COMILLAS
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GRADO EN INGENIERÍA EN TECNOLOGIAS INDUSTRIALES

Trabajo de Fin de Grado

Co-Adoption of Photovoltaic Systems and Electric Vehicles: Correlation Study and Diffusion models.

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Director: Subhonmesh Bose

Madrid

Julio de 2022

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Co-adoption of photovoltaic systems and electric vehicles: correlation study and diffusion models

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Acknowledgments

I want to express my gratitude to Professor Bose and Professor Souyris for allowing me to participate in this innovative project and introducing me to applied mathematics and structural economics. In addition, for all the support and help they have given me throughout the semester.

I would also like to thank the University of Illinois for giving me the opportunity of taking part in this exchange program. I have always been treated as one of the Illini family. I had an experience that I will never forget.

ADOPCIÓN CONJUNTA DE SISTEMAS FOTOVOLTAICOS Y VEHÍCULOS ELECTRICOS: ESTUDIO DE CORRELACIÓN Y MODELOS DE DIFUSIÓN.

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Director: Bose, Subhonmesh.
Entidad Colaboradora: University of Illinois at Urbana Champaign

RESUMEN DEL PROYECTO

La adopción de vehículos eléctricos (VE) se considera una vía viable para reducir la huella de carbono del sector del transporte. Hay muchos incentivos a nivel estatal y nacional que pueden estimular la adopción de vehículos eléctricos. Además, la adopción de VE por parte de un hogar individual suele influir en sus vecinos para que adopten más VE. Estos patrones de difusión de la adopción se han estudiado para muchas tecnologías, incluidos los paneles fotovoltaicos. Este proyecto estudia los patrones de co-adopción entre la fotovoltaica y la adopción de vehículos eléctricos.

En primer lugar, recogemos datos sobre dichas adopciones del Lawrence Berkeley National Laboratory y The Atlas EV Hub para realizar estudios de correlación. A continuación, simulamos un modelo de difusión paramétrico para la co-adopción.

Palabras clave: Vehículos Eléctricos, Sistemas Fotovoltaicos, Correlación, Función de Utilidad, Modelo Dinámico de Elección Discreta.

1. Introducción

Tanto la adopción de sistemas fotovoltaicos (FV) en viviendas como la compra de vehículos eléctricos (EV) están convirtiéndose en piezas clave en la actual transición energética. Por esta razón, entender el proceso de adopción de estas tecnologías es importante para diseñar políticas que fomenten dicha adopción.

Son muchos los incentivos e influencias que pueden hacer que un propietario de una vivienda en un determinado barrio se decida a adoptar una nueva tecnología. Por ejemplo, uno puede decidir comprar un vehículo eléctrico influenciado por la compara del mismo de un vecino o decidir comprar un panel solar debido a una rebaja y al ahorro en las facturas de los servicios públicos.

Los modelos de difusión son una herramienta que considera este tipo de variables para predecir la propagación en el tiempo y el espacio de diferentes tecnologías. Ya existen modelos de difusión que estudian tecnologías como los sistemas FV o EVs. Sin embargo, no tienen en cuenta el posible efecto que tienen entre ellos. No es raro pensar que estas tecnologías tienen una correlación ya que los sistemas FV pueden producir electricidad para alimentar a los vehículos mencionados. Esto sumado al interés del propietario en conseguir que la factura de electricidad no se dispare con la carga de su vehículo hace necesario plantearse un modelo de co-difusión que considera también este efecto.

2. Definición del Proyecto

Este proyecto estudia los coeficientes de correlación entre las adopciones de vehículos eléctricos y sistemas FV en varios estados de EE.UU. con datos reales. Nuestros estudios de correlación revelan que existe una correlación significativa en las adopciones de sistemas FV y VE. Este estudio motiva la segunda parte de este proyecto, un modelo matemático de co-adopción.

A continuación, propone un modelo de co-adopción de sistemas fotovoltaicos y vehículos eléctricos. A continuación, realiza simulaciones de una versión del modelo propuesto con el objetivo principal de demostrar que existe una diferencia considerable en la adopción de estas tecnologías cuando se considera su influencia mutua. Cabe señalar que este proyecto se basa en un trabajo anterior [1] en el que los autores implementaron un modelo dinámico de elección discreta (DDCM) para la adopción de sistemas fotovoltaicos en Austin, Texas.

3. Descripción del modelo/sistema/herramienta

En primer lugar, para el estudio de correlación empleamos un script de Python ejecutado en Jupyter Notebooks. Los resultados obtenidos para diferentes estados se obtuvieron comparando las matriculaciones de VE y de sistemas fotovoltaicos a lo largo del tiempo y la ubicación. Los datos del registro de vehículos eléctricos fueron proporcionados por The Atlas EV Hub y los datos del registro de sistemas fotovoltaicos se tomaron del Lawrence Berkeley National Lab. Considerando un registro como un nuevo adoptante de tecnología calculamos la correlación de instalación de estas tecnologías obteniendo resultados como la figura I.

En segundo lugar, el modelo desarrollado simula la propagación de estas tecnologías teniendo en cuenta la influencia que tienen entre ellas, la influencia de una nueva adopción sobre otro posible adoptador y el factor económico por adoptar. Las simulaciones del modelo se hacen considerando un entorno con un numero I de posibles consumidores en un tiempo T. Las simulaciones obtenidas, como se aprecia en la Figura II, muestran la propagación de estas tecnologías a lo largo del tiempo en un espacio definido de agentes.

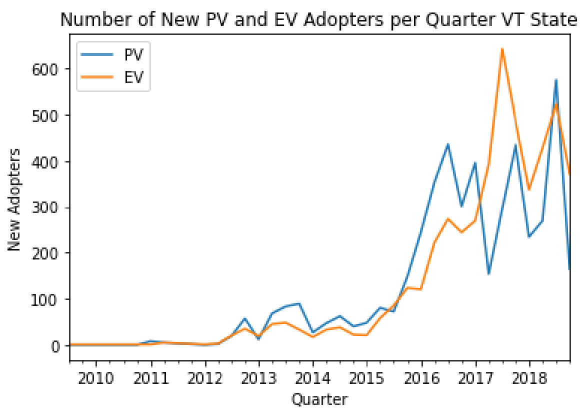

Figura I: Evolución de PV y EV por trimestres en el estado de Vermont.

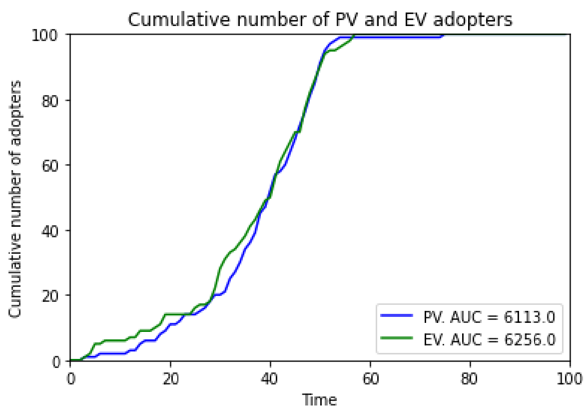

Figura II: Simulación del modelo; numero de adaptadores acumulados en un perido T.

4. Resultados

Este proyecto incluye dos tipos de resultados; los correspondientes al estudio de correlación y las distintas simulaciones del modelo de difusión desarrollado.

En el estudio de correlaciones, el proyecto incluye graficas como las de la Figura I para varios estados de EEUU, que muestran la evolución de esas tecnologías a lo largo del tiempo, además de coeficientes de correlación para los condados del mismo estado.

Por otro lado, también se aportan los resultados de simulaciones del modelo de difusión desarrollado que prueban distintas situaciones de evolución.

Los resultados obtenidos intentan demostrar la relación directa que tienen los vehículos eléctricos y los paneles fotovoltaicos, y que el modelo propuesto es optimo para su estudio de difusión.

5. Conclusiones

Después de un fuerte análisis de los resultados obtenidos, la primera parte del proyecto muestra que la relación entre los VE y los sistemas FV tienen una importante relación para tener en cuenta.

El modelo de difusión desarrollado puede considerarse una primera versión de lo que puede llegar a ser. La intención es llegar a desarrollar el modelo con datos reales para que pueda ser implementado en la realidad. Las simulaciones ejecutadas muestran el éxito de la idea de un modelo de co-difusión entre estas dos tecnologías. Las características de los resultados son similares a las de difusión de tecnologías de este tipo y dan pie a futuros avances en el desarrollo del modelo.

6. Referencias

[1] S. Souyris, J. A. Duan, A. Balakrishnan, and V. Rai, “Networks Effects and Incentives in Solar Panel Diffusion: A Dynamic Discrete Choice Approach,” Work. Pap. The University of Texas at Austin, pp. 1–45, 2021.

[2] Berkeley Lab, web page. Available at: https://emp.lbl.gov/tracking-the-sun. Accessed Mar. 2022.

[3] Atlas EV Hub, web page. Available at: https://www.atlasevhub.com/about. Accessed Mar. 2022.

CO-ADOPTION OF PHOTOVOLTAIC SYSTEMS AND ELECTRIC VEHICLES: CORRELATION STUDY AND DIFFUSION MODELS.

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Director: Bose, Subhonmesh.
Collaborating Entity: University of Illinois at Urbana Champaign

ABCTRACT

The adoption of electric vehicles (EVs) is believed to be a viable path to reducing the transportation sector's carbon footprint. There are many incentives at the state and national levels that can spur the adoption of EVs. In addition, the adoption of EVs by an individual household typically influences their neighbors to adopt more EVs. Such diffusion patterns of adoption have been studied for many technologies, including photovoltaic (PV) panels. This project studies co-adoption patterns between PV and EV uptakes.

First, we gather data on said uptakes from the Lawrence Berkeley National Laboratory and The Atlas EV Hub for correlation studies. Then, we simulate a parametric diffusion model for co-adoption.

Keywords: Electric Vehicle, Photovoltaic System, Correlation, Utility Function, Dynamical Discrete Choice Model

1. Introduction

Both the adoption of photovoltaic (PV) systems in homes and the purchase of electric vehicles (EVs) are becoming key elements in the current energy transition. For this reason, understanding the adoption process of these technologies is important to design policies that encourage adoption.

There are many incentives and influences that can make a homeowner in a given neighborhood decide to adopt a new technology. For example, one may decide to buy an electric vehicle influenced by a neighbor's electric vehicle comparison or decide to buy a solar panel because of a rebate and savings on utility bills.

Diffusion models are a tool that considers these types of variables to predict the spread in time and space of different technologies. Diffusion models already exist that study technologies such as PV systems or EVs. However, they do not take into account the possible effect they have on each other. It is not uncommon to think that these technologies have a correlation since PV systems can produce electricity to power the mentioned vehicles. This added to the owner's interest in making sure that the electricity bill does not skyrocket with the charging of his vehicle makes it necessary to consider a co-diffusion model that also considers this effect.

2. Project definition

This project studies the correlation coefficients between the adoptions of electric vehicles and PV systems in several U.S. states with real data. Our correlation studies reveal that there is a significant correlation in PV and EV system adoptions. This study motivates the second part of this project, a mathematical model of co-adoption.

Then, it proposes a model of co-adoption of PV systems and EVs. It performs simulations of a version of the proposed model with the main objective of demonstrating that there is a considerable difference in the adoption of these technologies when their mutual influence is considered. It should be noted that this project builds on previous work [1] in which the authors implemented a dynamic discrete choice model (DDCM) for PV system adoption in Austin, Texas.

3. Model description

First, for the correlation study we used a Python script executed in Jupyter Notebooks. The results obtained for different states were obtained by comparing EV and PV system registrations over time and location. EV registration data were provided by The Atlas EV Hub and PV system registration data were taken from Lawrence Berkeley National Lab. Considering a registry as a new technology adopter we calculated the installation correlation of these technologies obtaining results like Figure I.

Second, the developed a model the simulates the spread of these technologies considering the influence they have on each other, the influence of a new adopter on another potential one and the economic factor per adopter. The model simulations are made considering an environment with a number I of possible consumers at a time T. The simulations obtained, as shown in Figure II, show the propagation of these technologies over time in a defined space of agents.

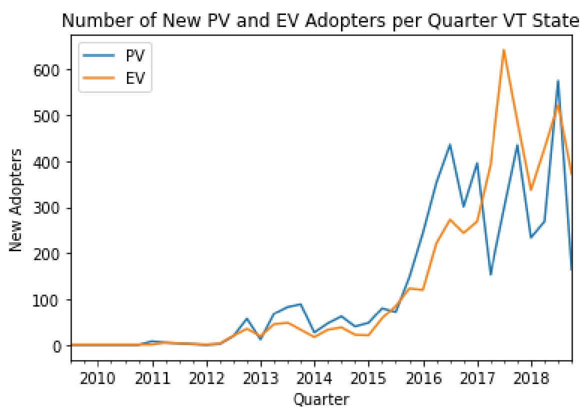

Figura I: Plot of the Evolution of PV and EV new Adopters by quarters for VT state.

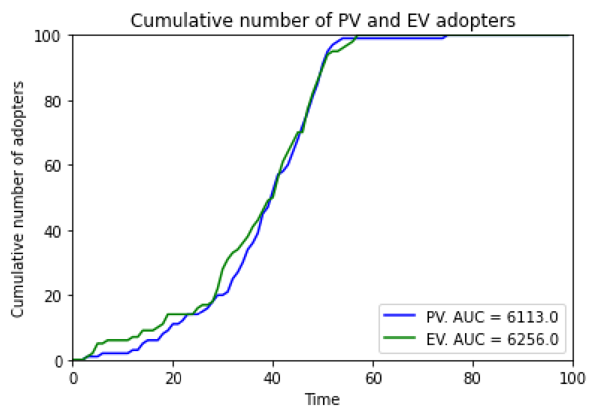

Figura II: Model simulations; cumulative of new adopters over period T.

4. Results

This project includes two types of results; those corresponding to the correlation study and the different simulations of the diffusion model developed.

In the correlation study, the project includes graphs such as those shown in Figure I for several US states, which show the evolution of these technologies over time, as well as correlation coefficients for the counties of the same state.

On the other hand, we also provide the results of simulations of the developed diffusion model that test different evolution scenarios.

The results obtained try to demonstrate the direct relationship between electric vehicles and photovoltaic panels, and that the proposed model is optimal for their diffusion study.

5. Conclusion

After a strong analysis of the results obtained, the first part of the project shows that the relationship between EVs and PV systems has an important relationship to take into account.

The diffusion model developed can be considered a first version of what it can become. The intention is to eventually develop the model with real data so that it can be implemented. The simulations run show the success of the idea of a co-diffusion model between these two technologies. The characteristics of the results are similar to those of diffusion of technologies of this type and give rise to future advances in the development of the model.

6. References

[1] S. Souyris, J. A. Duan, A. Balakrishnan, and V. Rai, “Networks Effects and Incentives in Solar Panel Diffusion: A Dynamic Discrete Choice Approach,” Work. Pap. The University of Texas at Austin, pp. 1–45, 2021.

[2] Berkeley Lab, web page. Available at: https://emp.lbl.gov/tracking-the-sun. Accessed Mar. 2022.

[3] Atlas EV Hub, web page. Available at: https://www.atlasevhub.com/about. Accessed Mar. 2022.

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1. Introduction

Power system is concentrating its efforts on transitioning to an efficient way to produce clean energy. Distributed solar adoption and electrification of ground transport will play a vital role in that transition. Understanding the adoption process of these technologies is important to design policies that foster such adoption.

The adoption of battery electric vehicles (BEVs) and plug-in hybrid vehicles (PHEVs) is growing. However, "EVs haven't yet achieved mainstream adoption at scale" [1]. The impending adoption growth could increase the electricity demand and have many other effects on the transportation sector, such as vehicle usage trends.

Studying how technology adoption evolves in a specific location is essential to plan a way to accelerate its adoption. It would help to understand what would make a single resident of a particular area make the decision to purchase a specific technology. Many incentives and influences could make a homeowner in a certain neighborhood decide to adopt new technology. For instance, one may decide to buy an electric vehicle because their neighbor decided to do the same or decide to buy a solar panel because of a rebate and savings on utility bills.

Existing a pattern in the way a consumer decides whether a specific technology is acquired or not would make it possible to create a model that could predict the household decision-making. Therefore, the adoption of these technologies is studied to understand how policy decisions might influence their adoption. Diffusion models are popular in technology adoption studies, e.g., see [2], [3], [4], [5], [6].

Diffusion models of PV and EV already exist; however, they ignore the influence the diffusion of one technology might have on the diffusion of another.

The decisions for a household to adopt PV systems and EVs are inter-dependent. A solar panel directly produces electricity for a particular house, and electric vehicles need that electricity. EV customers will typically have higher electricity bills since they need to charge their vehicles, which can incentivize the installation of a solar panel to produce the extra electricity needed.

If the adoption of PV systems and EVs happens to have a strong correlation, it would seem necessary to study their co-adoption considering their influence on one another. For this reason, we study correlations among adoptions of EVs and PV systems in various states across USA with data. Our correlation studies reveal that there is significant correlation in uptakes of PV systems and EVs. This study motivates the second part of this project, a mathematical model for co-adoption.

We propose a model for co-adoption of PV systems and EVs. Then, we run simulations of a version of the proposed model with the primary aim of demonstrating that there is a considerable difference in the adoption of these technologies when considering their influence on each other. It should be noted that this project is based on a previous work [7] where the authors implemented a dynamic discrete choice model (DDCM) for the adoption of photovoltaic systems in Austin, Texas.

We develop a discrete choice model to simulate PV systems and EVs adoption in tandem, considering economic considerations, peer effects, heterogeneity, and random shocks. The model's objective is to design incentives that would maximize their adoption.

2. Overview of the Report

This thesis is composed of five sections and two appendixes.

In Section 3, we provide a background of PV systems and EVs, including statistics of current adoption levels and incentives. The correlation study between uptakes of PV systems and EVs for multiple states within USA is presented in Chapter 4. Section 5 provides a literature review on DDCM and diffusion models used in [7] that are relevant for our work. In Section 6, we propose a DDCM for co-adoption of PV systems and EVs and simulate it to gain insights. In Chapter 7, we end this project with the concluding remarks. Finally, Appendix A provides a list of the acronyms used throughout the thesis, and Appendix B shows more detailed results of the correlation study.

3. Current Adoption Levels and Incentives for PV Systems and EVs Adoption.

Here we give a brief description of the most critical factors that affect these technologies. In addition, we comment some insights about the possible future concerns and plans that are predicted for them.

3.1 PV and EV Financial Incentives Situation and Explanation

In the following section, we explain the incentives situation of PV systems and EVs in the U.S. There are two main incentives: federal incentives, common to every state, and the different incentives that each state decides to implement.

There are federal tax credit incentives at a state level that allows one to deduct a certain percentage of the cost of installing a solar energy system or adopting another renewable technology from ones federal taxes. The policies vary across different technologies.

The federal tax credit for adopting a new electric vehicle after 2010 can be as high as $7,500. This incentive is specific to the type of vehicle adopted. Since there are many different types of electric vehicles, a detailed explanation of the exact incentive for every car would be long and especially irrelevant for the study. However, it suffices to say that it varies between $4,500 and $7,500 for most EVs and PHEVs [8].

For PV systems, the investment tax credit (ITC), also known as the federal solar tax credit, is 26% for constructions that started in 2021 and 2022, and 22% for construction beginning in 2023. The ITC was enacted in 2006 and has proven to be one of the most important federal policy mechanisms to incentivize clean energy in the United States; the solar industry in the U.S. has grown by over 10,000% [9]. The following table, with information gathered from the SEIA, summarizes the evolution of ITC over the years:

Table 1: History of the ITC.

Law	*Years*	*Residential ITC (%)*	*Commercial ITC (%)*
The Energy Policy Act of 2005 (P.L. 109-58)	2006	30%	30%
The Energy Policy Act of 2005 (P.L. 109-58)	2007	30%	30%
Tax Relief and Health Care Act of 2006 (P.L. 109-432)	2008	30%	30%
The Emergency Economic Stabilization Act of 2008 (P.L. 110-343) [1] *(8-year extension)*	2009	30%	30%
	2010	30%	30%
	2011	30%	30%
	2012	30%	30%
	2013	30%	30%
	2014	30%	30%
The Omnibus Appropriations Act of 2015 (P.L. 114-113) [2]	2015	30%	30%
	2016	30%	30%
The Tax Cuts and Jobs Act of 2017(P.L. 115-97)	2017	30%	30%
	2018	30%	30%
	2019	30%	30%
The Consolidated Appropriations act of 2020	2020	30%	30%
	2021	26%	26%
	2022	26%	26%
	2023	22%	22%
	2024	0%	10%

As seen in the table, in the past years there has been a clear step-down on ITC. However, starting at the end of 2023, there will be a clear difference between residential and commercial ITC since the first one will be dropped down to zero and commercial to 10%.

On top of the federal incentive, there are also city and state-level incentives available to encourage new technology adoption. In almost all cases, state and local programs stack with the federal incentive. The most common incentives, for both technologies, used by the different states are the following [10]:

[1] *Also eliminated the monetary cap ($2,000) for residential solar electric installations and permitted utilities and companies to pay the alternative minimum tax (AMT) to qualify for the credit.*

[2] *Extension + changed the previous "placed-in-service" standard for qualification for the credit to a "commence construction" standard for projects completed by the end of 2023*

- Tax Credits: In addition to the federal tax credit that every U.S. citizen can access, some states offer a deduction from your tax obligation as a part of your renewable project. There is also another related incentive called property tax incentive that provides a tax exemption from the added value of the technology to your property.
- Grants, Loans, and Rebates: They vary depending on the type of technology and size of the project for every state.
- PACE: Property-Assessed Clean Energy financing, allows property owners to borrow money from the local government to pay for energy improvements. The amount borrowed is typically repaid via a special assessment on the property over years [11].
- SRECs (Solar Renewable Energy Certificates): Homeowners in the states that participate in this type of market can sell credits to utility companies. These companies buy the SRECs from independent producers to satisfy their Renewable Portfolio Standards; whenever they can't generate the amount of renewable energy needed, they are able to buy it from other independent owners. Only 7 states have an SRECs market [12]: New Jersey, Massachusetts, Pennsylvania, Maryland, Washington D.C, Delaware, and Ohio.
- Performance-Based Incentives (PBIs): These types of incentives are paid based on the production efficiency over time. Feed-in tariffs are an example of PBIs.

  All these incentives can be applied to different customers: residential, agricultural, commercial and industrial.

3.2 PV Systems and EVs Adoption Situation

As seen in Figure 1, sales in the U.S. are expected to experience a growth of 29.5% through 2030 compared to 3.4% in 2021 [13].

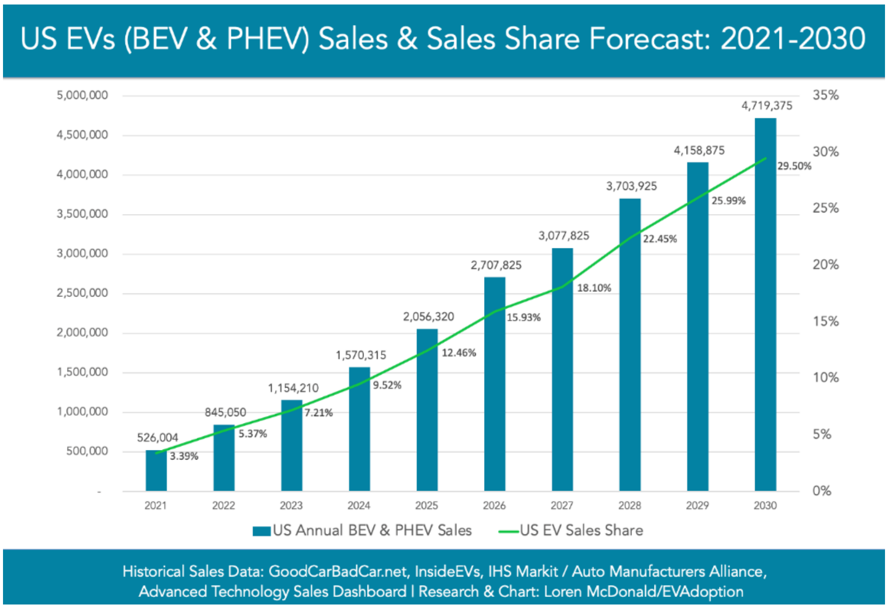

Figure 1: EV's sales forecast 2021-2023 [13].

The growth of this technology is evident. Recent surveys have shown that 30% of vehicle owners plan to buy an EV in their next car. In addition, 50% of people between 26 and 41 years old also plan to do so [14].

The purchase of these vehicles has an imminent task that the buyer must deal with, the vehicle's charging. However, it will be necessary to consider how to charge the EV and that the cost of electricity will increase. A survey conducted by Deloitte [15] shows that 75% of Americans would prefer to charge their EVs at home, meaning that the extra cost of electricity will be added to their electricity demand and bill. Additionally, 20% among them would consider using alternative energy sources such as solar for that cause.

The speed at which this technology is expanding in the market raises the question of what future consequences it may have and whether we are prepared to deal with them. Despite others, such as the increase in the demand for battery inputs, including lithium and cobalt, a consequence that would require early planning is the increase in demand for electricity. This consequence might seem obvious, but will there be enough supply to cater to the extra demand? For example, it is believed that if half the vehicles in America were EVs, the resources to produce the electricity needed would grow by 20% [14]. Distributed solar production can offset this increased demand.

The adoption of PV systems in residential areas also seems to be growing. In 2021, the solar market experienced for the fifth consecutive year, growth of 30% compared to 2020 [16], and as seen in Figure 2, it is not expected to decrease. There is an explanation to growth pause that is forecast to happen after 2023. As seen in Table 1, the investment tax credit (ITC) for residential areas will drop to 0% by 2024. The ITC has proven to be a vital incentive to expand PV technology all over U.S. Future predictions of Wood Mckenzie show that if another extension were to happen of the ITC, PV installation would increase by over 66% over the next decade [17].

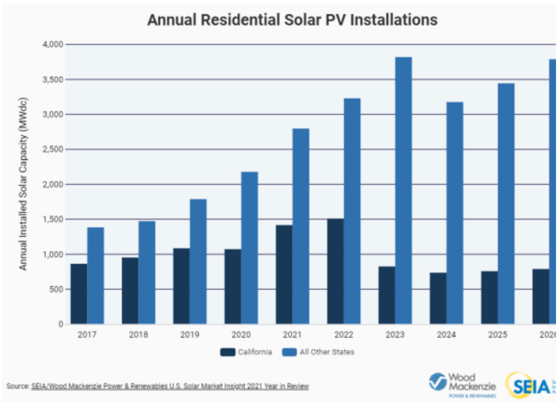

Figure 2: PV installations forecast with actual normative [16].

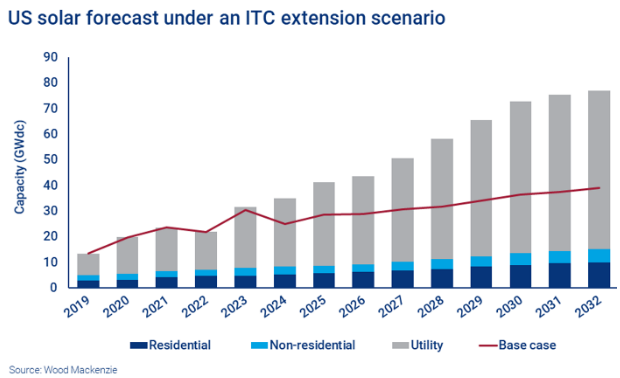

Figure 3: PV installations forecast with an extension of the actual ITC [17].

Regarding PV systems adoptions, there seems to be a trend heading toward the inclusion of storage in the PV systems installed; to be precise, battery storage attachments have been rising in the sector, reaching 8.1% in 2020, according to an annual report from the Berkley Lab [18]. Therefore, these trends that PV systems and

EVs adoption present, show that householders do have in mind to complement EVs adoption with solar panels. In addition, 66% of the individuals who own solar panels are more likely to have an EV [19]. Therefore, it seems that these two technologies have a strong relationship since it is possible to use one to satisfy the needs of the other.

Using solar with storage to help meet the demand of an electrified transportation sector is not the only aspect these technologies have in common. The SEIA confirms that there are many aspects that they share, for instance, similar growth trajectory and policy needs, and provides a list [20].

Solar and EVs are both market disruptors and benefit from rapid technology evolution. They are both challenging established markets with an existing customer base. Solar and EVs also benefit from grid modernization. The rapid changes in technology generation, production, and distribution have forced a modernization in the grid. This translates to how easily solar and EVs can interact with each other and the grid. In addition, the SEIA is promoting a program called "Solar + Decade" [21], which implies the mutual use of PV systems and EVs to overcome the possible future scenarios that the grid will face. This program wants to incentive many initiatives such as "solar + storage". They also claim to the necessity of embracing EVs as a "sister" technology [20].

As expected, the hypothesis that technologies such as PV systems and EVs are strongly related is well-founded, and even more, considering the future initiatives being considered for energy management. Consequently, it seems imperative to provide a diffusion model for co-adoption of PV systems and EVs to have the most accurate prediction of how the technologies will grow and how different influences such as the financial incentives can affect their evolution.

4. Correlation Study

The main objective of this study is to prove our hypothesis that the adoption of PV systems and EVs in residential areas is correlated. Concluding that the residential adoption of these two technologies is correlated would open the door to a wide range of further studies regarding them, such as a diffusion model for co-adoption. If there is a significant correlation, studying the adoption of the two technologies together would yield more accurate adoption models.

4.1 Process and Data Description

The results shown in section 4.2 were acquired as a result of comparing the registrations of EVs and PV systems over time and location. The data for EVs registration was provided by The Atlas EV Hub, an online platform that offers extended information on the EV market. On the other hand, the data for PV systems registration was taken from a report called *Tracking the Sun*, a project from the Lawrence Berkeley National Lab that describes data and information on PV adoption in the United States.

We calculated all the results from this study from a python script run on Jupyter Notebooks. Out of all the available information from both sources, we considered the zip code and the date for each registration. With those parameters, and considering every new registration a new adopter, we studied the behavior of uptakes of both technologies in a collection of U.S. states. The selected data was organized to have the sum of the county's PV systems and EVs registrations in every quarter.

The counties and periods where there were both PV systems and EVs adoptions were the ones of our most interest. The program calculates the correlation coefficient for those periods where there was a coincidence in the same location. The explanation for this data selection comes from the idea that for this study, the objective is to analyze the behavior of the technology's adoption when they co-exist.

We obtained two correlation calculations from this data. One calculates the correlation of the number of new adopters only by considering the time variable. In other words, it calculates the correlation of the number of new adopters of PV systems and EVs during a specific time range. The other calculates the correlation also considering the location variable; therefore, the correlation for each county over time is obtained.

To corroborate the zip codes from the input and organize the data into counties, we used a list with all the needed information. All this data was based on and acquired from the U.S Census Bureau and HUD's Office of Policy Development and Research. Thanks to this corroboration process, we found out that there were some data errors in the zip codes of some registrations during specific periods of time. This is the reason why for some of the results, the analysis encompasses shorter periods than others.

From all the data available, we studied the correlation of the six states from which there were enough data gathered to derive meaningful results. The timeline of the study ends in 2019. This decision was made after analyzing all the available data and concluding that the data was complete in that period. The data from 2019 to 2022 was not completely updated.

We have results for the states of New York, Connecticut, Minnesota, New Jersey, Vermont, and Wisconsin. The following table summarizes all the data available for each of the mentioned states.

Table 2: Summary table of the input data for PV and EV registrations.

State	**Nº EV Registrations**	**EV Time Range (years)**	**Nº PV Registrations**	**PV Time Range (years)**
New York	304,239	2011 - 2020	83,311	2001 - 2019
Connecticut	11,439	2011 - 2018	15,900	2012 - 2018
Minnesota	43,628	2013 - 2020	1,445	2002 - 2018
New Jersey	196,900	2000 - 2018	98,424	2000 - 2018
Vermont	33,140	2003 - 2019	11,200	2000 - 2018
Wisconsin	21,765	2018 - 2020	11,200	2003 - 2018

4.2 Results

We calculated the correlation for each state over time and the correlation for their counties. Therefore, there is a correlation table and two graphics for each state. One shows the number of new adopters of PV systems and EVs over time. The other shows a histogram with the correlation coefficient for its counties. In addition, Appendix B shows a list of the individual county correlation coefficient results for each of the mentioned states.

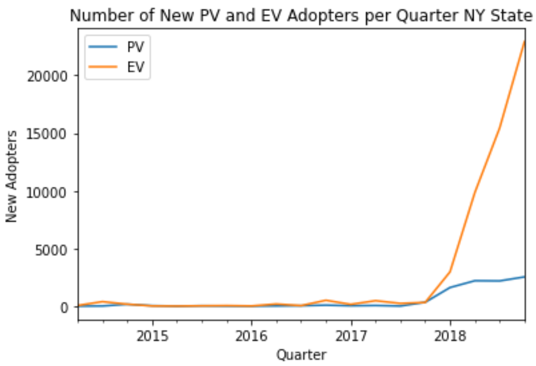

Figure 4: Plot of the Evolution of PV and EV new Adopters by quarters for NY state.

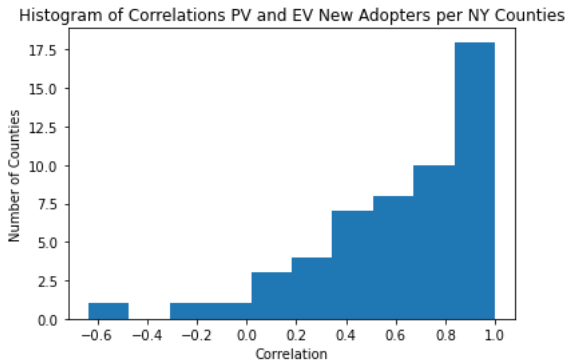

Figure 5: Histogram with the PV and EV correlation per NY Counties.

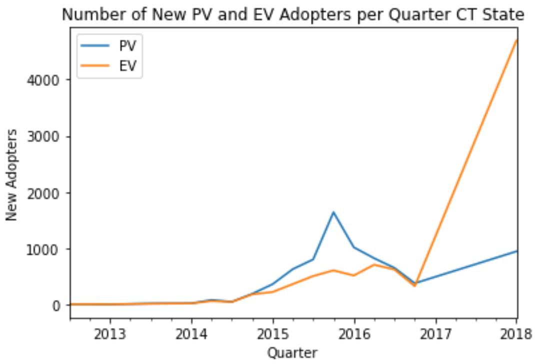

Figure 6: Plot of the Evolution of PV and EV new Adopters by quarters for CT state.

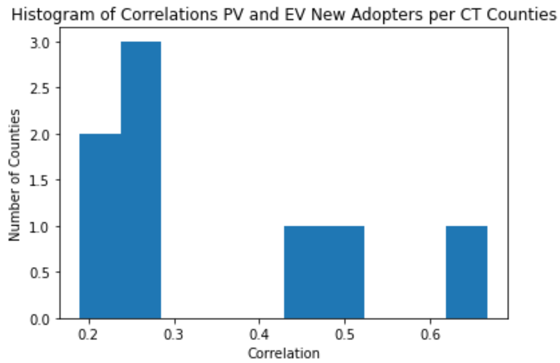

Figure 7: Histogram with the PV and EV correlation per CT Counties.

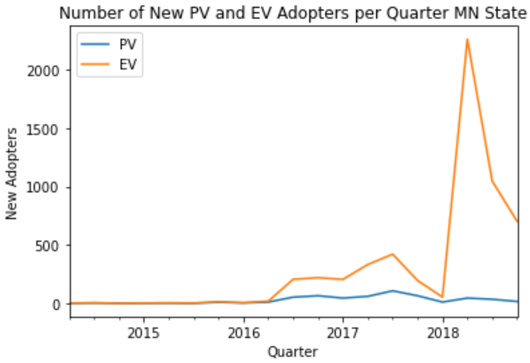

Figure 8: Plot of the Evolution of PV and EV new Adopters by quarters for MN state.

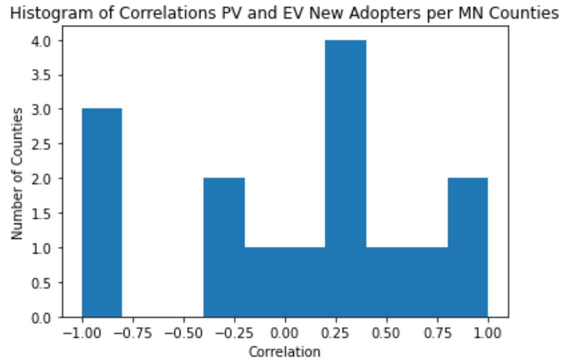

Figure 9: Histogram with the PV and EV correlation per MN Counties.

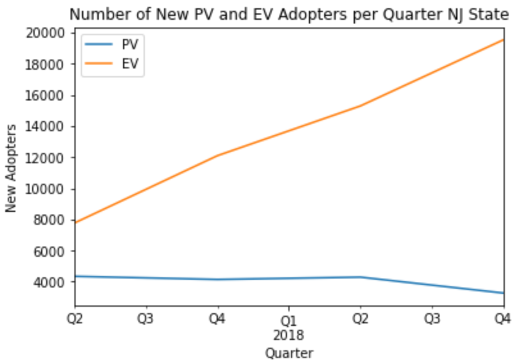

Figure 10: Plot of the Evolution of PV and EV new Adopters by quarters for NJ state.

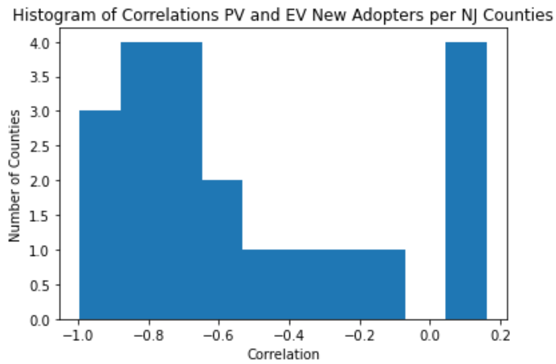

Figure 11: Histogram with the PV and EV correlation per NJ Counties.

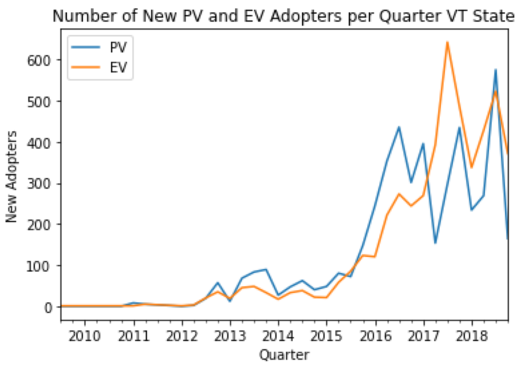

Figure 12: Plot of the Evolution of PV and EV new Adopters by quarters for VT state.

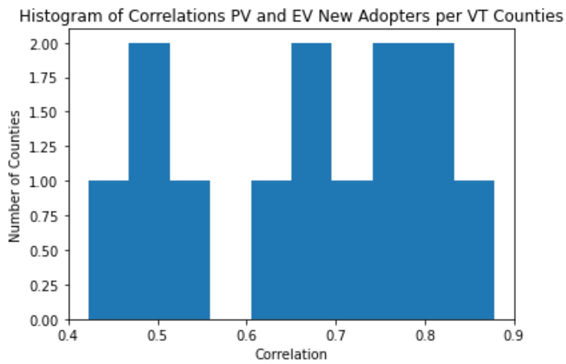

Figure 13: Histogram with the PV and EV correlation per VT Counties.

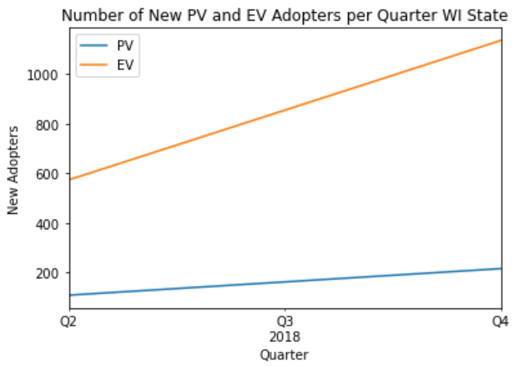

Figure 14: Plot of the Evolution of PV and EV new Adopters by quarters for WI state.

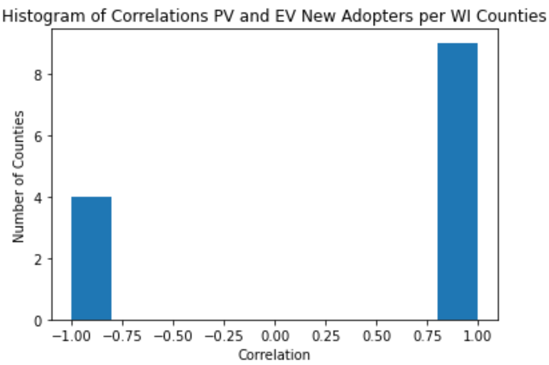

Figure 15: Histogram with the PV and EV correlation per WI Counties.

We make several important observations.

First, the county correlation study does not necessarily cover 100% of each state. We could only do the calculations for the counties from which we had data available. Appendix B shows the exact correlation coefficient calculated for each state's possible counties. In addition, we are only focusing the study on the locations where new adopters of both PV systems and EVs were recorded in data. For example, if there were no registrations for one of the technologies for a county, then that county was ignored in our calculations.

Second, as seen in Figures 4, 6, 8, 10, 12, and 14, the time range for which the correlation coefficient is calculated for every state is different. This results from the organization and filtering process done to all the input mentioned in section 4.2. In this process, we confirm that the registration zip codes of the new adopters are legitimate, and we organize the data to see if there are uptakes of both technologies in the same timeline. This necessary corroboration process ignores all the registrations with data errors and, as a result, the time range of the study of each state differs.

The following table summarizes the numerical results of the studies:

Table 3: Summary Table of important observations of the 6 studies.

		Timeline		
State	**Correlation**	**Begin Date**	**End Date**	**Counties Studied**
NY	0.911576	2014 Q2	2019	53/62
CT	0.47339	2012 Q3	2018	8/8
MN	0.315692	2014 Q2	2019	15/87
NJ	-0.809013	2017 Q2	2019	21/21
VT	0.82134	2009 Q3	2019	13/14
WI	1	2018 Q2	2019	14/72

Before drawing any conclusions, it would be interesting to analyze the individual results of each state to understand their meaning and the relevance they might have to the study.

The state of New Jersey seems to contradict our hypothesis. As seen in Table 3, the correlation coefficient calculated is -0.809, meaning that for this state, the behavior of EVs and PV systems new adopters seem to have a strong negative correlation. As appreciated in Figure 10, when new adopters of EVs tend to grow, PV systems new adopters drop.

New Jersey's new PV systems adopters have indeed decreased since 2018 [22]. In addition, the state financial incentive for solar in NJ appears more focused on commercial solar adoption rather than on its residential counterpart. Most of the solar incentives available in this state are promoting the commercialization of solar energy [23]. This state is also the only one, out of the six states present in the study, with an SRECs market, as explained in section 3. These companies buy the SRECs from independent producers to satisfy their Renewable Portfolio Standards; whenever they cannot generate the amount of renewable energy needed, they can buy it from other independent owners [12]. On the other hand, the number of new adopters over the period studied would make sense to be higher since; as seen in Table 2, New Jersey is the state with more PV systems registrations compared to the others and is the 8th state in the solar market ranking according to the SEIA.

It is also important to mention that the study for the state of New Jersey is one from which we experienced a lot of data loss when organizing and filtering the input data. This explains why the timeline for when the correlation is studied is considerably shorter than the others.

The results for the states of New York and Vermont show to be favorable to the study's hypothesis. They both happen to have a strong correlation, over 0.8, and there is no evidence of data loss; the timeline of both studies almost covers that of the input data available. In addition, as seen in Table 3, we were able to get results for almost all the counties of both states; 53 of 62 for NY and 13 of 14 for VT. Going over the results shown in Appendix B, more than 46% of the counties of these two states have a strong correlation (over 0.7). For the state of Vermont, 0% of the counties have a lower correlation than 0.3, as for NY, only a 23% have a lower correlation than 0.3.

The states of Minnesota and Connecticut also support the theory that there is a positive correlation between the uptakes of PV systems and EVs. The results show a medium correlation coefficient; 0.47 for Connecticut and 0.31 for Minnesota. For CT, there is no considerable data loss, the timeline of the study seems appropriate, and there are results for 100% of the state's counties. On the other hand, while the timeline for the study of MN is also appropriate, there are results for 15 of 87 counties. This represents only 17% of the state. However, this observation is not alarming considering that the number of PV systems registrations, available in Table 2, is just 1,445 from 2002 to 2018; and compared to the 43,628 new EVs adopters, the calculated correlation coefficients represent the few counties for which there are data available for residential PV systems and EVs uptakes.

Finally, going over the promising results of Wisconsin, we discover that this individual study had the most considerable data loss. The period studied is not even a year, and there are results for less than 20% of the state's counties. From Table 2, the number of PV systems and EVs registration of the data available does not explain these observations; on the contrary, it proves that there has been a considerable loss of data input. Despite this apparent issue, for the short time range studied, the strong obtained results suggest that, for this state, it would not seem odd to expect a positive result if studied in a longer timeline.

4.3 Concluding Remarks

The objective of this correlation study is to prove that a positive correlation exists between the new adopters of PV systems and EVs. For that task, we presented a series of results for six states where the correlation of these two technologies was calculated over time and for counties where data was available.

In the presented results, three states, New York, Vermont, and Wisconsin, show a strong positive correlation; two, Minnesota and Connecticut, with a medium positive correlation; and New Jersey, with a strong negative correlation. The results then show that five out of the six studies prove that the hypothesis first presented is possible and true.

As mentioned in section 4.3, some observations in the individual state studies could determine the relevance of the obtained findings. The results for the states of New Jersey and Wisconsin presented some results that we could consider irrelevant since there was a considerable amount of data loss, and as a result, the time range for which the correlation was calculated was significantly short. Compared to the periods that cover the studies of the other states, all been more than five years, the results of these two states could be considered less relevant than the others. Therefore, we can conclude that the four most relevant studies, New York, Vermont, Minnesota, and Connecticut, prove a positive correlation between EVs and PV systems uptakes.

5. Literature Review

There is extended literature dedicated to the investigation of models for technology diffusion. Technology diffusion cumulative adoption over time usually represents an S-form, and as Rogers explains [24], depending on the level of evolution, different types of adopters are found. Most importantly, his theory explains that other previous adopters strongly influence new adopters. Diffusion models typically are based on the Bass model, and it has been successfully used for market prediction of the integration of many products at an aggregated level [25].

The model proposed in the research is a DDCM in which householders are able to analyze the benefits between adopting at a certain moment or in the future when costs are lower, considering the peer effects of adoption in their neighborhood. The model was developed to differentiate adopters by wealth and geographic location to consider the influence that these different adopters could have on each other. To estimate the model's parameters and extended data of PV systems adoption in Austin, Texas was used. This model builds upon an earlier work by Rust, see [26], that differs with the ones existing because it doesn’t study the technology diffusion at an aggregated level.

From all the technical aspects that could be mentioned, for the intentions of the modeling exercise that will follow, it is only necessary to mention the ones that affect the most. The utility function present in the model is a linear combination of the following elements:

- The net present value of installing a PV system in that exact household.
- The influence of neighbors.
- Unobserved heterogeneity is modeled as a time-variant random effect that could affect the householder.

The simulations ran, showed high accuracy compared with real data. The study shows that the best model simulated for two years set had 4.89% average percentage error, which is more accurate than other models based on the Bass model.

The paper concluded by mentioning that wealthy agents were more likely to adopt PV systems and that neighbor influence plays a major role in the technology diffusion. More importantly, it shows that the model can be useful to consider policy incentives planning. It shows that not necessarily the incentive with the highest budget is the optimum for maximum diffusion. The period of time and the requirements of the incentives are as relevant. If the period is too short, then diffusion never accelerates, but if the period is too long, the adopters tend to prolong the decision to adopt. In conclusion, on the urge to maximize PV system adopters, having a limited budget, incentives need to be planned carefully, and the model is a perfect tool to reach that goal.

Given the success of DDCM for PV systems adoption, we present a DDCM for co-adoption of PV systems and EVs.

6. DDCM for Co-Diffusion

The objective of this chapter is to develop a co-diffusion model that includes economics and peer effects, heterogeneity and random shocks for PV systems and EVs. Furthermore, using the model we simulate the diffusion under different scenarios, and demonstrate that the diffusion of the technologies is much different when considering each other's influence.

The consumers are indexed by $i \in I$, being I the set of consumers present in the given space, and time is denoted by $t = 1, 2, \dots, T$, being T the end of the horizon. The type of technology is indexed by k and k', with $k = 1$ for PV and $k = 2$ for EV.

The parameters and states that compose the utility function are listed below:

Table 4: Model notation

Structural Parameters	
NPV^k	Represents the net present value (NPV) of technology k.
α^k	Technology $k's$ base constant for the utility function.
$\beta_{k'}^k$	Peer effects of technology k' over technology k.
δ^k	Economic effect over technology k
ρ_i^k	Consumer i heterogeneity regarding technology k. This parameter represents the believes that an agent i has on technology k. (Random variable Normal Distribution with mean equal to 0 and standard deviation equal to 1).
${\epsilon_1}_{i,t}^k$	Random shock of consumer i at time t regarding adopting technology k. (Random variable of Type I distribution).
${\epsilon_0}_{i,t}^k$	Random shock of consumer i at time t regarding non adopting technology k. (Random variable of Type I distribution).

States at time t	
$A_{i,t}^{k}$	Equal to 1 if consumer i has adopted technology k before time t.
$N_{k,t}$	Number of technology k adopters at time t.

We formulate the utility function for a consumer i of adopting a technology k at time t as follows:

$$u_{i,t}^{k} = \alpha^{k} + \sum_{k'=1}^{k} \beta_{k'}^{k} N_{k',t} + \delta^{k} NPV^{k} + \rho_{i}^{k} + \epsilon_{i,t}^{k}\,. \tag{1}$$

As seen, it is a linear combination of the peer effects and the economic incentive of adopting a certain technology. Consumer i adopts technology k at time t if he has not adopted yet and $u_{i,t}^{k} \geq \epsilon_{0}{}_{i,t}^{k}$.

The decision variable $a_{i,t}^{k}$ is equal to 1 if the consumer i decides to adopt technology k at time t and is equal to 0 otherwise:

$$a_{i,t}^{k} = \begin{cases} 0, & if \quad A_{i,t}^{k} = 1, \\ 0, & if\ u_{i,t}^{k} < \epsilon_{0}{}_{i,t}^{k}, \\ 1, & otherwise. \end{cases} \tag{2}$$

And the state transition functions are defined as:

$$A_{i,t+1}^{k} = A_{i,t}^{k} + a_{i,t}^{k}\,, \tag{3}$$

$$N_{k,t+1} = N_{k,t} + \sum_{i} a_{i,t}^{k}\,. \tag{4}$$

For the given problem, the decision of a consumer to adopt a technology only considers the information available at that moment in time: the number of PV systems and EVs adopted at the moment, and the NPV for the adoption. We study a model where what happened in the past or what is expected to happen in the future is not taken into consideration. Also, we consider a simple model for peer effects, where every adoption affects other adoption decisions equally.

6.1 Simulations and Analysis

The objective of this simulation exercise is to prove that with this model for co-adoption it is possible to study the adoption of PV systems and EVs together, and to demonstrate that, if the model is viable, that the adoption evolution is substantially different than when modelled individually. For the simulations we expect to obtain the typical S-Shape of the adoption over time over the whole population in Section 5.

We created an environment composed of 100 consumers and we studied the adoption evolution for a period of 100 steps, i.e., $I = 100$ and $T = 100$. To fix the parameter values we ran the simulations with the values obtained for the model that studied PV adoption in Austin, Texas [2], shown below in Table 5.

Table 5: Parameters values fixed for the simulations.

α^k	-6,8
$\beta^k_{k'}$	0,03
δ^k	0,00028
NPV^k	6000

Note that the parameters for the exercise will stay constant for both technologies and only the cross-peer effects, β_2^1 and β_1^2, are set to 0 to study the evolution without the influence of one on the other. We chose NPV^k, was decided to be fixed at 6000, similar to the range of values used in the Austin's research [27].

Two models are studied. Model 1 has in consideration of the cross-peer effects, mentioned in the table, and Model 2 does not, and only considers the individual influence of each technology. Therefore, Model 1 is design with peer effect parameters $\beta_2^2 = \beta_1^1 = \beta_1^2 = \beta_2^1 = 0{,}03$ and Model 2 with $\beta_2^2 = \beta_1^1 = 0{,}03$ and $\beta_1^2 = \beta_2^1 = 0$.

The results are shown below.

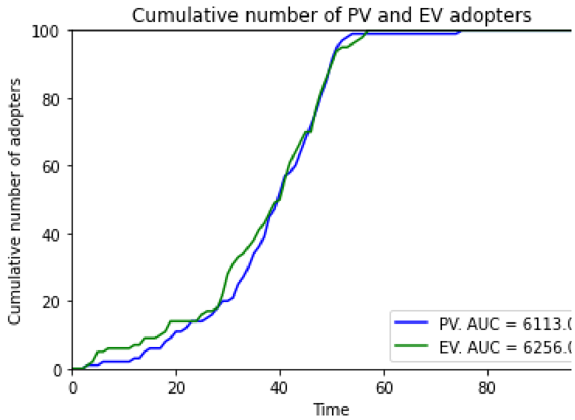

Figure 16: Model 1. Cumulative number of PV and EV adopters over time T. (Existence of cross-peer effect).

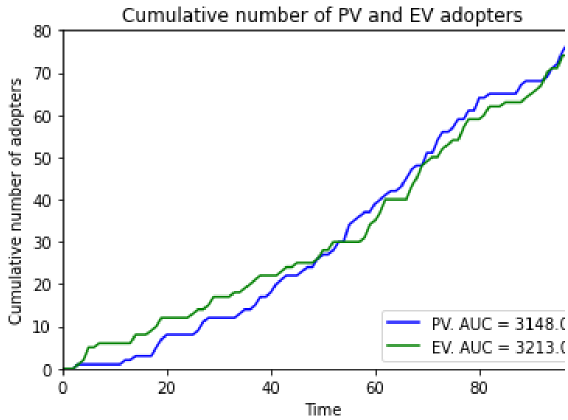

Figure 17: Model 2. Cumulative number of PV and EV adopters over time T. (No cross-peer effect).

As seen in Figures 16 and 17, the adoption evolution of PV systems and EVs, when studied without the influence that these technologies have on each other, is entirely different. The difference between the curves is apparent. We also used the area under the curves (AUC) as a comparison tool to have a numeric value to compare. The AUC for both curves in Model 1 is double the ones in Model 2. In addition, Model 1 has the expected typical S-Shape for technology diffusion well represented.

As mentioned before, the values of the parameters are synthetic, and the results are for simulating and testing purposes only. They do not represent a particular state or reality. However, some insights can be taken as a motivation for future work. The curves in Model 1 show the typical exponential growth at half a period when technology has gained in popularity.

In the following figures, other simulations of variations of Model 1 are shown. The following values given to the parameters are for testing. The intention is to guide and compare the graphics if some of the hypothesis discussed in the thesis. Therefore, for the following simulations, we studied some hypothetical cases.

As discussed in Section 3, there is a belief that PV owners are more likely to adopt EVs, meaning that the value β_1^2 could be higher than β_2^1. Moreover, the NPV for adopting EVs is not realistic to have a similar value to the NPV for adopting PV systems. When adopting PV systems, there is a direct income for the generation of energy, while for EV adoption, there is an economic gain or cost versus the alternative transportation mediums. The following figures try to simulate a more realistic model considering the mentioned hypothesis with the intention of representing a more realistic curve, even though the values are synthetic.

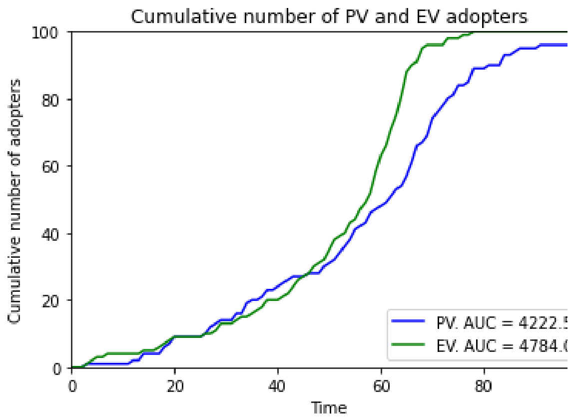

Figure 18: Model 3. Cumulative number of PV and EV adopters over time T. (Existence of cross-peer effect).

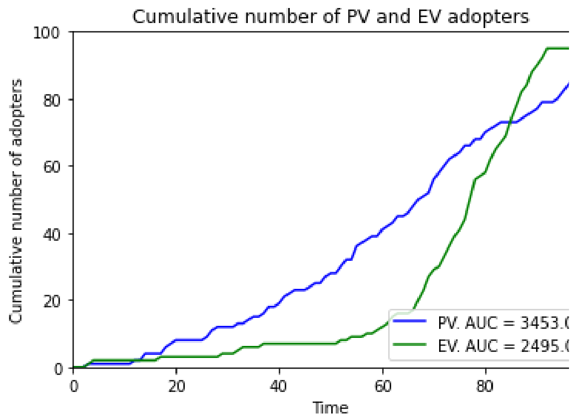

Figure 19: Model 4. Cumulative number of PV and EV adopters over time T. (Existence of cross-peer effect).

Table 6: Parameter values table per model.

Model	NPV^1	NPV^2	β_1^2	β_2^1
1	6000	6000	0,03	0,03
3	6000	3000	0,05	0,02
4	6000	-1000	0,05	0,02

Table 6 shows the parameters that we changed from the initials of Model 1. Note that Models 3 and 4 show the PV systems and EVs diffusion considering the hypothesis mentioned. The peer influence of PV systems over EVs has increased, and EV's influence over PV systems has decreased. In addition, Model 3 is set to have an NPV for EVs lower than the one for PVs, and Model 4 has been lowered to the extent of being negative.

The results still show the same characteristics described before. Even with variations, all three models show that considering the cross-influence is key to obtain the most accurate diffusion model possible. If the cross-influence is as strong as it looks, it opens a wide range of new approaches that could help incentivize adoption. For instance, Model 4 is fixed to have a negative NPV for adopting EVs, and that would seem very unattractive to a consumer; however, as shown in Figure 19, the growth of PV systems manages to boost the adoption of EVs at the end of the set period.

6.2 Model Conclusions

The exercise proves the significant difference between the adoption predictions of the two proposed models, with co-adoption and without. The results also indicate that the proposed model, if augmented with more realistic values for NPV, peer effects and such, is rich enough to capture the dynamics of the co-diffusion of EVs and PV systems. Furthermore, having proved a considerable correlation between PV systems and EVs, it seems necessary to consider that influence for the desired model. These two reasons prove that the cross-peer effect changes the distribution of PV systems and EVs and are motivation enough to continue refining this model further.

The simulations have also introduced some interesting insights that motivate future work. As explained in previous chapters, proper use of the proposed diffusion model could help clear the path to accelerate PV systems and EVs adoptions and even help policymakers design efficient budget plans to incentive such technologies. By incentivizing properly one of the technologies it is possible to maintain the growth in adoption of the other.

7. Concluding Remarks

Through this thesis, we demonstrated that it is possible and necessary to develop a diffusion model for the co-adoption of PV systems and EVs with a DDCM.

For the first part of the study, we explained and demonstrated considerable influence between photovoltaic panels and electric vehicles in residential areas. Then, we carried out a correlation study for six different states in the U.S.: New York, Connecticut, Minnesota, New Jersey, Vermont, and Wisconsin. For each of the six states, the registration of PV systems and EVs overtime was calculated and analyzed. With the data available from the Berkeley Lab and Atlas EV Hub, the correlation coefficient of the two technologies was calculated at a county level. The analysis revealed the existence of a correlation between PV systems and EVs uptakes, motivating the second part of the thesis.

The second part of this thesis consisted of developing a model that intended to demonstrate that a diffusion model for PV systems and EVs co-adoption differs widely from an individual diffusion model approach. The model had a utility function for adopting both technologies. It was a linear combination of the peer effect and the economic outcome of adopting a new technology. The model simulated the decision-making of a particular customer to adopt PV systems or EVs at a specific moment in time, considering the influence of the technologies adopted by other peers and the NPV of adopting at that moment. For this version, the agent was not influenced by past or future predictions and all the peers' adoptions had the same influence on the customer concerned. Through the simulations, we demonstrated that adoption predictions for a model design with co-adoption are very different from those that model these technologies individually.

The simulations also led to a series of insights that motivate future work. The strong correlation in the adoption of PV systems and EVs, opens a range of different approaches in which their adoption could be maximized. By incentivizing the growth of one of the technologies' adoption, the other one could be affected and grow in parallel.

In conclusion, the presented work in this thesis demonstrates that the correlation between PV systems and EVs is strong enough to be taken into consideration and that the model proposed with cross-technology peer effects changes the distribution of these technologies.

As explained at the beginning of the thesis, the long-term objective of the project is to develop a DDCM for co-adoption of PV systems and EVs. In other to do so, it is first necessary to create a develop a theorical DDCM framework desired. We will briefly describe some of the future steps that will follow this thesis.

The modeling exercise, in addition of having the objective explained in Section 6, it is also the first step for achieving the complete framework. The model design in that section considered the peer effects of installing a technology equally. In reality this is not true, one's next-door neighbor would obviously have more influence over him than someone that lives miles away. In order to simulate this, one can create a space in which the consumers are spread randomly, and each agent will be influenced depending on the distance from the other adopters.

In addition, we want to consider forward looking consumers. The consumer would compare the benefits of adopting the technology at time t or waiting for other future time. Finally, the consumer would have to choose between accepting and investing in the technology with all its economic consequences or not investing [28].

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Appendix A: List of Acronyms

EV	Electric Vehicles
PV	Photovoltaic Panels
PHEV	Plug-in Hybrids Vehicles
BEVs	Battery Electric Vehicles
ITC	Investment Tax Credit
SEIA	Solar Energy Industries Association
SREC	Solar Renewable Energy Certificates
NY	New York State
CT	Connecticut State
NJ	New Jersey State
VT	Vermont State
WI	Wisconsin State
MN	Minnesota State
DDCM	Dynamic Discrete Choice Model
NPV	Net Present Value
AUC	Area Under the Curve

Appendix B: County Correlation Results per State

State of New York

Table B1: Correlation coefficient per county of NY.

County Name	County FIPS	Correlation
Albany	001	0.394745
Bronx	005	0.890491
Broome	007	0.791272
Cattaraugus	009	0.937201
Cayuga	011	0.887357
Chautauqua	013	0.753905
Clinton	019	0.955938
Columbia	021	0.538647
Dutchess	027	0.915316
Erie	029	0.923773
Essex	031	0.548442
Franklin	033	0.216777
Fulton	035	0.344865
Genesse	037	0.142857
Greene	039	0.138431
Jefferson	045	0.636560
Kings	047	0.906222
Livingston	051	-0.190611
Madison	053	-0.636364
Monroe	055	0.912381
Montgomery	057	0.977140
Nassau	059	0.815951
New York	061	-0.131393
Niagara	063	0.969629
Oneida	065	0.633631
Onondaga	067	0.822972
Ontario	069	0.402229
Orange	071	0.665979
Orleans	073	0.455709
Oswego	075	0.990087
Otsego	077	0.911489
Putnam	079	0.410272
Queens	081	0.919758

Rensselaer	083	0.720774
Richmond	085	0.683915
Rockland	087	0.784886
St. Lawrence	089	0.452574
Saratoga	091	0.193153
Schenectady	093	0.113851
Schoharie	095	0.661924
Schuyler	097	1.000000
Steuben	101	0.346050
Suffolk	103	0.215201
Sullivan	105	0.513145
Tioga	107	0.680688
Tompkins	109	0.541962
Ulster	111	0.823219
Warren	113	0.837388
Washington	115	0.753814
Wayne	117	0.919126
Westchester	119	0.904284
Wyoming	121	0.976656
Yates	123	0.489735

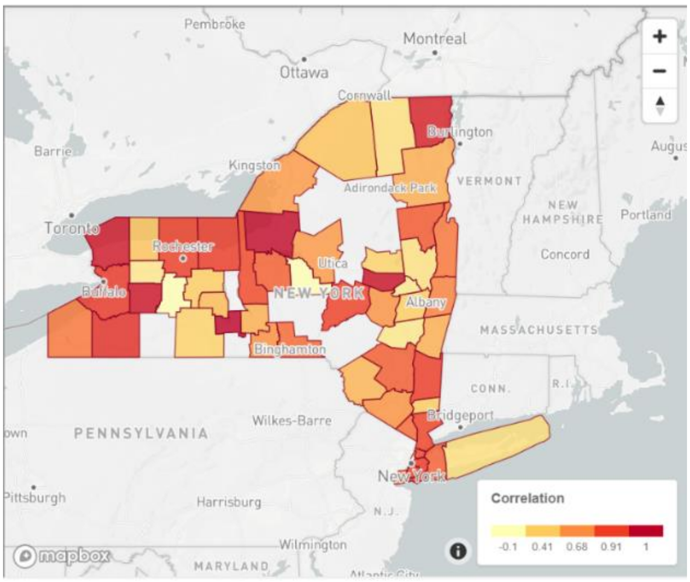

Figure B1: Heat map for correlation per county for NY.

State of Connecticut

Table B2: Correlation coefficient per county of CT.

County Name	County FIPS	Correlation
Bridgeport	001	0.498986
Hartford	003	0.464302
Litchfield	005	0.243063
Middletown	007	0.243353
New Heaven	009	0.666871
New London	011	0.277655
Rockville	013	0.216769
Willimantic	015	0.190058

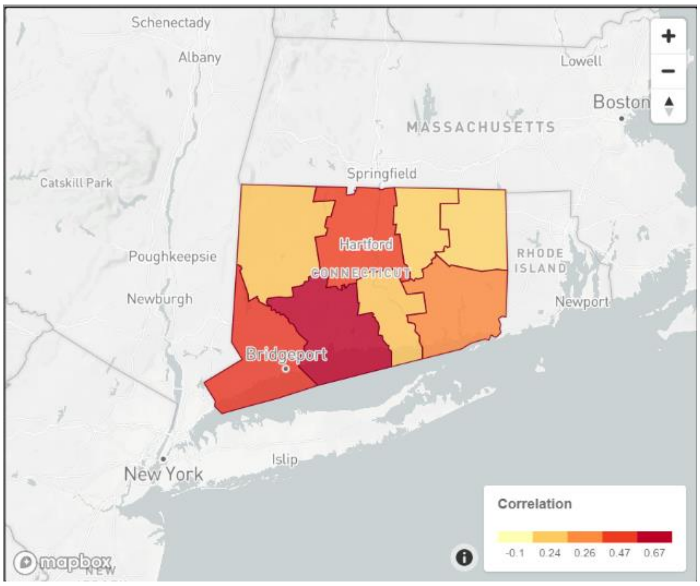

Figure B2: Heat map for correlation per county for CT.

State of Minnesota

Table B3: Correlation coefficient per county of MN.

County Name	County FIPS	Correlation
Chisago	025	1.000000
Dakota	037	0.170488
Goodhue	049	-0.944911
Hennepin	053	0.291134
Olmsted	109	1.000000
Ramsey	123	0.228904
Rice	131	0.593999
St. Louis	137	-0.866025
Scott	139	-0.125926
Stearns	145	0.799456
Steele	147	-0.296432
Wabasha	157	-1.000000
Washington	163	0.299387
Winona	169	-0.231423
Wright	171	0.242180

State of New Jersey

Table B4: Correlation coefficient per county of NY.

County Name	County FIPS	Correlation
Atlantic	001	-0.973862
Bergen	003	-0.545675
Burlington	005	-0.786160
Camden	007	-0.727538
Cape May	009	-0.543623
Cumberland	011	-0.289345
Essex	013	-0.894856
Gloucester	015	-0.784314
Hudson	017	-0.739084
Hunterdon	019	0.265198
Mercer	021	-0.853028
Middlesex	023	-0.126016
Monmouth	025	-0.319636
Morris	027	0.120910
Ocean	029	-0.591979
Passaic	031	0.219519
Salem	033	-0.828995
Somerset	035	-0.661322
Sussex	037	0.220149
Union	039	-0.991765
Warren	041	-0.659582

State of Vermont

Table B5; Correlation coefficient per county of VT.

County Name	County FIPS	Correlation
Addison	001	0.656508
Bennington	003	0.784234
Caledonia	005	0.507645
Chittenden	007	0.688237
Franklin	011	0.514880
Grand Isle	013	0.422502
Lamoille	015	0.621314
Orange	017	0.755877
Orleans	019	0.825788
Rutland	021	0.700456
Washington	023	0.807545
Windham	025	0.503500
Windsor	027	0.878219

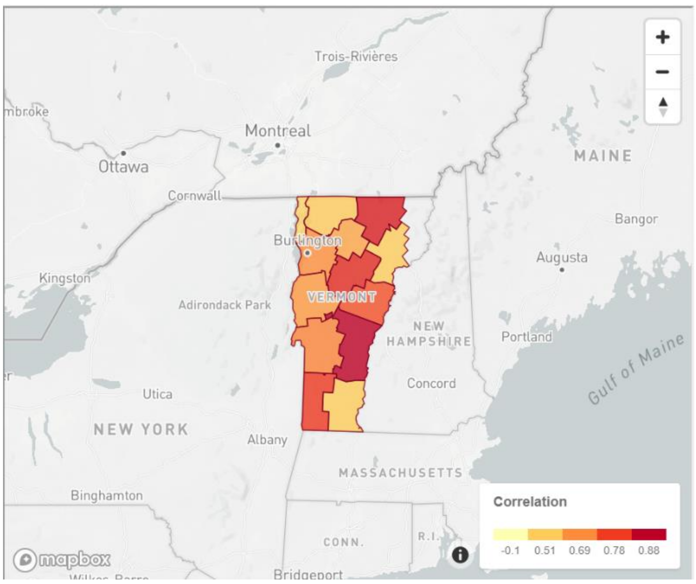

Figure B3: Heat map for correlation per county for VT.

State of Wisconsin

Table B6: Correlation coefficient per county of WI.

County Name	County FIPS	Correlation
Brown	009	-1.0
Dane	025	1.0
Eau Claire	035	1.0
Milwaukee	079	1.0
Outagamie	087	1.0
Portage	097	1.0
Racine	101	1.0
Rock	105	1.0
Saint Croix	109	-1.0
Sauk	111	1.0
Sheboygan	117	-1.0
Waukesha	133	1.0
Winnebago	139	-1.0
Wood	141	1.0

Appendix C: Alignment of the project with Sustainable Development Goals

This thesis is aligned with the following sustainable development goals:

- Goal 7: Ensure access to affordable, safe, sustainable, and modern energy. The model will be essential for expanding renewable energy technologies in residential areas. The model would help to understand the best way to expand PV and EV in residential areas for a specific place. Having the key to maximizing the use of electric vehicles and installing PV panels in residential houses will help create sustainable cities.

- Goal 8: Promote inclusive and sustainable economic growth, employment, and decent work. The model could help policymakers plan the periods and budget dedicated to the incentives for maximum adoption of PV and EV.

- Goal 13: Take urgent action to combat climate change and its impacts. Helping the residential sector in the transition to clean energy use will help to decrease the emissions of CO_2 to the atmosphere.