The Effects of Electricity Billing Structures and Electricity Rates on the Profitability of Solar Photovoltaic Projects: Evidence from Poultry Farms

by

Jose Roberto Garcia Gamez

A thesis submitted to the Graduate Faculty of
Auburn University
in partial fulfillment of the
requirements for the Degree of
Master of Science

Auburn, Alabama
August 6, 2022

Approved by

Joshua M. Duke, Chair, Professor and Department Head, Agricultural Economics and Rural Sociology

Adam Rabinowitz, Co-Chair, Assistant Professor, Agricultural Economics and Rural Sociology

Dennis Brothers, Co-Chair, Associate Extension Professor, Agricultural Economics and Rural Sociology

Abstract

Increasing prices for fossil fuels contribute to rising electricity prices. This coupled with the drop in the cost of solar photovoltaic (PV) panels has led to a rapid growth in PV adoption. Commercial poultry is a growing agricultural sector with substantial energy needs, which has led to interest in PV as a means of decreasing input costs. Research questions remain, however, about whether PV systems are profitable and what size systems should be built to be the most profitable. Also, various utility rates (sell and buy prices) and compensation structures for PV (such as net metering, net billing, and buy-all, sell-all) have significant impacts on profitability. Because these rates and structures vary across utilities, it is beneficial for poultry growers and those providing advice to growers to understand these impacts. We collect original load data from a commercial poultry farm located in northern Alabama and use a government-developed software platform to simulate the effects of varying billing rates, billing structure, and system size. The simulation is run thousands of times to develop a Monte-Carlo distribution of profitability over all treatments. We then use descriptive statistics on the variation of profitability across trials and a regression to estimate the average effect of each treatment, holding other drivers constant. Findings show that net metering provides the highest profitability, ceteris paribus; for instance, over the expected life of the system, net metering on average produces $14,630 more profitability than net billing and $16,513 more than buy-all, sell-all structures. The results also show how various system sizes affect profitability under different billing rates and structures, revealing which system is likely to be most profitable in various areas of the U.S.

Acknowledgments

To my grandmother Zoila, my mother Enna my aunt Carolina and my sister Ana, the most important women in my life, for always believing in me and supporting me in every aspect of my life. I am what I am today because of what you all did for me, know that I will always love all of you.

To Dr. Duke, for being not only an advisor but a mentor to me and showing me economics is both an art and a science. Thank you for believing in me and for your patience.

To my advisors Mr. Brothers and Dr. Rabinowitz, I'm thankful for all the times you helped me and your comments and suggestions on this thesis I would have never completed this without your help.

To my friends and Zamorano colleagues in Auburn, thank you for making my days better with your support.

To my aunt Diana and my uncle Agustin in Mexico, I am here today because of your help and nobility, I will be grateful for the rest of my life.

Lastly to Mia, thank you for being with me everyday I'm grateful to have you in my life.

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List of Abbreviations

PV	Photovoltaic Systems
NREL	National Renewable Energy Laboratory
SAM	System Advisor Model
NRDB	National Radiation Database
NM	Net Metering
NB	Net Billing
BASA	Buy All Sell All
NPV	Net Present Value

Introduction

Increasing prices for fossil fuels contribute to rising electricity prices and greenhouse gas emissions. A rapidly changing society deeply concerned about climate change has no doubt made an impact in renewable energy policy. So much so that many world leaders have made climate change one of their focal issues, with some committing to achieve carbon neutrality before 2050. Achieving neutrality given that a continually increasing population poses a challenge. Many believe this challenge could be addressed by shifting electricity consumption from traditional non-renewable energy sources to zero-carbon emission sources, such as nuclear power, wind, and solar energy. As evidence, according to the Energy Information Administration (EIA, 2020) 12% of the energy production in the US now comes from renewable sources, a three-fold increase when compared to the year 2000. The EIA has also projected that this increase in renewable energy production and consumption will only continue through the year 2050. This increase in renewable energy is shored up by less waste and less pollution produced compared to traditional nonrenewable resources.

The rapidly increasing adoption of photovoltaic systems (termed PV herein) in the poultry industry arises in part, because of the decrease in PV materials and installation costs. For instance, Barbose et al. (2014, 2015, 2016) showed that the median installation cost for PV has dropped 50% from an average of $8/watt to $4/watt in less than 6 years; similarly, PV material costs 75% less (from $4/watt to $1/watt). PV adoption has also increased because of public policies—especially incentive programs. Policymakers have implemented a variety of incentives such as tax credits (either personal or corporate), sales tax exemptions, low-interest loan programs, grant programs, net energy metering (NEM) laws among others. According to the Database of State Incentives for Renewables & Efficiency (DSIRE) there are 234 incentive programs available in the US and its territories, including both regulatory policies and financial incentives.

The agricultural section is especially well positioned for PV use because of high energy needs and a desire for "sustainable" food production designations. For instance, the biggest poultry production and processing company, Tyson, has announced plans to reach net-zero greenhouse gas emissions throughout its entire supply chain by the year 2050. One of the key drivers for this initiative is the shift of 50% of Tysons electrical consumption from fossil fuels to renewable energy by 2030. Thus Tyson, a company that produces 45 million chickens a week through 3,890 chicken supply partners, could potentially be a tipping point for poultry farmers to adopt renewable energy sources as their main source of electricity (Tyson Sustainability Report, 2021). This shift would provide benefits not only for environmentally conscious consumers and poultry production companies, but especially for contract poultry growers, who already operate on thin margins. For instance, Simpson et al. (2007) found that electricity costs are the second highest variable cost in broiler production, similarly Tabler et al. (2004) report that electricity costs account for 25% of the annual gross farm income, therefore the implementation of PV systems could help offset part of these costs.

Commercial poultry farms have large electrical loads used primarily for cooling. The chickens are in enclosed houses that require growers to carefully control the temperature and air quality. According to the Cobb Broiler Management Guide (2018), production losses can occur from heat stress depending on the maximum temperature, duration of such exposure, and the relative humidity of the air. When not controlled properly, feed intake, growth and fertility drop due to the stress. Consequently, mortality, immunosuppression, and cannibalism rise. Because most poultry growers are contract producers, the loss of production due to such stress could potentially mean significant income loss for the farmers (Cobb Broiler Management Guide, 2018).

Other researchers have studied PV and its applications for poultry, some studies were conducted in the distant past when PV systems were more expensive. Cain et al. (1977) was amongst the first ones to research the applicability of solar energy for poultry applications in Maryland. Though his results seemed promising, he concluded that the high price of the technology made it unfeasible when compared to fossil fuel derived energy. His results also showed that though total replacement with PV would be unfeasible, however his results suggest the use of solar thermal collectors could provide a portion of the energy while being less expensive than propane. Cain and Van Dyne (1977) concluded that at the time the cost of solar technology was a limiting factor as it was unprofitable when compared to the use of natural gas or diesel for heating in broiler production.

Later research done in the 1980s focused on optimization of system size through linear modeling. Hardy et al. (1983) focused on optimization through linear programming for solar collectors, by comparing systems that delivered between 20 – 60% of the annual heating needs. The author argued that the high cost of the technology becomes a barrier to adoption as only smaller system sizes seemed profitable. Bazen & Brown (2009) examined PV adoption in Tennessee, concluding that, when properly incentivized, PV systems would be profitable. Byrne, Glover & Van Wicklen (2005) showed that in Delaware a 1.5 kW system size over 25 years is only marginally more expensive than grid connected electricity; however, Byrne, Glover & Van Wicklen (2005) do argue that this could happen because of “congestion”, referring to those cases where the load demands cannot be met by the current grid system, thus creating a cost for the utility company. Byrne (2005) then suggests the use of “Time of Use” rate, this allows for variable rates according to the time of day. Byrne, Glover & Van Wicklen (2005) concluded that the feasibility of PV for commercial poultry is highly sensitive to changing electricity prices meaning that the feasibility depends on the rates. Mohammadi et al. (2020) showed that in the long run the cost of electricity production through solar panels when compared to grid connection is more cost effective. Bazen & Brown (2009) showed that, though there is a potential for feasibility in the applications of PV systems in poultry, the adoption of PV in poultry would not be financially beneficial unless incentive programs were applied.

The study closest to ours is Brothers et al. (2022), where they compared the profitability of two PV generation profiles, three different solar deals (composed of both retail and avoided costs), and system size. Brothers et al. (2022) found that due to the load profile in broiler production and the variation among rate structures, profitability varies greatly depending on the utility compensation, system size, and billing structure. They concluded that smaller systems are more profitable regardless of the solar availability. However, Brothers et al. (2022) did not consider net metering billing structures and had an unfavorable assumed split between buy and sell rates. The authors also note the lack of variability on weather data. For these reason, though Brothers et al. (2022) represented rates, structures, and weather in three poultry growing locations, they did not consider a fuller range of options as we do herein.

This paper seeks to contribute further guidance about how a grower can select the most profitable PV system size given the institutions they cannot change (billing rates and structures). This paper investigates how charge rates, fixed costs, month to true up, and different billing structures impact the net present value (NPV) of PV. By using original data on loads from an actual poultry house, we employ NREL’s System Advisor Model (SAM 2021.12.2) to estimate different NPV for each treatment with replication. We also use solar data from Cullman, Alabama, available from 1998-2020 to develop 25 years of random solar irradiance in order to evaluate three different system sizes (45 kW, 75 kW, 130 kW), three different compensation policies for excess generation: Net Energy Metering (NM), Net Billing (NB), and Buy all Sell all (BASA). We use data from Open EI (*Utility Rate Database | Open Energy Information*, 2015), this is a free storehouse of rate structure information from utilities across the US. To measure the effect of electricity rates a simulation approach is used to generate fixed monthly costs and varying compensation rates for electricity. We also include the addition of 12 months to represent different true-up months. True-up is the month that energy generated verses energy used from the grid is reconciled. We simulate 5,112 unique NPV calculations and then analyze using a multiple regression model to determine the statistical significance and be able to estimate regression coefficients that will help us predict the NPV of future PV installations.

The specific contributions to the research literature include the following. First, this paper uses a stochastic modeling approach to the variables, where previous research relied on single simulations which limits the ability to do a more detailed analysis. Second, this paper uses original solar data from a broiler house, meaning that unlike solar PV estimation for residential or industrial manufacturing this adds a variability component in usage profiles generating high peaks of consumption, and very low peaks of consumption due to the nature of broiler production itself.

The paper is structured as follows: Section 2 provides background information on the current situation of these incentive policies and information on electricity consumption for poultry farms. Section 3 provides the theoretical model, where the model is discussed and how we have adapted previous models to suit our need by noting the importance of the chosen variables. Section 4 provides our empirical framework where we discuss the estimation equations and the models used for regression. Section 5 describes the data and descriptive statistics used for the generation of the values for solar production, and the stochastic values used to generate the values for the stochastic variables. Section 6 provides our results. Finally, Section 7 provides our summary and policy implications.

Modeling of the Experiment

This section shows how we model our experiment. We begin by introducing a policy literature review where we explain the different billing structures that will later determine three of our treatments. This is followed by the theoretical model section where we describe our theoretical model and the assumptions we make for our research. We then describe our simulation setting, shown in Figure 1, then the stochastic variables that compose the rest of our treatments. Finally, we describe our econometric approach to our simulated data through regression modelling to be able to quantify the effects of our treatment variables and draw analytical conclusions,

Background on Billing Rates and Mechanisms

This section provides a background on the composition of grid connected solar systems compensation and policies. This enables an understanding of how these statutory and regulatory policies and options might address one of the biggest challenges for PV adoption—the installation costs. Because the development of PV systems usually requires significant upfront investments, some government agencies and utility companies offer incentives. These incentives can come from four sources according to Hay (2016): federal, state and local governments, and utility companies. The analysis in this paper does not incorporate tax or federal credits because it is known that it would result in a higher NPV of the same magnitude as the present value of the credit itself. Currently 41 of 50 US states have adopted some form of NEM legislation (Inskeep, Kennerly, & Proudlove 2015). Idaho and Texas have voluntary NEM policies depending on the utility company, and lastly only three states have no NEM programs whatsoever (DSIRE 2016).

Compensation mechanisms can vary within the same state or zip code. Utility companies also vary their offers across consumers, including base rates, capacity limits, and time of use structures, energy credit rollover, among others. With all these possible variables, it raises the question on how PV adopters can maximize their private benefits when faced with so many constraints that are institutional rather than choice.

Because compensation mechanisms have a direct impact on NPV, or the value of a PV investment, it is crucial that consumers understand the differences between these metering and billing structures. Zinaman (2017) identified three primary compensation mechanisms components. First, there is a metering and billing arrangement, this refers to how consumption and generation related energy flows are measured. There are three main types of metering and billing arrangements:

1) Net Energy Metering (NM): Billing system that allows a PV owner to export excess energy to the utility grid and generating a credit in kWh. This credit can later be used to offset consumption of electricity in the same billing cycle.
2) Buy All, Sell All (BASA): Billing system that offers a long-term standard rate to the PV owner for all the electricity their system generates. The customer is still billed for all the electricity they consume independently of the electricity they produce.
3) Net Billing (NB): This is a metering and billing arrangement where customers can consume the electricity produced by their PV system or export the excess generation at a predefined sell rate.

The second factor is the sell rate design, this describes the compensation a PV owner receives for the electricity exported to the grid. Lastly, there is the retail rate design, which defines the retail tariff structure, or time-of-use purchase rates the PV owner must pay to the utility company. This paper focuses on how the different metering and billing arrangements combined with varying static rates affect the NPV of PV.

Theoretical Model

Previous authors have built optimization models to study PV; however, Brothers et al. (2022) is the only paper to our knowledge that used the SAM model to generate simulation trials. This paper builds on that design and builds a model that can interface with the SAM model to collect Monte Carlo data. This section also explains why the selected treatments offer insight.

Assuming a poultry grower already has an existing operation, the decision problem is reduced to whether to add a PV system and, if so, how large. This decision—assuming risk neutrality—can be formulated as whether (1) the NPV of adding a PV system of a given size is positive or (2) which system size produces the largest NPV. Let NPV = f($\mathbf{X}^{E}$, $\mathbf{X}$; $\mathbf{Y}^{E}$, $\mathbf{Y}$), where vectors $\mathbf{X}$ are potential choice variables and $\mathbf{Y}$ are exogeneous variables. Some choice variables will be controlled as treatments in this paper's experiment, denoted $\mathbf{X}^{E}$. However, there are many other potential choice variables ($\mathbf{X}$), which the researchers will not systematically vary—either holding them fixed at reality-informed averages or allowing them to vary within the NREL SAM simulation, which is described below. Many exogeneous factors affect NPV, such as weather, electric utility policies, etc. Some of these factors will be controlled in our experiment ($\mathbf{Y}^{E}$) because they are specific to a location (weather, solar availability, etc.) or to poultry operations (the electric profile of a representative poultry farm).

There are many exogenous drivers that we could vary but we allowed SAM to control as fixed for model simplicity. SAM uses 10 main categories of variables: location and resource, system design, grid limits, lifetime and degradation, installation costs, operating costs, financial parameters, incentives, electricity rates and electricity loads. These variables can be varied depending on the research to be done (see Figure 1, boxes II and III). For our analysis we vary factors that reflect our treatments. Several location-specific variables (see Figure 1, box II) will be controlled as treatments in our experiment. For the first category of location and resource we will input a TMY file obtained from the National Radiation Database and hold the weather profile constant across all simulations. For system design, we vary system capacity, while keeping everything else in that category constant. Grid limits, lifetime and degradation, installation and operating costs, financial parameters and incentives are held fixed using the default values provided by SAM (see Figure 1, box II fixed). The electricity rates and structures are varied using data from the National Utility Rate Database, which we will then use to generate new values that will be evaluated as part of our treatments. Lastly, the load data comes directly from a grower who provided one year of hourly electricity consumption for their house. This component was held fixed for all simulations.

The representative farmer's decision problem in a setting would be to maximize the discounted stream of profits from a change to a PV system:

$$\underset{\boldsymbol{X^E}}{MAX}\, NPVt = ft(\boldsymbol{X^E}, \boldsymbol{X}; \boldsymbol{Y}^E, \boldsymbol{Y}), t = 1 \ldots T,$$

where T is the terminal time of the PV system lifespan and where salvage value is assumed to be \$0. Typically, this setting would be parameterized as an inter-temporal optimization problem—with or without some variables drawn from a known probability distribution—which ideally would have a choice variable of t^* indicating the optimal time to build the system and possibly a system size choice variable. However, we do not use an dynamic framework, assuming the only option is to build the system today or not. There are still far too many drivers of profitability to collect data and use statistical inference—say in a quasi-experimental setting—to determine how real-world poultry growers are making these decisions. As such, the only option to solve this problem is to reduce the choice variables as much as possible and then use an expert-informed, existing simulation as an experimental setting.

Simulation Experiment

The simulations use the National Renewable Energy Laboratory (NREL) software System Advisor Model (SAM). There are eight stages in our experiment process (see Figure 1). SAM allows the calculation of different financial metrics for renewable energy projects. We use NPV as the dependent variable, which combines into a single measure all the costs and benefits of the lifespan of the PV system, in this case we assume a lifespan of 25 years, with a 15 year debt. SAM uses models from Short et al. (1995). The NPV calculation is a standard discounting formula:

$$NPV = \sum_{n=0}^{N} \frac{F_n}{(1+d)^n} \text{ , where}$$

F_n is the net cash flow in year n, N is the expected lifespan of the system, and d is the discount rate. This matches our model where we specify the choice and exogenous variables in the function as $(\boldsymbol{X^E}, \boldsymbol{X}; \boldsymbol{Y}^E, \boldsymbol{Y})$.

Thus, the NPV model stated before is dependent on the net cash flows in every year of the system's lifecycle. SAM utilizes the most common cashflow metric, which according to Ruegg et al. (1990) is "end-of-the-period cashflows", which refers to how the cashflows are grouped, in this case the cashflows are aggregated at the yearly level. The calculation of this cashflows relies on the difference between revenues and costs, as stated before. For the purpose of this paper, we can identify the source of revenue and the sources of costs. Revenue for solar systems consists of the income generated by the selling of excess electricity. Costs associated with the system are the actual cost of the system, the insurance cost, cost of operations and maintenance and finally the tax costs.

We formulate our experiment using SAM to isolate the choice variable for system size (*SS),* (see Figure 1, stage III in red) including the three main billing structures (*NM*, *NB*, *BASA*) (see Figure 1, stage III in green) and over a reality-informed set of pricing (*BUY*) (see Figure 1, stage V). We access the Utility Rate Database in order to obtain data on pricing rates; with this data we can generate random values from the given distributions. We can then assume a time of use schedule of only one tier and using SAM parametric simulation, and we can take the random values generated from the previous data and substitute them in the parametric inputs. SAM allows the inclusion of the three billing mechanisms under the general electricity rates option by creating indicator variables for any of the metering options. We run the simulations by size separately to capture the effects of the system size choice variable (*SS*). This process generated 5,112 observations 576 replications for *NB* and *NM* interacted with three system sizes (45,75,130) for a total of 3,456 and 552[1] replications for *BASA* interacted with three system sizes (45,75,130) for a total of 1,656, which combined is 5,112 observations total.

[1] 552 observations were generated only for BASA as SAM software performed this automatically and given computation limitations only 552 simulations where used.

Econometric Analysis of Simulation Data

We use a regression to analyze the simulation data on the effects of billing structures and mechanisms across PV installations. All models will have the net present value (*NPV*) as the dependent variable. Because of near and perfect collinearity, models 1-3 will use subsets of the following list of variables: fixed monthly cost (*FMC*), the electricity buy rate (*BUY*), the electricity sell rate (*SELL*), an interaction term of the buy rate multiplied by the sell rate (*BUYxSELL*), the inclusion of three indicator variables for the billing structure, Net Metering (*NM*), Net Billing (*NB*) , Buy-All, Sell-All (*BASA*), and lastly an interaction term for billing structures multiplied by the system size (*NMxSS*, *BASAxSS*). This yielded three models where we hold each of the possible billing structures and their interactions as a reserve category.

Model 1: Interaction Effects (IE) model

$$NPV_i = \beta_0 + \beta_1(FMC) + \beta_2(BUY) + \beta_3(SELL) + \beta_4(BASA) + \beta_5(NB) + \beta_6(SS) + \beta_7(NBXSS) + \beta_8(BASAXSS) + \beta_9(BUYXSELL) + \varepsilon$$

The appendix presents Sub-IE Model 1a, which is the same as Model 1 except *NB* is the reserve category. In Sub-IE Model 1b, *BASA* is the reserve category.

Model 2: Main Effects Model

$$NPV_i = \beta_0 + \beta_1(FMC) + \beta_2(BUY) + \beta_3(SELL) + \beta_4(NM) + \beta_5(NB) + \beta_6(SS) + \beta_7(BUYxSELL) + \varepsilon$$

The independent variables are those that we hypothesize to have an impact on *NPV*. In net metering, *BUY* = *SELL*. This requires including both interaction terms of buy and sell and running the models holding different billing structures as reserve categories to address multicollinearity. The other assumptions based on the billing structures reflect that the buy rate will always be higher than the sell rate in the cases of Net Billing and Buy All, Sell All. We hypothesize that some variables will have a positive effect on the *NPV*. We hypothesize that *NM*, because it is arguably the best billing structure, will have a positive effect with the largest magnitude. *NB* will have a positive effect, but to a lower magnitude than *NM*, and lastly *BASA* we hypothesize will have a negative effect on *NPV*. Regarding the rates we believe that *BUY* will have a negative impact on *NPV* (for the cases of *NB*, and *BASA*) as its associated with a cost. Similarly, we hypothesize the *FMC* will have a negative impact as it is a cost as well. On the other hand, we hypothesize *SELL* will have a positive impact as it reflects positive cashflows from revenue. *BUYxSELL* allows us to measure the overall magnitudes of *BUY* and *SELL*.[2]

We hypothesize that increasing the *SS* variable will increase the *NPV* of PV as a general rule even though previous research by Brothers et al. (2022) suggests that smaller systems would be more profitable. We explore the possibility that including additional billing structures in addition to NB, and by expanding the possible *BUY* and *SELL* rates onto a continuum across a large range, we could see optimum system sizes change in response to these additional options. For this paper the *BUY* rates where generated and we eliminated all the negative values, this was done because a negative *BUY* rate would mean that the utility company is paying the PV owner for consuming electricity which would never happen in real life. After this the *SELL* rates where generated, the *SELL* rates for *NM* where equal to the *BUY* rates, however for the other two billing structures *NB* and *BASA* the *SELL* rates were generated by multiplying the previously generated *BUY* rates with a random number between 0.01 – 0.99. As such we expect that for

[2] For this research we did try to use a Buy to Sell ratio and a Sell to Buy ratio, however this created multicollinearity and didn't allow us to capture the magnitude of the Buy and Sell variables and because of that we have included an interaction instead.

most cases *SELL* will tend to be approximately 50% of the *BUY* rate which is different than Brothers et al. (2022) where the best deal they evaluated was only 30%.

In this paper, we use a continuous system size instead of indicator variables (*SS45*, *SS75*, *SS130*), so that we may draw inference over this range 45 – 130 kWh. Using indicator variables may be the easiest to interpret but assumes that there is a monotonically increasing or decreasing relationship as system size increases; otherwise, the statistical significance of the continuous system size coefficient could be incorrect and/or the true relationship be hidden. This would be the case, for instance, if *SS75* produced the highest *NPV*. However, the appendix presents the models with indicator variables, and this shows the relationship is monotonically increasing.

Data

This section explains data collection processes, summary statistics on the input data, and the data cleaning process. Data collection can be separated into three stages. The first stage gathers load data (hourly profiles of energy consumption) and weather data for solar irradiance (see Figure 1, stage I). The second stage develops the treatment variables used for the simulation process, by this we refer to the collection of means and standard deviations of the fixed monthly costs, and the buyback rates across the nation (see Figure 1, stages II, III, IV, and V). The final stage is the output data from the simulation (see Figure 1, stage VI, and VII) which will be used in the regression (see Figure 1, stage VIII).

Weather and Poultry Load Data

For the weather data, the format chosen was a TMY (typical meteorological year), such data contain one year of hourly data accessed through the NSRDB (National Solar Radiation Database). One key advantage of using this type of data is TMY data files contain a whole year (8,760 observations) of hourly data that best represents median weather conditions over a multiyear period. This data is produced by analyzing multiyear data sets and 12 months are chosen from that time frame that best represent median conditions. For this paper the solar data comes from hourly observations from Cullman, Alabama, (34.17379° N, -86.84301° E) from the years 1998 – 2020. From this, we generate a totally random meteorological year that represents the weather conditions of the area. Cullman, Alabama, was chosen as the location because the load data used also contains 8,760 observations of electricity consumption for a poultry house near Cullman, Alabama, and as such it coincides with the weather data. Summary statistics for both the weather and load data are in Table 1.

Data for Simulation

We rely on simulated data for this paper mainly because the data are unavailable and simulation data are relatively inexpensive to collect. In order to be able to generate values for the simulation we used data from OpenEI which is a platform that contains The URDB (Utility Rate Database). This database provides rate structure information for 3,827 EIA recognized utility companies. The original dataset contains 50,066 different rate structures from different utility companies, however as part of our data cleaning process, and to represent more closely rates typically available to poultry operations, we selected only commercial rates with peak capacity of 500 kw for single phase wiring only. This yielded 813 (Figure 2) rate structures across the US from which we collected means and standard deviations of the fixed monthly charges and electricity rate structures. It is worth mentioning that for this paper, we only consider static single rates. There are two reasons on why we chose to only use single rates, the first one is because of the data source, OpenEI through their utility database does not contain many observations with multiple rate schedules that would be useful for this research, the second reason has to do with the inputs on SAM, if we incorporated such rates the analysis would have been more complicated and as such only static single rates are used. Summary statistics for the simulation data are provided in Table 2.

Results

This section first presents descriptive statistics on the experimental data from the simulation. Then, a regression is used to interpret the experimental data. The final subsection explores the implications of the regression results, allowing an estimate of how one might choose an optimal system size under different billing arrangements.

The experiment results have several indicators of validity despite using only 5,112 iterations. The reason for not running more trials is that each experiment treatment combination (see figure 1) had to be inputted in SAM separately. In addition, SAM also requires the data to be prepared in very specific formats, and the preparation is not done automatically. As such, 5,112 observations was the number of iterations the researchers could conduct within the time constraints. Nonetheless, the regression results presented below show that the number of iterations was sufficient to isolate the impact of the different treatments.

Descriptive Results

Summary statistics (Table 3) show an average *NPV* of $53,936 across all treatments, meaning that on average PV systems for this given load profile and solar availability are profitable. However, *NPV* ranges from -$46,577 to $379,623, which means that even with the model assumptions some growers may see negative or very high profits from PV. As load data, weather data, and costs are the same for all simulations, this substantive variability arises from the underlying varying factors in SAM, and the fact that there is an incorporation of simulations (outliers) where choices made would not necessarily be options in real life

When the experimental data are separated into treatments of three billing arrangements and three system sizes, descriptive statistics are more readily interpretable because the only remaining variability should be from the stochastic choices made in SAM (Table 4). There are positive median *NPV* for each of the nine treatment combinations. However, the median *NPV* values are considerably higher under *NM* than *NB*, both of which are considerably higher than *BASA*—as we hypothesized. The last column of Table 4 lists the percent of iterations under each treatment combination where the *NPV* is negative. The results show that under *NM*, only 0.34 - 3.47% of iterations were negative, which in turn suggests that most growers should make money from installing PV—as long as the poultry growers situation matches the assumptions in the experiment's model. *NB* also has a very low number of iterations, where the grower would lose money. In contrast, *BASA* has 43.47 - 45.10% of iterations where the grower would lose money. This means that growers in regions with *BASA* billing structures should be most cautious about PV; note that the regression results allow more precise predictions under different billing rates.

Table 4 also shows that the median *NPV* increases with larger system sizes. For 45 kWh systems, *NM* increases median *NPV* by $8,160 more than *NB* and $39,004 more than *BASA*. For the medium size systems *NM* increases median *NPV* by $15,371 more than *NB* and by $60,706 when compared to *BASA*. Finally, on the largest system size *NM* increase *NPV* increases median by $28,284 more than *NB* and by $90,953 when compared to *BASA*.

Regression Results

The regressions in Table 5 explains a considerable portion of the variation in the dependent variable (R^2=0.37). Because the data are generated through a simulation in which stochastic processes generated observations, it is unsurprising that 63% of the variation is not controlled by the independent variables. If there is not a substantively important systematic process in the uncontrolled variation that varies with heterogeneous poultry farm characteristics, then our controlled regression results should be correct for poultry growers. In other words, there is a lot affecting the profitability of PV, but commercial poultry farming involves many risks, and our regression controls the most important institutional and choice variables in decision making surrounding PV.

The results obtained from an OLS regression explaining *NPV* are described in this section. As part of our models, we estimated several additional models to address multicollinearity in billing rate variables, to rotate the reserve categories on billing structure treatments, to examine different specifications of the system size treatment variables, and to conduct robustness checks (see Appendix Table A1, A2, A3). For instance, we estimated a main effects model as shown in Table A1 with the use of dummy variables as identifiers for our system size treatments (*SS45, SS75, SS130*); as observed in the appendix we can identify that system size is significant at the $p < 2e\text{-}16$, this shows that the coefficients were indistinguishable from zero and as such can be rejected at the 1% level or better. By changing the reserve category and finding significance on these variables we can more easily conclude that the treatments are indeed different from each other —as opposed to a separate statistical difference test. As part of our main results, we use a continuous variable for our treatments. We argue that using a continuous measure improves the interpretation of the coefficients in our applied analysis. We run a different interaction model (Table A2) as a robustness check, we developed one interaction effects model with the addition of true-up month as part of our analysis. that model contained 11 categorical variables for months (*FEB – DEC* holding *JAN* as our reserve category) and later we evaluate the same model by holding our different billing structure treatments as a reserve category. This model allowed us to determine that true-up month has no significant effect in explaining the *NPV*; therefore, we decided not to include these variables as part of our final model. Secondly, if such variables would have had statistically significant impact, the interpretation of such variables could be wrong, as this significance would only be true if the load distribution was exactly the same for other projects, which is not the case in reality. Instead, we focus on the Main Effects Model, and the Interaction Effects Model for this analysis.

We first interpret the main effects model (MEM) in Table 5 because it offers a baseline explanation of the billing structure treatments. We hold the other treatments constant without complicating interpretations with interaction effects. Each billing structure treatment (*NM*, *NB*, *BASA*) Table 5 shows that the coefficients were indistinguishable from zero and as such can be rejected at the 1% level or better. On average, the *NPV* of PV decreases by $52,200 ($p < 2$ e-16) in locations where the billing structure is *BASA* when compared to the reserve category (*NM*). Similarly, *NB* decreases *NPV* by $5,649, relative to *NM*. We find that the null hypothesis that the coefficient was indistinguishable from zero can be rejected at the 1% level or better, and thus we can conclude that there are significant differences across the billing structures.

Observing the pricing structures in the main effects model, we see that both *BUY* and *SELL* show the null hypothesis that the coefficient was indistinguishable from zero can be rejected at the 1% level or better. Explaining the *NPV*, we determine that *NPV* will increase on average by $52,240 times the buy rate, (though we hypothesized *BUY* would have a negative impact on *NPV* we observe that this is not the case, we argue that because we included *BUY*SELL* as an interaction captures part of the effect), and $333,000 times the sell rate. The interpretation of the variables could be easily misinterpreted. What the results from this model show is that an increase of $1 per kWh on the *SELL* rate will increase the *NPV* on average $333,000; however, electricity rates are measured in cents and thus a better interpretation would be an increase in $0.01/kWh on the *SELL* rate will increase the *NPV* on average by $33,000. This result shows that for most cases, and particularly *NB* and *BASA*, the profitability of a PV installation relies more on the rate that the producer is selling, rather than the rate at which the producer is buying the electricity. Observing the *SS*, we observe a positive and significant impact on *NPV* meaning that larger systems will provide higher *NPV*.

The main effects model is an incomplete explanation of the drivers of *NPV* because one anticipates treatment interactions. For instance, we expect that increasing *SS* by one unit will have a different effect across different billing structures. The principal interaction effects model (IEM) in Table 5 and the models shown in the appendix (Table A3) are the same model, but the billing structure reserve category was rotated. Model 1 shows the effect of NB and BASA relative to the reserve *NM*. Model 2's reserve is *NB*. Model 3's reserve is *BASA*.

In the IEM in table 5, we observe similarities across the models. In all models, the results suggest that *FMC* has no effect on *NPV* that can be statistically distinguished from zero. This could be explained by two underlying reasons, the first one being that for commercial poultry installations the average *FMC* of only $111 has little contribution to system cost and would be easily covered by the first excess generation. The second reason is, given that the yearly cost is on average $1,332, it is insignificant when compared to the other costs associated with PV installations. Overall, given our selected variables, we can conclude that fixed monthly cost has no significant and substantive impact on the long-term, overall profitability of PV.

All models show that *BUY, SELL, NB*, and *SS,* increased *NPV*, where the null hypothesis that the coefficient was indistinguishable from zero can be rejected at the 1% level or better. In the case of *SELL,* the coefficient interpretation suggests that an increase on the sell rate by $1 will increase the *NPV* on average by $337,500; however, as mentioned previously the correct interpretation for this application would be that an increase in sell rate of $0.01/kWh will increase the *NPV* on average by $33,750. Furthermore, the *NB* coefficient is significant and on average will increase the *NPV* by $14,630. In addition, *BUY* increased *NPV*, where the null hypothesis is that the coefficient was indistinguishable from zero can be rejected at the 5% level or better. The largest positive expected effect from the billing structure treatments came from *NM*, followed by *NB*, and lastly *BASA*. However, in order to conclude that *NB* and *BASA* are different we chose to calculate the confidence intervals in order to determine whether there is an overlap. At a significance level of $\alpha = 0.95$ we determine that the values for *NB* lie between $6,392 – $22,873 and in case of *BASA* the confidence interval ranges from -$10,498 – $6,738, therefore we find that at a 95% confidence interval there are no significant statistical differences between these two variables.

The model also shows negative drivers to *NPV*. In this case *NB*SS* , *BASA*SS* and *BUY*SELL* decreased *NPV*, where the null hypothesis that the coefficient was indistinguishable from zero can be rejected at the 1% level or better. For *NB*SS*, an addition of 1 kW in system capacity, (in cases where *NB* is the billing structure) *NPV* will decrease on average $241 when compared to the reserve category (*NM*) and installations where *BASA* is the billing structure the *NPV* will decrease by $602 per every increase in system capacity of 1kW when compared to *NM*. This result is consistent with our hypothesis given that we know that *NM* will always yield a higher *NPV*. Such decrease can be interpreted as such that in cases where the billing structure is *NB* or *BASA* increases in system size will generate a negative increase on the *NPV*, which is not surprising given that previous research has shown consistently that smaller system sizes will usually be more profitable under such billing structures.

Model Application

The experiment results show how PV profitability varies, relatively, with choices made by the grower and billing rates and structures beyond the grower's control. Both the data from the descriptive statistics and the regression show that *NM* as a billing structure will increase the profitability of PV by 25% to 100% when compared to other billing structures, however its worth noting that this estimation yielded no negative *NPV* we argue that because on average the split between *BUY* and *SELL* of roughly 50% yields deals that are always profitable on average. Given that electricity is the biggest variable cost in contract poultry production (Simpson, 2007), PV may be a viable option for poultry growers, not only as a cost reduction, but also perhaps even as a source of income in cases where electricity consumption is at its lowest. Through our research we hope to keep poultry growers from installing overly large systems that will not be profitable in the long run, particularly in locations where the billing structure is *BASA*.

Furthermore, we compare how the *NPV* is affected as we increase the system size under different structures, we evaluate the IEM by varying the *SS* variable continuously and by using indicator variables for our billing structure treatments we can compare how the profitability of PV is affected. As seen on Figure 4, we observe the different slopes when comparing *BASA* to the other billing structures. As such we can infer that the marginal profit from installing one extra unit of system size varies substantively with the billing structure. We can argue that the grower's decision on what system size to build should not be decided exclusively on the load, which is the common practice in the solar industry, but rather on the maximization of *NPV* on the long run which this is even more crucial in the case of poultry production when compared to flat load consumption (say a factory). This scenario could be applicable to not only poultry, but in all cases where load profiles follows a biological growth curve. It is vital that the billing structures are considered in such cases where there will be excess production in the beginning of cycles, followed by very high usage peaks.

Conclusion

Solar adoption has been increasing since the early 2000's as companies and consumers become more environmentally conscious and as solar technology prices continue to decline. As agricultural production (particularly poultry) relies on fossil fuels for energy, the increase in the cost of such fuels has influenced the adoption of PV in many cases as a cost reduction technology. In cases such as contract poultry farming, electricity accounts for the biggest cost to the producer. Because of this, poultry farms are now considering shifting from fossil fuels to renewable energy sources. However, when producers are faced with the choice of shifting from fossil fuels to renewable energy, it is vital that producers understand how to make the right choices.

In order to determine what system size to install, it is important that producers choose a size not based on covering their entire consumption load, but rather build a system that throughout a 25 year analysis provides the highest *NPV.* As mentioned earlier the, *NPV* is a product of multiple factors including billing structures and rates, and because these structures and rates vary across locations, it is vital that we are able to provide some guide for decision making. As such we collect original load data from a poultry farm and use a NREL developed software to calculate how the *NPV* changes as we change the system size, the billing structure and the electricity rates. Finally in order to analyze the effects of these policies we employed a multiple linear regression model to determine the effect of these variables on the NPV. We find that Net Energy Metering provides the highest profitability, this is $14,633.37 dollars more profitable than NB and $16,513.38 more profitable than BASA.

Though our research provides some reference on how the billing structures, system size and rates affect the profitability of PV this model shouldn't be considered a "recipe" for solar installations. Our scope of research is somewhat limited. For instance, we only employ data from one poultry house, from one year and from only one location. The lack of load data is one of the main limitations we face, second, we do not consider the cost side of the equation. Though our costs are held fixed, it is possible that varying costs of materials and installation could potentially have a significant effect on the profitability of PV, potentially increasing NPV as equipment costs continue to decline. Lastly, with fewer time and resources restrictions, more simulations could be done to provide a better dataset that allows for more precise results.

Nevertheless, though our research presents some limitations, this study does allow for policy implications. When considering such, it is vital to understand that changes in billing structure policy affects producers, utility companies and governments. For instance, if net energy metering policies where to be implemented it would greatly benefit producers to be able to offset the cost of their bill and in cases where there is excess electricity (assuming the buyback rate is higher than the cost /kWh) it could potentially mean a producer might profit. From the utilities perspective there are advantages as well. For instance, at peak hours of sunlight the excess electricity can be used to cover demand from nearby areas. However, if there is no regulation on system size, it is possible that the utility companies would have to assume the extra cost of an overproduction of electricity. Among other benefits for utility companies is the possibility of having distant grid locations where poultry farms often are located supported by localized distributed energy production from PV, thus improving voltage drops and decreasing potential outages. Lastly, the impact on government institutions is quite interesting. Though we have no solid evidence of this in our paper, perhaps the implementation of net energy metering policies could potentially act as a substitution effect on tax credits and grants, thus incentivizing the installation of PV at lower cost to government. On the other hand, states where net energy metering is not present will require subsidies that allow compensation in response to a lack of net energy metering policies. Ultimately, legislators and public service commissions have the opportunity to increase the implementation of renewable energy across the US with promotion of positive net metering policies, while at the same time promoting the interests of utility companies and environmental concerns. We hope that this research serves as a background for further research, as mentioned before future research could potentially compare different varying loads across different sectors, consider further variations in locations and weather among others.

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Tables

Table 1. Summary statistics of weather and load data.

Variable Name	Description	Unit	No. of Observations	Mean	Std. Deviation	Min	Max
DHI	Direct Normal Irradiance	w/m2	52,559	64.09	99.48	0	499
DNI	Diffused Horizontal Irradiance	w/m2	52,559	201.56	325.84	0	1038
GHI	Global Horizontal Irradiance	w/m2	52,559	182.69	275.93	0	1053
Load	Electricity consumption per hour	kWh	8,760	19.82	20.87	0	84.48

Note: Source NRDB.

Table 2. Summary statistics of random variables.

Variable Name	Description	Unit	No. of Observations	Mean	Std. Deviation	Min	Max
Fixed Monthly Charge	Fixed monthly charge regardless of electricity production or consumption	$ / Month	813	43.76	64.66	0.34	370
Buy Rate	Electricity buy rate	$ / kWh	813	0.09	0.06	0.0025	0.873

Note: Source Utility Rate Database.

Table 3. Descriptive Statistics of Simulation Results

Variable	Description	Unit	Type	Institutional or Choice	Mean	Median	Min	Max
NPV	Net Present Value	$	Continuous	N/A	53,936	43,146	-46,577	379,263
FMC	Fixed Monthly Cost	$	Continuous	Institutional	111.93	84.61	0.03	370
MONTH	Month for true up (Jan-Dec)	0 or 1	Indicator	Institutional	5.5	5.5	0	11
BUY	Electricity buy rate	$	Continuous	Institutional	0.10	0.09	0.0003	0.34
SELL	Electricity sell rate	$	Continuous	Institutional	0.06	0.05	0.000004	0.34
SS	System size	kWh	Continuous	Choice	83.33	75	45	130
SS45	System size of 45 kWh	0 or 1	Indicator	Choice	0.33	0	0	1
SS75	System size of 75 kWh	0 or 1	Indicator	Choice	0.33	0	0	1
SS130	System size of 130 kWh	0 or 1	Indicator	Choice	0.33	0	0	1
NM	Net Metering	0 or 1	Indicator	Institutional	0.33	0	0	1
NB	Net Billing	0 or 1	Indicator	Institutional	0.33	0	0	1
BASA	Buy All, Sell All	0 or 1	Indicator	Institutional	0.32	0	0	1

Note: Data output was generated through SAM v 2021.12.2.

Table 4. Descriptive Results

Billing Structure	System Size kWh	Median NPV	Min	Max	% Of installations with NPV < $0
	45	$46,565.10	-$1,069.00	$154,038.00	0.34%
Net Metering (NM)	75	$71,302.35	-$5,660.00	$273,565.00	2.26%
	130	$113,293.00	-$14,627.00	$379,263.00	3.47%
	45	$38,170.50	-$1,160.00	$149,627.00	0.52%
Net Billing (NB)	75	$56,876.65	-$5,267.00	$219,276.00	2.60%
	130	$78,182.95	-$14,606.00	$330,130.00	5.03%
	45	$4,267.49	-$16,107.00	$114,802.00	43.47%
Buy All, Sell All	75	$4,759.51	-$26,871.00	$161,596.00	44.38%
	130	$7,446.60	-$46,576.00	$272,322.00	45.10%

Note: Original work from authors.

Table 5. Regression results for Interaction Effects Model and Main Effects Model

Variable	IEM NPV ($) (s.e.)	p-value	MEM NPV ($) (s.e.)	p-value
Intercept	-16,050*** (3,579)	0.0000007	7,029*** (2,898)	0.01
FMC	53.17 (89.5)	0.55	49.7 (91.05)	0.58
BUY	48,690*** (20,000)	0.01	52,240*** (20,340)	0.01
SELL	337,500*** (38,550)	< 2 e-16	333,000*** (39,000)	< 2 e-16
BASA	-1,880 (4,397)	0.66	-52,200*** (2,278)	< 2 e-16
NB	14,630*** (4,205)	0.0005	-5,649*** (1,976)	0.004
SS	797*** (31.7)	< 2 e-16	520*** (18.7)	< 2 e-16
*NB*SS*	-241.03*** (44.8)	0.000000007		
*BASA*SS*	-602*** (45.2)	< 2 e-16		
*BUY*SELL*	-705,500*** (190,200)	0.0002	-697,000*** (193,400)	0.0003
N	5,112		5,112	
R^2	0.37		0.35	

Note: All continuous predictors are mean-centered and scaled by 1 standard deviation. *** p < 0.01.

Figures

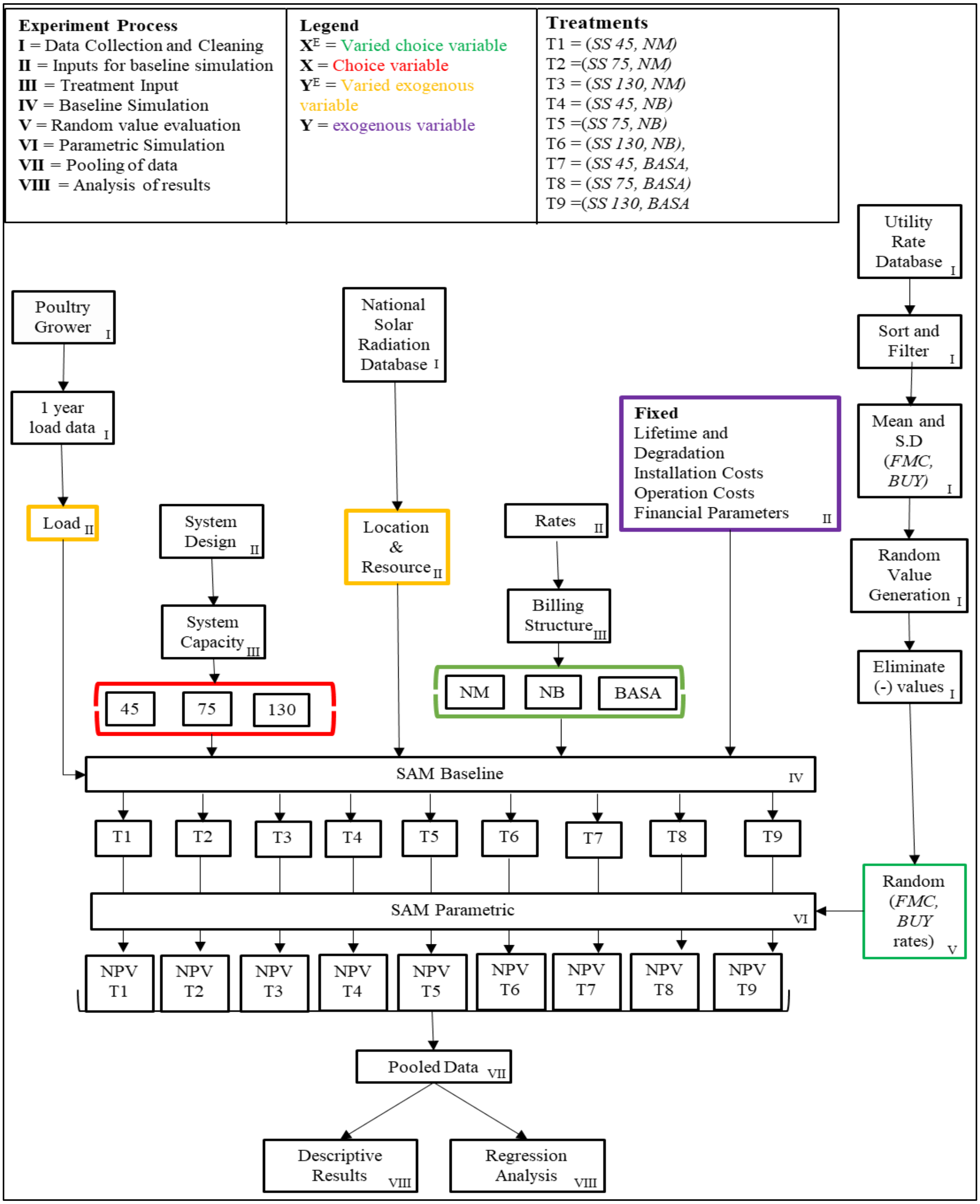

Figure 1. Experiment Modeling Diagram.

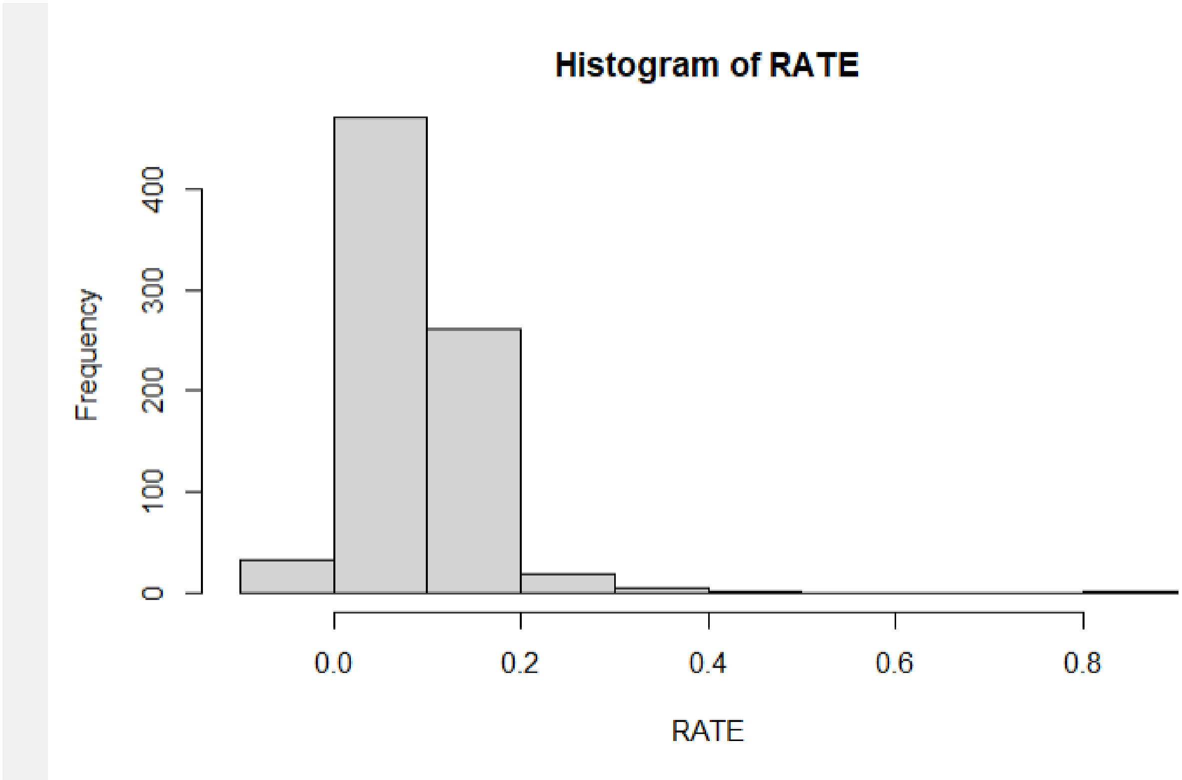

Figure 2. Histogram of rates ($), obtained from Utility Rate Database.

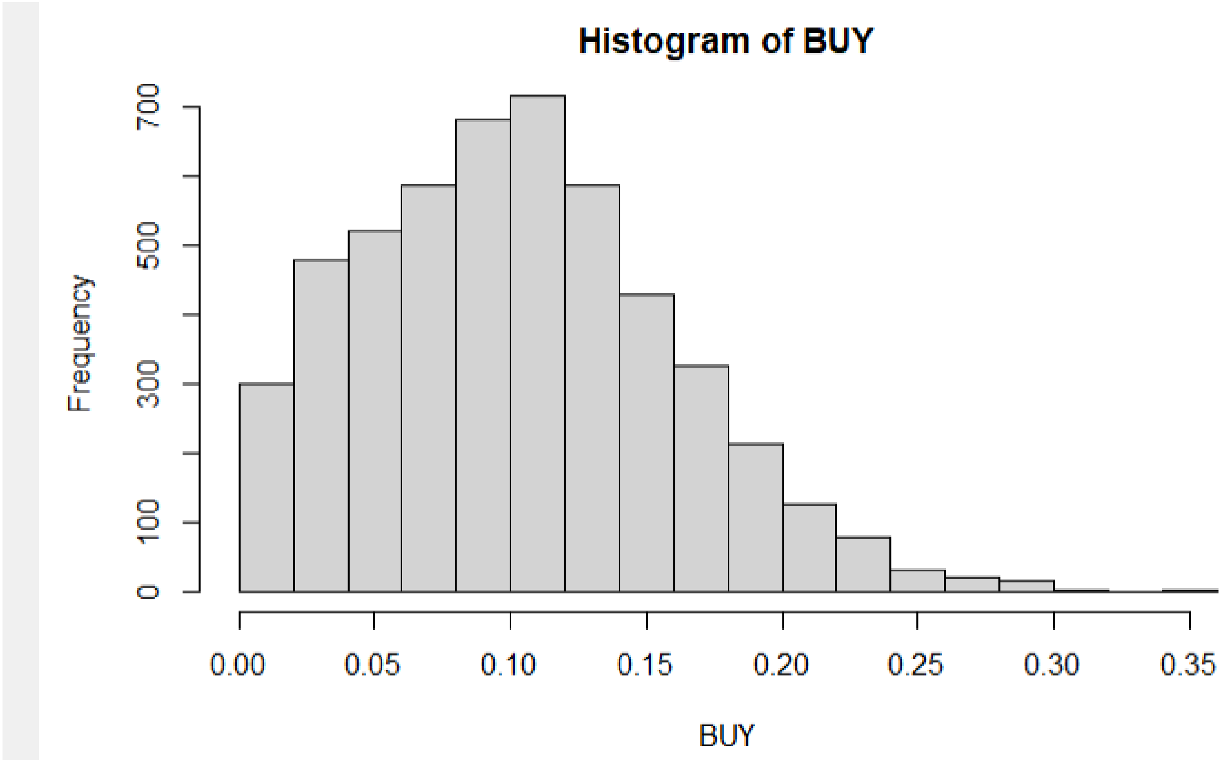

Figure 2. Histogram of *BUY* rates ($), obtained from data generation process through SAM.

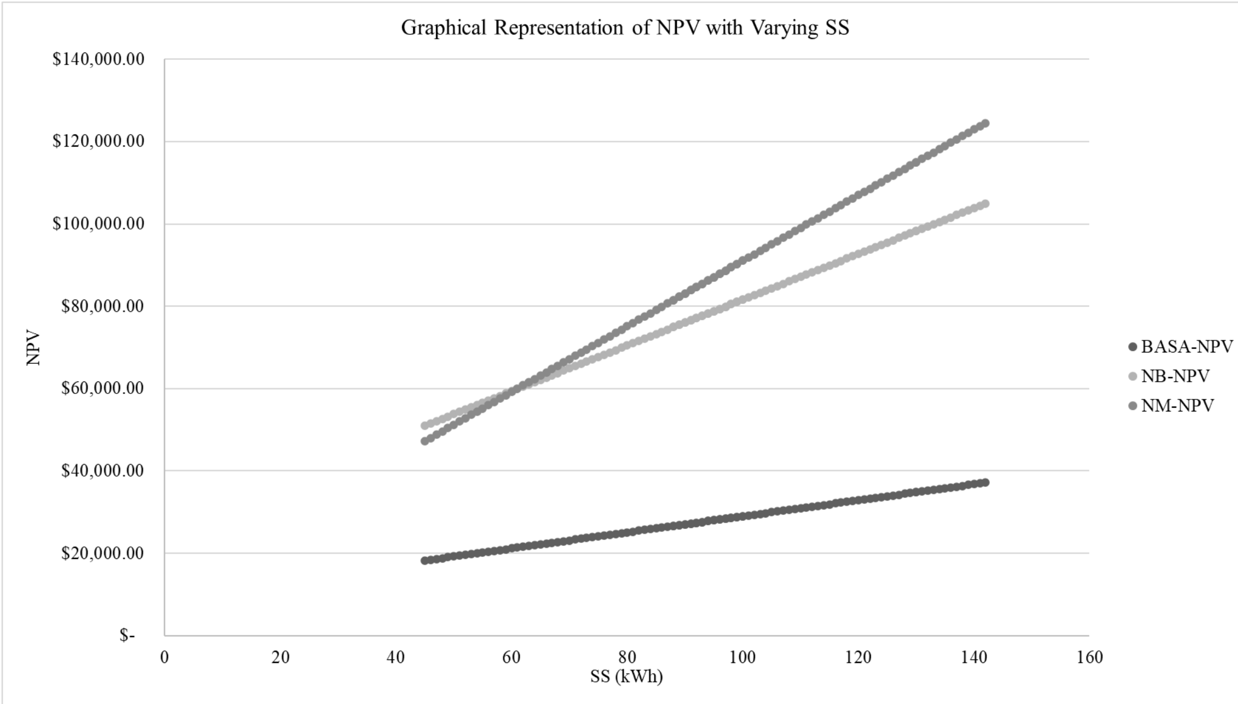

Figure 4. NPV under varying system sizes and billing structures.

Appendix

Previous Models

As mentioned previously, we did several models before the last ones we reported. As part of the data collection, we also included True-Up month as a variable (indicated using 11 indicator variables, FEB = February, MAR = March … NOV = November, DEC = December, holding January as the reserve category). In addition to that, we also included BTSR (Buy to Sell Ratio) and STBR (Sell to Buy Ratio). However, these models showed multicollinearity, higher standard errors and lastly including the True-up month could potentially indicate significance in certain months, however such significance would only reflect the impact in cases where the loads are distributed exactly like the load profile we used for this analysis. The results for these models are shown in Table A1.

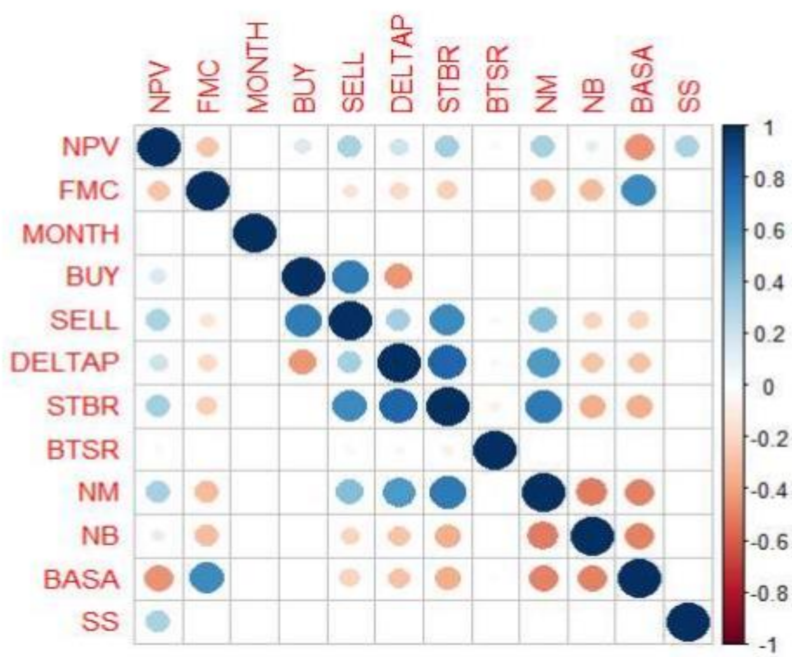

Figure 1A. Correlation Plot generated through R.

The models that we previously evaluated are:

Sub-Model 1A Net Metering as a reserve category, with the addition of true up month

$$\boldsymbol{NPV_i} = \beta_0 + \beta_1 FMC + \beta_2 BUY + \beta_3 SELL + \beta_4 BASA + \beta_5 NB + \beta_6 SS + \beta_7 NB * SS + \beta_8 BASA * SS + \beta_9 BUY * SELL + \beta_{10} FEB \vdots \beta_{20} DEC + \varepsilon, \quad i = 1 \ldots 5112$$

Sub-Model 2A Net Billing as a reserve category, with the addition of true up month

$$\boldsymbol{NPV_i} = \beta_0 + \beta_1 FMC + \beta_2 BUY + \beta_3 SELL + \beta_4 BASA + \beta_5 NM + \beta_6 SS + \beta_7 NM * SS + \beta_8 BASA * SS + \beta_9 BUY * SELL + \beta_{10} FEB \vdots \beta_{20} DEC + \varepsilon, \; i = 1 \ldots 5112$$

Sub-Model 3A BASA as a reserve category, with the addition of true up month

$$\boldsymbol{NPV_i} = \beta_0 + \beta_1 FMC + \beta_2 BUY + \beta_3 SELL + \beta_4 NB + \beta_5 NM + \beta_6 SS + \beta_7 NM * SS + \beta_8 NB * SS + \beta_9 BUY * SELL + \beta_{10} FEB \vdots \beta_{20} DEC + \varepsilon, \quad i = 1 \ldots 5112$$

Table A2 shows the results from these models, as we can observe the true up month shows that each coefficient on months are not statistically different from each other at the $p < 0.1$ level or better. As such we can infer that the true up month has no significant impact on the *NPV*, and even if they where it could lead to misinterpretation as this significance would only be true for loads distributed exactly like the load data we use.

Table A1. Regression results for models with true-up month as indicator variables.

Variable	Model 1A NPV ($) (s.e.)	Model 2A NPV ($) (s.e.)	Model 3A NPV ($) (s.e.)
Intercept	-13,160***	1,397	-15,110***
	(4185)	(3994)	(4376)
FMC	52.36	52.36	52.36
	(89.5)	(89.5)	(89.5)
BUY	48,180***	48,180***	48,180***
	(20,002)	(20,002)	(20,002)
SELL	338,000***	338,000***	338,000***
	(38,650)	(38,650)	(38,650)
BASA	-1,949	-16,500***	
	(4,397)	(4,240)	
NB	14,550***		16,500***
	(4,205)		(4,240)
SS	797***	556***	194.3***
	(31.38)	(31.68)	(32.37)
*NB*SS*	-241***		361.4***
	(44.81)		(45.3)
*BASA*SS*	-603***	-361***	
	(45.29)	(45.3)	
FEB	-5,308	-5,308	-5,308
	(3,177)	(3,177)	(3,177)
MAR	-5685	-5685	-5685
	(3,179)	(3,179)	(3,179)
APR	-5977	-5977	-5977
	(3,176)	(3,176)	(3,176)
MAY	-673.46	-673.46	-673.46
	(3,176)	(3,176)	((3,176)
JUN	-4,253	-4,253	-4,253
	(3,176)	(3,176)	(3,176)
JUL	-3,994	-3,994	-3,994
	(3,176)	(3,176)	(3,176)
AUG	6,57	657.29	657.29
	(3176)	(3,176)	(3,176)
SEPT	-3,239	-3,239	-3,239
	(3,177)	(3,176)	(3,176)
OCT	-784.27	-784.27	-784.27
	(3,176)	(3,176)	(3,176)
NOV	-1,544	-1,544	-1,544
	(3,177)	(3,176)	(3,176)
DEC	-1,377.12	-1,377.12	-1,377.12
	(3,176)	(3,176)	(3,176)
*BUY*SELL*	-688,800***	-688,800***	-688,800***
	(190,070)	(190,070)	(190,070)
NM		-14,550***	1,949
		(4,205)	(4,397)
*NM*SS*		241.2***	602.6***
		(44.81)	(45.29)
N	5,112	5,112	5,112
R^2	0.37	0.37	0.37

Table A2. Regression results for interaction effects model with different reserve categories.

Variable	IEM 1 NPV ($) (s.e.)	IEM 2 NPV ($) (s.e.)	IEM 3 NPV ($) (s.e.)
Intercept	-16,050*** (3,579)	-1,418 (3370)	-17,930 *** (3,816)
FMC	53.17 (89.51)	53.17 (89.51)	53.17 (89.51)
BUY	48,690*** (20,000)	48,690 *** (20,000)	48,690 *** (20,000)
SELL	337,500*** (38,550)	337,500 *** (38,550)	337,500 *** (38,550)
BASA	-1,880 (4,397)	-16,510*** (4,240)	
NB	14,630*** (4,205)		16,510*** (4,240)
SS	797*** (31.7)	555*** (31.69)	194 *** (32.37)
*NB*SS*	-241.03*** (44.81)		361.4*** (45.3)
*BASA*SS*	-602*** (45.2)	-361.4 *** (45.3)	
*BUY*SELL*	-705,500*** (190,200)	-705,500*** (190,200)	-705,500 *** (190,200)
NM		-14,630*** (4,205)	1,880 (4,397)
*NM*SS*		241.3*** (44.8)	602*** (45.29)
N	5,112	5,112	5,112
	0.37	0.37	0.37

Table A3. Regression results for Main Effects Models with different reserve categories

Variable	MEM1	P-Value	MEM2	P-Value	MEM3	P-Value
Intercept	7,029*** (2,898)	0.01	1,380 (2,672)	0.6	-45,210*** (3,142)	< 2e-16
FMC	49.7 (91.05)	0.585	49.7 (91.05)	0.585	49.7 (91.05)	0.585
BUY	52,240*** (20,340)	0.01	52,240*** (20,340)	0.01	52,240*** (20,340)	0.01
SELL	333,000*** (39,000)	< 2e-16	333,000*** (39,000)	< 2e-16	333,000*** (39,000)	< 2e-16
BASA	-52,200*** (2,278)	< 2e-16	-46590*** (1,966)	< 2e-16		
NB	-5,649*** (1,976)	0.004			46,590*** (1,966)	< 2e-16
SS	520*** (18.74)	< 2e-16	520*** (18.74)	< 2e-16	520*** (18.74)	< 2e-16
*BUY*SELL*	-697,000*** (193,400)	0.0003	-697,000*** (193,400)	0.0003	-697,000*** (193,400)	0.0003
NM			56,490*** (1,966)	0.004	52,240*** (2,278)	< 2e-16
N	5112		5112		5112	
R^2	0.35		0.35		0.35	

Note: All continuous predictors are mean-centered and scaled by 1 standard deviation. *** p < 0.01; ** p < 0.05; * p < 0.1.

Table A4 . Regression results for models with system size as indicator variables.

Variable	IV-M1	IV-M2	IV-M3
Intercept	79,724*** (2,114)	52,830*** (2135)	35,121*** (2119)
FMC	4.34 (9.2)	4.34 (9.2)	4.34 (9.2)
BUY	23,713*** (21,779)	23,713*** (21,779)	23,713*** (21,779)
SELL	215,123*** (21,779)	215,123*** (21,779)	215,123*** (21,779)
BASA	-53,477*** (2,252)	-53,477*** (2,252)	-53,477*** (2,252)
NB	-6,887*** (1,938)	-6,887*** (1,938)	-6,887*** (1,938)
SS45	-44,603*** (1617)	-17,708*** (1617)	
SS75	-26,894 (1617)		17,708*** (1617)
SS130		26,894*** (1617)	44,603*** (1617)
NM			1,880 (4397.11)
N	5112	5112	5112
R^2	0.35	0.35	0.35

Note : Original work from authors.