally, the coronavirus pandemic significantly reduced economic activity all around the world in the first quarter of 2020. This means that there may be significant disruption in the SP market from both the demand and supply side, and future studies should also take this into consideration.

# Chapter 6

# Conclusion

This thesis studied the demand for residential SP systems in NS using a negative binomial logit hurdle model (NBLHM), which allows to model the decision to install and conditional on that the number of installations, separately. The results suggest that the cost of SP systems, rebate and median income plays the most significant role in determining whether SP system installations will take place in a DA. I find a price elasticity of demand of -1.26. However, the model does not take into account the dynamic behavior of consumers.

I find that since the introduction of rebate, the number of SP system installations in NS increased, despite a gradual reduction in rebate. The provincial rebate program is expected to continue at least until 2022 and I forecast installations in NS for the years 2020, 2021 and 2022 assuming an annual \$0.20/Watt rebate reduction from 2020 onward. I find that, given there were 500 SP system installations in 2019, this gradual rebate reduction will result in total 1,882 SP system installations from 2020 to 2022, with an installed capacity of 17.50MW. This corresponds to electricity generation of 23,595 MWh from 2019 to 2022 and a reduction in GHG emissions of 16,681 metric tons $CO_2$ equivalent or reduction in emissions from 3,055 households' electricity use in one year in NS.

SP market in NS is at an early stage of development. The provincial government, with assistance from Efficiency Nova Scotia, is undertaking several training initiatives and promoting SP systems through marketing campaigns in several regions of the province to facilitate SP adoption. The results from this thesis can aid policy makers to promote further growth of SP and meet overall goals toward reducing GHG emissions in the province, and ultimately having a carbon-neutral economy. Future studies can address the dynamics of consumer behavior and use a discrete choice model to analyze the SP market in NS and Canada.

# Appendix A: Correlation and Variance Inflation Factor

Table A.0.1: Correlation Test

| | Rebate |
|---|---|
| Rebate | 1.00 |
| Cost-before-rebate | -0.834 |
| Median income | 0.010 |
| Population density | 0.006 |
| Age | 0.002 |
| Age squared | 0.002 |
| % Post-secondary education | -0.007 |
| Owner-occupied households | -0.009 |
| Installations | 0.046 |

Note: Installations is the dependent variable

Table A.0.2: Variance Inflation Factor

| Variable | VIF | 1/VIF |
|---|---|---|
| Rebate | 3.28 | 0.30 |

Notes: VIF is variance inflation factor.

A VIF value greater than 10 can indicate presence of collinearity.

# Appendix B: Average Marginal Effects of Logit Model

Table B.0.1: Average Marginal Effects of Logit Model for Specifications 1 and 2

| | Specification 1<br>Average Marginal Effect | Specification 2<br>Average Marginal Effect |
|---|---|---|
| Cost-before-rebate | -0.148*** | |
| | (0.026) | |
| Cost-after-rebate | | -0.018*** |
| | | (0.003) |
| Rebate | -0.087*** | |
| | (0.015) | |
| Median income | 0.031*** | 0.035*** |
| | (0.010) | (0.011) |
| Population density | -0.003** | -0.004** |
| | (0.001) | (0.002) |
| Age | -0.004 | -0.004 |
| | (0.005) | (0.005) |
| Age squared | 0.00005 | 0.00006 |
| | (0.000) | (0.000) |
| % Post-secondary education | 0.0004 | 0.0005 |
| | (0.000) | (0.000) |
| Owner-occupied households | 0.0001*** | 0.0001*** |
| | (0.000) | (0.000) |

Notes: Dependent variable is the number of residential SP installations by WattsUp Solar.
The number of observations is 4,560.
Cost-after-rebate = cost of installations before rebate − rebate for each DA-year pair.
Clustered standard errors at the dissemination area level in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

# Appendix C: Robustness Check

Table C.0.1: Robustness Check using a Different Shadow Price for Specification 1

| | | | Hurdle Model | |
|---|---|---|---|---|
| | PRM | NBRM | Logit | TNBREG |
| Cost-before-rebate | -2.034*** | -1.854*** | -2.070*** | -0.654 |
| | (0.353) | (0.352) | (0.403) | (0.591) |
| Rebate | -0.700*** | -0.615*** | -0.911*** | 1.383** |
| | (0.219) | (0.230) | (0.244) | (0.653) |
| Median income | 0.787*** | 0.659*** | 0.890*** | -2.089 |
| | (0.237) | (0.254) | (0.261) | (1.301) |
| Population density | -0.061 | -0.049 | -0.064* | -0.017 |
| | (0.042) | (0.042) | (0.039) | (0.115) |
| Age | -0.032 | 0.052 | -0.079 | 0.991 |
| | (0.139) | (0.151) | (0.123) | (0.622) |
| Age squared | 0.001 | -0.000 | 0.001 | -0.011 |
| | (0.001) | (0.002) | (0.001) | (0.007) |
| % Post-secondary education | 0.016 | 0.017 | 0.010 | 0.092** |
| | (0.010) | (0.011) | (0.009) | (0.042) |
| Owner-occupied households | 0.003*** | 0.004*** | 0.003*** | 0.008*** |
| | (0.001) | (0.001) | (0.001) | (0.003) |
| Constant | -6.246 | -7.633* | -5.880 | -26.443 |
| | (3.930) | (4.282) | (3.874) | (16.48) |
| $\alpha$ | | 1.038** | | 21.13*** |
| | | (0.454) | | (1.230) |
| Observations | 4,560 | 4,560 | 4,560 | 200 |

Notes: Dependent variable is the number of residential SP installations by WattsUp Solar.
PRM is Poisson regression model. NBRM is negative binomial regression model. TNBREG is truncated negative binomial regression model.
Clustered standard errors at the dissemination area level in parentheses.
Missing cost of installations replaced with average cost at the county level. $\alpha$ is overdispersion parameter used in NBRM and TNBREG.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.0.2: Robustness Check using Rebate: Three-Month Project Implementation Period for Specification 1

| | | | Hurdle Model | |
|---|---|---|---|---|
| | PRM | NBRM | Logit | TNBREG |
| Cost-before-rebate | -3.432*** | -2.967*** | -3.748*** | -0.985 |
| | (0.489) | (0.545) | (0.711) | (0.655) |
| Rebate | -1.784*** | -1.481*** | -2.200*** | 1.045 |
| | (0.283) | (0.356) | (0.418) | (0.671) |
| Median Income | 0.673*** | 0.602** | 0.794*** | -2.071 |
| | (0.228) | (0.249) | (0.255) | (1.289) |
| Population density | -0.071* | -0.061 | -0.080** | -0.014 |
| | (0.038) | (0.042) | (0.036) | (0.115) |
| Age | -0.041 | 0.015 | -0.104 | 0.958 |
| | (0.132) | (0.157) | (0.123) | (0.605) |
| Age squared | 0.001 | 0.000 | 0.001 | -0.011 |
| | (0.001) | (0.002) | (0.001) | (0.007) |
| % Post-secondary education | 0.016* | 0.017* | 0.011 | 0.091** |
| | (0.010) | (0.010) | (0.009) | (0.041) |
| Owner-occupied households | 0.003*** | 0.003*** | 0.003*** | 0.007*** |
| | (0.001) | (0.001) | (0.001) | (0.003) |
| Constant | -0.288 | -2.535 | 1.152 | -25.74 |
| | (3.969) | (4.902) | (4.328) | (16.84) |
| $\alpha$ | | 0.558 | | 22.16*** |
| | | (0.671) | | (1.017) |
| Observations | 4,560 | 4,560 | 4,560 | 200 |

Notes: Dependent variable is the number of residential SP installations by WattsUp Solar.
PRM is Poisson regression model. NBRM is negative binomial regression model. TNBREG is truncated negative binomial regression model.
A three-month project implementation period is assumed.
Clustered standard errors at the dissemination area level in parentheses.
$\alpha$ is overdispersion parameter used in NBRM and TNBREG.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.0.3: Robustness Check using Rebate: Five-Month Project Implementation Period for Specification 1

| | | | Hurdle Model | |
|---|---|---|---|---|
| | PRM | NBRM | Logit | TNBREG |
| Cost-before-rebate | -3.605*** | -3.140*** | -3.999*** | -1.125* |
| | (0.465) | (0.575) | (0.713) | (0.610) |
| Rebate | -1.947*** | -1.632*** | -2.425*** | 0.798 |
| | (0.264) | (0.381) | (0.407) | (0.569) |
| Median income | 0.656*** | 0.599** | 0.787*** | -2.089 |
| | (0.224) | (0.246) | (0.252) | (1.301) |
| Population density | -0.066* | -0.058 | -0.078** | -0.019 |
| | (0.037) | (0.041) | (0.036) | (0.116) |
| Age | -0.014 | 0.037 | -0.093 | 0.836 |
| | (0.123) | (0.153) | (0.121) | (0.597) |
| Age squared | 0.000 | -0.000 | 0.001 | -0.009 |
| | (0.001) | (0.002) | (0.001) | (0.007) |
| % Post-secondary education | 0.015 | 0.017 | 0.010 | 0.092** |
| | (0.010) | (0.010) | (0.009) | (0.041) |
| Owner-occupied households | 0.003*** | 0.003*** | 0.003*** | 0.007*** |
| | (0.001) | (0.001) | (0.001) | (0.003) |
| Constant | -0.111 | -2.375 | 1.820 | -22.72 |
| | (3.790) | (4.830) | (4.205) | (15.72) |
| $\alpha$ | | 0.375 | | 22.54*** |
| | | (0.821) | | (4.454) |
| Observations | 4,560 | 4,560 | 4,560 | 200 |

Notes: Dependent variable is the number of residential SP installations by WattsUp Solar.
PRM is Poisson regression model. NBRM is negative binomial regression model. TNBREG is truncated negative binomial regression model.
A five-month project implementation period is assumed.
Clustered standard errors at the dissemination area level in parentheses.
$\alpha$ is overdispersion parameter used in NBRM and TNBREG.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.0.4: Robustness Check using a Different Shadow Price for Specification 2

| | | | Hurdle Model | |
|---|---|---|---|---|
| | PRM | NBRM | Logit | TNBREG |
| Cost-after-rebate | -0.491*** | -0.486*** | -0.419*** | -1.111*** |
| | (0.089) | (0.089) | (0.085) | (0.348) |
| Median income | 0.769*** | 0.670*** | 0.861*** | -2.107 |
| | (0.237) | (0.254) | (0.258) | (1.341) |
| Population density | -0.082** | -0.064 | -0.085** | -0.017 |
| | (0.041) | (0.041) | (0.037) | (0.114) |
| Age | -0.055 | 0.040 | -0.101 | 0.971 |
| | (0.144) | (0.151) | (0.125) | (0.616) |
| Age squared | 0.001 | -0.000 | 0.001 | -0.011 |
| | (0.002) | (0.002) | (0.001) | (0.007) |
| % Post-secondary education | 0.017* | 0.018* | 0.011 | 0.093** |
| | (0.010) | (0.010) | (0.009) | (0.042) |
| Owner-occupied households | 0.003*** | 0.004*** | 0.003*** | 0.008*** |
| | (0.001) | (0.001) | (0.001) | (0.003) |
| Constant | -10.57*** | -12.02*** | -10.51*** | -21.90 |
| | (3.969) | (4.177) | (3.867) | (17.22) |
| $\alpha$ | | 1.286*** | | 18.61*** |
| | | (0.373) | | (1.219) |
| Observations | 4,560 | 4,560 | 4,560 | 200 |

Notes: Dependent variable is the number of residential SP installations by WattsUP.
PRM is Poisson regression model. NBRM is negative binomial regression model. TNBREG is truncated negative binomial regression model.
Clustered standard errors at the dissemination area level in parentheses.
Missing cost of installations replaced with average cost at the county level. Cost-before-rebate = cost of installations − rebate for each DA-year pair.
$\alpha$ is overdispersion parameter used in NBRM and TNBREG.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.0.5: Robustness Check using Rebate: Three-Month Project Implementation Period for Specification 2

| | | | Hurdle Model | |
|---|---|---|---|---|
| | PRM | NBRM | Logit | TNBREG |
| Cost-after-rebate | -0.506*** | -0.507*** | -0.446*** | -1.023*** |
| | (0.083) | (0.085) | (0.080) | (0.341) |
| Median income | 0.760*** | 0.661*** | 0.852*** | -2.073 |
| | (0.236) | (0.253) | (0.258) | (1.292) |
| Population density | -0.084** | -0.066 | -0.087** | -0.014 |
| | (0.040) | (0.041) | (0.037) | (0.115) |
| Age | -0.060 | 0.035 | -0.106 | 0.957 |
| | (0.144) | (0.151) | (0.126) | (0.602) |
| Age squared | 0.001 | -0.000 | 0.001 | -0.011 |
| | (0.002) | (0.002) | (0.001) | (0.007) |
| % Post-secondary education | 0.017* | 0.018* | 0.011 | 0.091** |
| | (0.010) | (0.010) | (0.009) | (0.041) |
| Owner-occupied households | 0.003*** | 0.004*** | 0.003*** | 0.007*** |
| | (0.001) | (0.001) | (0.001) | (0.003) |
| Constant | -10.34*** | -11.77*** | -10.25*** | -20.61 |
| | (3.958) | (4.153) | (3.865) | (17.623) |
| $\alpha$ | | 1.269*** | | 17.18** |
| | | (0.374) | | (8.051) |
| Observations | 4,560 | 4,560 | 4,560 | 200 |

Notes: Dependent variable is the number of residential SP installations by WattsUp Solar.
PRM is poisson regression model. NBRM is negative binomial regression model. TNBREG is truncated negative binomial regression model.
Clustered standard errors at the dissemination area level in parentheses.
A three-month project implementation period is assumed and cost-after-rebate = cost of installations before rebate − rebate for each DA-year pair. $\alpha$ is overdispersion parameter used in NBRM and TNBREG.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.0.6: Robustness Check using Rebate: Five-Month Project Implementation Period for Specification 2

| | | | Hurdle Model | |
|---|---|---|---|---|
| | PRM | NBRM | Logit | TNBREG |
| Cost-after-rebate | -0.469*** | -0.474*** | -0.411*** | -0.911*** |
| | (0.082) | (0.084) | (0.078) | (0.308) |
| Median income | 0.764*** | 0.663*** | 0.855*** | -2.079 |
| | (0.237) | (0.254) | (0.258) | (1.296) |
| Population density | -0.085** | -0.066 | -0.087** | -0.020 |
| | (0.041) | (0.041) | (0.037) | (0.117) |
| Age | -0.063 | 0.029 | -0.107 | 0.826 |
| | (0.146) | (0.151) | (0.126) | (0.600) |
| Age squared | 0.001 | -0.000 | 0.001 | -0.009 |
| | (0.002) | (0.002) | (0.001) | (0.007) |
| % Post-secondary education | 0.017* | 0.018* | 0.011 | 0.092** |
| | (0.010) | (0.010) | (0.009) | (0.041) |
| Owner-occupied households | 0.003*** | 0.004*** | 0.003*** | 0.008*** |
| | (0.001) | (0.001) | (0.001) | (0.003) |
| Constant | -10.395*** | -11.746*** | -10.334*** | -21.636 |
| | (3.982) | (4.184) | (3.879) | (16.610) |
| $\alpha$ | | 1.295*** | | 20.93*** |
| | | (0.369) | | (0.888) |
| Observations | 4,560 | 4,560 | 4,560 | 200 |

Notes: Dependent variable is the number of residential SP installations by WattsUp Solar.
PRM is poisson regression model. NBRM is negative binomial regression model. TNBREG is truncated negative binomial regression model.
Clustered standard errors at the dissemination area level in parentheses.
A five-month project implementation period is assumed. Cost-after-rebate = cost of installations before rebate − rebate for each DA-year pair.
$\alpha$ is overdispersion parameter used in NBRM and TNBREG.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

# Appendix D: Sensitivity Analysis

Table D.0.1: Sensitivity Analysis for Specification 1

| | | | Hurdle Model | |
|---|---|---|---|---|
| | PRM | NBRM | Logit | TNBREG |
| Cost-before-rebate | -3.381*** | -2.914*** | -3.741*** | -0.610 |
| | (0.486) | (0.543) | (0.707) | (0.532) |
| Rebate | -1.735*** | -1.428*** | -2.191*** | 1.318** |
| | (0.286) | (0.364) | (0.417) | (0.637) |
| Median income | 0.723*** | 0.642*** | 0.807*** | -1.165 |
| | (0.203) | (0.217) | (0.226) | (0.789) |
| Population density | -0.059 | -0.052 | -0.070** | 0.128 |
| | (0.037) | (0.040) | (0.034) | (0.156) |
| Owner-occupied households | 0.003*** | 0.003*** | 0.003*** | 0.005** |
| | (0.001) | (0.001) | (0.001) | (0.002) |
| Constant | -0.726 | -1.430 | -0.449 | -6.238 |
| | (2.727) | (2.680) | (3.206) | (8.453) |
| $\alpha$ | | 0.586 | | 17.212*** |
| | | (0.679) | | (0.693) |
| Observations | 4,560 | 4,560 | 4,560 | 200 |

Notes: Dependent variable is the number of residential SP system installations by WattsUp Solar. PRM is Poisson regression model. NBRM is negative binomial regression model. TNBREG is truncated negative binomial regression model.

$\alpha$ is overdispersion parameter used in NBRM and TNBREG.

Clustered standard errors at the dissemination area level in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D.0.2: Sensitivity Analysis for Specification 2

| | | | Hurdle Model | |
|---|---|---|---|---|
| | PRM | NBRM | Logit | TNBREG |
| Cost-after-rebate | -0.511*** | -0.513*** | -0.445*** | -1.054*** |
| | (0.084) | (0.087) | (0.081) | (0.361) |
| Median income | 0.825*** | 0.714*** | 0.880*** | -1.183 |
| | (0.217) | (0.220) | (0.232) | (0.797) |
| Population density | -0.0678* | -0.0569 | -0.0761** | 0.128 |
| | (0.039) | (0.039) | (0.034) | (0.157) |
| Owner-occupied households | 0.00298*** | 0.00346*** | 0.00306*** | 0.00480** |
| | (0.001) | (0.001) | (0.001) | (0.002) |
| Constant | -11.22*** | -10.13*** | -12.05*** | -4.393 |
| | (2.402) | (2.417) | (2.524) | (8.601) |
| $\alpha$ | | 1.281*** | | 16.94*** |
| | | (0.395) | | (0.471) |
| Observations | 4,560 | 4,560 | 4,560 | 200 |

Notes: Dependent variable is the number of residential SP installations by WattsUp Solar. PRM is Poisson regression model. NBRM is negative binomial regression model. TNBREG is truncated negative binomial regression model. Cost-after-rebate = cost of installations before rebate − rebate for each DA-year pair. $\alpha$ is overdispersion parameter used in NBRM and TNBREG. Clustered standard errors at the dissemination area level in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

## References

Academic. (2019). Counties of Nova Scotia. Retrieved March 19, 2020, from https://enacademic.com/dic.nsf/enwiki/115832851

Asaee, S. R., Ugursal, V. I., and Beausoleil-Morrison, I. (2019). Development and analysis of strategies to facilitate the conversion of Canadian houses into net zero energy buildings. *Energy policy*, *126*, 118–130.

Boccard, N. (2009). Capacity factor of wind power realized values vs. estimates. *Energy policy*, *37*(7), 2679–2688.

Bollinger, B., and Gillingham, K. (2012). Peer effects in the diffusion of solar photovoltaic panels. *Marketing Science*, *31*(6), 900–912.

Burke, P. J., Widnyana, J., Anjum, Z., Aisbett, E., Resosudarmo, B., and Baldwin, K. G. (2019). Overcoming barriers to solar and wind energy adoption in two asian giants: India and Indonesia. *Energy Policy*, *132*, 1216–1228.

Burr, C. (2014). Subsidies, tariffs and investments in the solar power market. *University of Colorado-Boulder Working Paper*.

Cameron, A. C., and Trivedi, P. K. (2013). *Regression analysis of count data* (Vol. 53). Cambridge University Press.

Canada Energy Regulator. (2019a). Canada's energy future 2019. Retrieved March 23, 2020, from https://www.cer-rec.gc.ca/nrg/ntgrtd/ftr/2019/index-eng.html

Canada Energy Regulator. (2019b). Canada's renewable power landscape 2016 – energy market analysis. Retrieved from https://www.cer-rec.gc.ca/nrg/sttstc/lctrct/rprt/2016cndrnwblpwr/prvnc/ns-eng.html

Canada Energy Regulator. (2019c). Nuclear generation in Canada. Retrieved March 20, 2020, from https://www.cer-rec.gc.ca/nrg/sttstc/lctrct/rprt/2018nclrnrg/nclrgnrtn-eng.html

Canada Energy Regulator. (2019d). Provincial and territorial energy profiles – Nova Scotia. Retrieved March 07, 2020, from https://www.cer-rec.gc.ca/nrg/ntgrtd/mrkt/nrgsstmprfls/ns-eng.html?=undefined&wbdisable=true

Canada Energy Regulator. (2020). Provincial and territorial energy profiles – Nova Scotia. Retrieved April 08, 2020, from https://www.cer-rec.gc.ca/nrg/ntgrtd/mrkt/nrgsstmprfls/ns-eng.html

Canadian Solar Industries Association. (2019). Nova Scotia residential solar. Retrieved from https://www.cansia.ca/uploads/7/2/5/1/72513707/cansia_nova_scotia_residential_solar_market_outlook_and_labor_force_study_-_final_report__2019-04-09_.pdf

Canadian Solar Institute. (2020). 5 day solar PV design and installation workshop. Retrieved March 07, 2020, from https://www.solarinstitute.ca/CSI_5DAY_SolarPV_Design_and_Install.html

Chapados, N. (2014). Effective Bayesian modeling of groups of related count time series. *arXiv preprint arXiv:1405.3738*.

Chen, W., and Wei, P. (2018). Socially optimal deployment strategy and incentive policy for solar photovoltaic community microgrid: A case of China. *Energy Policy*, *116*, 86–94.

Chin, H. C., and Quddus, M. A. (2003). Modeling count data with excess zeroes: an empirical application to traffic accidents. *Sociological methods & research*, *32*(1), 90–116.

Clean Foundation. (2020). Clean energy financing. Retrieved from https://clean.ns.ca/energy-financing

Corning, D. (2019). Solar homes program updates. Retrieved March 21, 2020, from https://www.cansia.ca/uploads/7/2/5/1/72513707/dave_corning_solarhomes_presentation_-_2019.pdf

Crabtree, G. W., and Lewis, N. S. (2007). Solar energy conversion. *Physics today*, *60*(3), 37–42.

Cragg, J. G. (1971). Some statistical models for limited dependent variables with application to the demand for durable goods. *Econometrica (pre-1986)*, *39*(5), 829.

Curtius, H. C. (2018). The adoption of building-integrated photovoltaics: barriers and facilitators. *Renewable Energy*, *126*, 783–790.

Denty, K., and Jacques, D. (2018). Halifax Solar City program update and extension. Retrieved from https://www.halifax.ca/sites/default/files/documents/city-hall/standing-committees/181101essc1212.pdf

Department of Energy and Mines. (2013). Developmental tidal feed-in tariff program. Retrieved from https://energy.novascotia.ca/sites/default/files/Developmental-Tidal-Feed-in-Tariff-Program-Discussion-Paper.pdf

Department of Energy and Mines. (2019). Programs and projects. Retrieved from https://energy.novascotia.ca/renewables/programs-and-projects/comfit

Dewald, U., and Truffer, B. (2011). Market formation in technological innovation systems—diffusion of photovoltaic applications in Germany. *Industry and Innovation*, *18*(03), 285–300.

Djebbar, R., Belanger, D., Boutin, D., Weterings, E., and Poirier, M. (2014). Potential of concentrating solar power in Canada. *Energy Procedia*, *49*(Supplement C), 2303–2312.

Dong, C., Wiser, R., and Rai, V. (2014). *Incentive pass-through for residential solar systems in California* (Tech. Rep.). Lawrence Berkeley National Lab.(LBNL), Berkeley, CA (United States).

Duan, H., Zhang, G., Wang, S., and Fan, Y. (2018). Peer interaction and learning: Cross-country diffusion of solar photovoltaic technology. *Journal of Business Research*, *89*, 57–66.

Efficiency Nova Scotia. (2020). Efficiency trade network directory. Retrieved March 21, 2020, from https://www.efficiencyns.ca/trade-network/find-a-contractor/search/?st=residential&sa=halifax-county&bt=contractor-or-service-provider&c=solar-equipment&p=solar-pv

Energy Sage. (2017). What are the most efficient solar panels on the market. Retrieved from https://news.energysage.com/what-are-the-most-efficient-solar-panels-on-the-market/

Energy Sage. (2018). How do solar photovoltaic (PV) cells work? Retrieved January 05, 2020, from https://news.energysage.com/how-solar-photovoltaic-cells-work/

Englin, J., and Shonkwiler, J. S. (1995). Estimating social welfare using count data models: an application to long-run recreation demand under conditions of endogenous stratification and truncation. *The Review of Economics and statistics*, 104–112.

Environment and Climate Change Canada. (2019). Greenhouse gas sources and sinks. Retrieved March 07, 2020, from https://www.canada.ca/en/environment-climate-change/services/climate-change/greenhouse-gas-emissions/sources-sinks-executive-summary-2019.html

Environmental Protection Agency. (2020). Greenhouse gas equivalencies calculator. Retrieved March 24, 2020, from https://www.epa.gov/energy/greenhouse-gas-equivalencies-calculator

Gardner, W., Mulvey, E. P., and Shaw, E. C. (1995). Regression analyses of counts and rates: Poisson, overdispersed Poisson, and negative binomial models. *Psychological bulletin*, *118*(3), 392.

Gerarden, T. (2017). *Demanding innovation: The impact of consumer subsidies on solar panel production costs* (Tech. Rep.). Technical report, Working paper, Harvard University.

Gil, K. (2008). 5 day solar PV design and installation workshop. Retrieved February 05, 2020, from https://science.nasa.gov/science-news/science-at-nasa/2002/solarcells

Gillingham, K., and Tsvetanov, T. (2019). Hurdles and steps: Estimating demand for solar photovoltaics. *Quantitative Economics*, *10*(1), 275–310.

Government of Canada. (2019). An agreement on the equivalency of federal and Nova Scotia regulations for the control of greenhouse gas emissions from electricity producers in Nova Scotia, 2020. Retrieved March 23, 2020, from https://www.canada.ca/content/dam/eccc/documents/pdf/cepa/Canada-NovaScotiaEquivalencyAgreementGHG2020-eng.pdf

Graziano, M., and Gillingham, K. (2015). Spatial patterns of solar photovoltaic system adoption: the influence of neighbors and the built environment. *Journal of Economic Geography*, *15*(4), 815–839.

Green Energy Futures. (2014). Canada's first concentrated solar thermal plant. Retrieved April 10 , 2020, from http://www.greenenergyfutures.ca/episode/88-welcome-canadas-only-concentrated-solar-thermal-plant

Greene, W., et al. (2007). Functional form and heterogeneity in models for count data. *Foundations and Trends® in Econometrics*, *1*(2), 113–218.

Groote, D. O., and Verboven, F. (2016). Subsidies and myopia in technology adoption: Evidence from solar photovoltaic systems. *KU Leuven, Department of Economics, DPS*, *16*.

Halifax Regional Municipality. (2020a). Solar City program - solar energy generation with micro-inverters. Retrieved September, 2019, from `https://catalogue-hrm.opendata.arcgis.com/datasets/0360f99bea8e471d98d789045d08447c_0`

Halifax Regional Municipality. (2020b). Solar projects. Retrieved from `https://www.halifax.ca/home-property/solar-projects/about-solar-city-halifax`

Hughes, J. E., and Podolefsky, M. (2015). Getting green with solar subsidies: evidence from the California solar initiative. *Journal of the Association of Environmental and Resource Economists*, *2*(2), 235–275.

Im, S., Bayus, B. L., and Mason, C. H. (2003). An empirical study of innate consumer innovativeness, personal characteristics, and new-product adoption behavior. *Journal of the academy of marketing science*, *31*(1), 61–73.

International Renewable Energy Agency. (2019). Renewable power generation costs in 2018. *Report, International Renewable Energy Agency, Abu Dhabi*.

Islam, T., and Meade, N. (2013). The impact of attribute preferences on adoption timing: The case of photo-voltaic (PV) solar cells for household electricity generation. *Energy Policy*, *55*, 521–530.

King, G. (1988). Statistical models for political science event counts: Bias in conventional procedures and evidence for the exponential Poisson regression model. *American Journal of Political Science*, 838–863.

King, G. (1989). Variance specification in event count models: From restrictive assumptions to a generalized estimator. *American Journal of Political Science*, 762–784.

Lobel, R., and Perakis, G. (2011). Consumer choice model for forecasting demand and designing incentives for solar technology. *Available at SSRN*, *1748424*, 1–42.

Long, J. S. (1997). Regression models for categorical and limited dependent variables. *Advanced quantitative techniques in the social sciences*, *7*.

Lund, H. (2007). Renewable energy strategies for sustainable development. *Energy*, *32*(6), 912–919.

Martinez, E., Polo, Y., and Flavian, C. (1998). The acceptance and diffusion of new consumer durables: differences between first and last adopters. *Journal of Consumer Marketing*.

McEachern, M., and Hanson, S. (2008). Socio-geographic perception in the diffusion of innovation: Solar energy technology in Sri Lanka. *Energy Policy*, *36*(7), 2578–2590.

Mills, A. D., Millstein, D., Wiser, R. H., Seel, J., Carvallo, J. P., Jeong, S., and Gorman, W. (2019). Impact of wind, solar, and other factors on wholesale power prices: An historical analysis—2008 through 2017.

Mullahy, J. (1986). Specification and testing of some modified count data models. *Journal of econometrics*, *33*(3), 341–365.

Müller-Steinhagen, H. (2013). Concentrating solar thermal power. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering*

*Sciences*, *371*(1996), 20110433.

Natural Resources Canada. (2017). Photovoltaic and solar resource maps. Retrieved from `https://www.nrcan.gc.ca/18366`

Natural Resources Canada. (2020). Electricity facts. Retrieved March 03, 2020, from `https://www.nrcan.gc.ca/science-data/data-analysis/energy-data-analysis/energy-facts/electricity-facts/20068#L1`

Noll, D., Dawes, C., and Rai, V. (2014). Solar community organizations and active peer effects in the adoption of residential PV. *Energy policy*, *67*, 330–343.

Nova Scotia Power. (2018). Rate stability. Retrieved February 29, 2020, from `https://www.nspower.ca/about-us/who-we-are/how-we-operate/regulations/rate-stability-plan`

Nova Scotia Power. (2019). Nova Scotia Power reaches 30 renewable energy milestone. Retrieved from `https://www.nspower.ca/about-us/press-releases/details/2019/06/10/nova-scotia-power-reaches-30-renewable-energy-milestone`

Olli, E., Grendstad, G., and Wollebaek, D. (2001). Correlates of environmental behaviors: Bringing back social context. *Environment and behavior*, *33*(2), 181–208.

Paidipati, J., Frantzis, L., Sawyer, H., and Kurrasch, A. (2008). *Rooftop photovoltaics market penetration scenarios* (Tech. Rep.). National Renewable Energy Lab.(NREL), Golden, CO (United States).

Podolefsky, M. (2013). Tax evasion and subsidy pass-through under the solar investment tax credit. *Discussion Papers in Economics. Working Paper*(13-05).

Qureshi, T. M., Ullah, K., and Arentsen, M. J. (2017). Factors responsible for solar PV adoption at household level: A case of Lahore, Pakistan. *Renewable and Sustainable Energy Reviews*, *78*, 754–763.

Rai, V., and Beck, A. L. (2017). Play and learn: serious games in breaking informational barriers in residential solar energy adoption in the United States. *Energy research & social science*, *27*, 70–77.

Rogers, E., and Sexton, S. (2014). Effectiveness of subsidies for residential rooftop solar adoption: Lessons from California. *North Carolina State University Working Paper*.

Sallee, J. M. (2011). The surprising incidence of tax credits for the Toyota Prius. *American Economic Journal: Economic Policy*, *3*(2), 189–219.

Shama, A. (1982). Speeding the diffusion of solar energy innovations. *Energy*, *7*(8), 705–715.

Statistics Canada. (2017). Census demographic data. Retrieved from `https://www150.statcan.gc.ca/n1/en/type/data?MM=1`

Statistics Canada. (2019). Table 25-10-0015-01 electric power generation, monthly generation by type of electricity. Retrieved from `https://www150.statcan.gc.ca/t1/tbl1/en/tv.action?pid=2510001501`

Wayne, G., Christie, C. S., and Sarah, D. M. (2018). Prices and productivity of solar electricity in Nova Scotia. Retrieved from `http://solarns.ca/sites/solarns.ca/files/2018-10/NS_Solar_Price_report_2018.pdf`

Weaver, C. G., Ravani, P., Oliver, M. J., Austin, P. C., and Quinn, R. R. (2015). Analyzing hospitalization data: potential limitations of Poisson regression. *Nephrology Dialysis Transplantation*, *30*(8), 1244–1249.

Whiteman, A., Esparrago, J., Rueda, S., Elsayed, S., and Arkhipova, I. (2019). Renewable capacity statistics 2019. Retrieved from `https://www.irena.org/publications/2019/Mar/Renewable-Capacity-Statistics-2019`

Winkelmann, R. (2008). *Econometric analysis of count data*. Springer Science & Business Media.

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*. MIT press.

Yen, S. T., and Huang, C. L. (1996). Household demand for finfish: a generalized double-hurdle model. *Journal of agricultural and resource economics*, 220–234.

Zhai, P., and Williams, E. D. (2012). Analyzing consumer acceptance of photovoltaics (PV) using fuzzy logic model. *Renewable Energy*, *41*, 350–357.

Zhang, X., Shen, L., and Chan, S. Y. (2012). The diffusion of solar energy use in HK: what are the barriers? *Energy Policy*, *41*, 241–249.