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Modelling the Emission Offsetting Potential of Rooftop Solar Panels

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This thesis is worth 30 study points.

Abstract

This study empirically investigates the emission-offsetting potential of rooftop solar panels in a group of cities across three continents. By use of experimental big data from the Google Environmental Insights Explorer (GEIE) collected over two months in early 2023 as well as additional official data sources, the link between the potential rooftop solar (RPV) offset ratio and a set of city characteristics are estimated by use of linear regression methods. The data consist of 352 observations from a large group of cities in Australia, Canada, the United Kingdom, and the United States between 2018 and 2021. The main independent variable is population density, and additional control variables are the availability of public mass transportation, country, topography, and year.

Quantile regressions (Q 0.5), considering the skewed distribution of the dependent variable, reveal that population density is linked to the potential RPV offset ratio at the one per cent significant level and with a negative sign. Countries where the RPVs are installed are also significant, with the largest offsetting potential in Australia compared to the reference country Canada. The years 2020 and 2021 are also significant, indicating that reduced transport emissions due to lockdowns, travel restrictions, and the aftermath of the global COVID-19 pandemic relate to the offsetting potential. A robustness analysis shows that the negative relationship with population density, in principle, does not appear until beyond approximately 2000 inhabitants per square kilometre.

Contents

Foreword

Sustainability has fascinated me for many years, both in my work as a store manager at Coop and in my personal life. While living at Sunnmøre, I considered installing rooftop solar panels at my house, but at the time, I assumed it would be too expensive and not financially beneficial in the long run. I enrolled in the Sustainability Management master's program to learn more about how I could contribute to making the grocery retail industry more sustainable. During my first semester, I researched Coop's sustainability efforts and was particularly interested in their investment in rooftop solar panels. This sparked my fascination with the potential of rooftop solar energy and its role in transitioning away from fossil fuels, leading me to undertake this regression analysis for my master's thesis. Being able to write most of this thesis from Greece has also been motivating since solar has a broader spread there than it has here in Norway. There I also got to see the other end of the coin when driving past small mountainsides covered in solar panels, completely stripped of nature. This increased my motivation to work on this analysis and show the potential of rooftop solar panels.

I want to express my gratitude to my supervisor, Eva Hagsten, for her invaluable support, guidance, and expertise in quantitative analysis and to my professor Martin T. Falk for his inspirational insight and expertise on Stata. I am deeply grateful to my family for their love and support during these past months. Additionally, a big thank you goes out to my classmates for the enjoyable breaks from the chaos and their support.

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Liv-Randi Røyset

1 Introduction

Sustainability is high on the agenda for both policymakers and businesses. The United Nations (UN) sustainable development goals (SDGs) (United Nations, 2015) for 2030 is a tool used across many countries and by researchers (Stafford-Smith et al., 2017). In addition to the SDGs, the Paris Agreement is a commonly used framework for sustainability efforts (Kobayakawa, 2021). The Paris Agreement aims to limit the temperature rise to less than two degrees Celsius of pre-industrial levels (United Nations, n.d.a). To reach this goal, a rapid transition toward renewable energy is needed (Creti & Nguyen, 2018). This is covered by SDG 7, affordable and clean energy (United Nations, 2015). Wehrle et al. (2021) point out that the transition from fossil fuels and gas to renewable energy sources is one of the most pressing issues to reach the targets for emission reduction before 2030. One of the main benefits of this is that the technology is developed to a degree sufficient to achieve the targets and that the only thing needed now is to speed up the adoption of the available technologies (United Nations, 2022).

In recent years several socio-political events have made the energy market unstable (McWilliams et al., 2022). This, and general concerns about the climate, highlights the need for local and renewable energy systems. Examples of this are severe droughts and Russia invading Ukraine (McWilliams et al., 2022). These events have led to rising prices and insecurities for the end users. The invasion also triggered Europe to sanction Russia heavily, and in return, Russia cut off its gas exports to large parts of Europe. For countries like Germany, heavily dependent on Russia for the import of gas, this led to an urgent need for alternative energy sources (Wiertz et al., 2023). Germany filled this need through increased fossil energy production and significant investments in renewable energy (Wiertz et al., 2023). In total, the interest in renewable energy is booming, leading to 2022 being the year when the production of renewable energy surpassed that of coal in Europe (IEA, 2022). In addition, some companies in certain parts of Europe, such as Norway, have several months-long waiting lists for installations of rooftop solar panels on private buildings, and the industry for solar installation is also experiencing a growing interest in their markets (Solenergiklyngen, 2022).

There are several ways to produce renewable energy, and the most prominent current alternatives are solar- and wind power. Out of the global electricity produced in

2022, 12 per cent came from wind and solar (Wiatros-Motyka, 2023). One of the more debated forms of renewable energy is nuclear power. This is, in theory, considered a renewable source of energy, but it produces nuclear waste (Bollfrass & Herzog, 2022). Furthermore, the invasion of Ukraine has shown how nuclear power plants can be used as strategic elements in wartime since damage to a nuclear power plant would be catastrophic. Not only would it be catastrophic for the city or country of the plant but also for neighbouring countries in large areas (Bollfrass & Herzog, 2022). Despite this, nuclear power is still being produced and promise accessibility of energy during geo-political events (Wiertz et al., 2023).

Renewable energy production methods commonly need vast land areas (Dhunny et al., 2019). Hydropower, as an example, is found to be conflicting in land usage with protecting surface water bodies (Wagner et al., 2015). Even though solar power generation is currently being tested in different combinations of land use (Dinesh & Pearce, 2016), it is still used as a highly land-demanding form of renewable energy in its standard form (Dhunny et al., 2019). However, the opportunity cost is expected to be lower when installed on rooftops that are currently not in use than land-based solar farms (Benis et al., 2018).

For this analysis, the focus will be on solar power, and more specifically on roof-mounted solar panels, also called rooftop solar panels or rooftop photovoltaic panels (RPVs). This choice is due to the vast need for more energy generation and limited space to generate said energy (Balta-Ozkan et al., 2021). Utilising unproductive space, such as rooftops on private buildings, skyscrapers, and office buildings, could help bridge the gap between energy demand and renewable energy production (Benis et al., 2018). The purpose of this study is to investigate aspects of importance for the RPV offsetting potential in a large group of cities in Canada, Australia, the United Kingdom, and the United States of America (United States). To visualise the practical usage of the electricity produced, the RPV offset potential is presented as a percentage ratio of the extent to which it may offset transport emissions.

The purpose of the study will be achieved through multivariate regression analyses, where different variables will be used to enrich the understanding of the dependent variable, the potential RPV offset ratio. The main independent variable in the analysis is population density, which is combined with multiple dummy control variables. The study will be embedded in a framework based on the diffusion of innovation theory (Rogers, 2003), although it relates to the potential diffusion in this case. Experimental big data used for the analysis is mainly experimental data collected from the Google Environmental Insight Explorer (GEIE) (GEIE, n.d.a). GEIE only provides data on selected cities and regions and is available for 2018 to 2021. Comparing the data over these years ensure that events such as the global Covid-19 pandemic are accounted for (GEIE, n.d.a). Google constantly develops the dataset, and the data for this exercise is gathered in January-February 2023.

This analysis is the first to relate experimental big data to the potential RPV has to offset transport emissions in a large group of cities in four countries across three continents.

The remaining study is organised as follows: In Chapter 2, the conceptual background and the framework based on the diffusion of innovations theory is presented. Chapter 3 covers the empirical methods, including the different versions of regression analyses. In Chapter 4, the data retrieval process is described, alongside descriptive statistics, visualising the main aspects of the data. Chapter 5 starts by presenting the results of the different multivariate regression analyses, including the robustness check, before continuing with a more thorough discussion of the quantile (Q 0.5) regression analysis findings before the conclusions are presented in Chapter 6.

2 Conceptual Background

2.1 Diffusion of Innovation Theory

Rogers' (2003) theory on diffusion of innovations is used as a starting point for the analysis. This theory builds on the perception that any innovation will take a relatively long time to get normalised into society, even when there is an obvious advantage to adopting it (Rogers, 2003). Rogers also defines diffusion as "*the process in which an innovation is communicated through certain channels over time among the members of a social system*." (Rogers, 2003, p. 5). This definition encompasses four main elements: innovation, communication channels, time, and social system. Each of these elements impacts the diffusion of the innovation, stressing the main areas that can result in either diffusion or non-diffusion of the innovation (Rogers, 2003).

Firstly, multiple characteristics are highlighted for an innovation to be adopted by the end users. The innovation needs to have some form of advantage over other options while also being compatible with the needs, experiences, and values of the users. Complexity levels, meaning how easy the innovation is to learn, are also critical. If it takes a long time to learn how to live with an innovation, this could slow or hinder the diffusion of said innovation. Finally, an innovation also benefits from its trialability and observability. This means that an innovation will need a shorter time for its diffusion if the user can test the solution before adopting it themselves, and if they can observe the results of adopting the innovation before doing so (Rogers, 2003).

Communication channels focus on where people generally communicate and to whom they trust with their information (Rogers, 2003). For example, Rogers (2003) states that individuals will be more inclined to adopt an innovation that someone they have a relationship with is trying to convince them to adopt. This means that people will adopt an innovation faster if someone they know and trust has already adopted it, and they recommend it, than if they are sold on the idea by a salesperson or a business professional. This results from them being less similar to the professionals than they are to their closer relations, or in other words, they are heterophilous (Rogers, 2003).

The third element of the diffusion of innovation is time. Time is used to describe three main features. These are how much time is needed by the individual to decide to adopt the innovation, how early or late the individual adopted the innovation compared to other individuals in the same system, and lastly, to measure the innovations rate of adoption in a given system over a given period of time (Rogers, 2003).

The fourth and final element of diffusion of innovation is the social system. All human beings are part of multiple social systems at any given time, be it a workplace, a friend group, a municipality or region, a country, or just the total human population. Different social systems have different power structures and norms and react differently to different innovation forms (Rogers, 2003). When deciding to adopt an innovation or not, the social system comes into play in three main ways. These are categorised by Rogers (2003) as optional innovation decisions, collective innovation decisions, and authority innovation decisions. An optional innovative decision is one that the individual can freely choose whether to adopt or not. On the other hand, the collective innovation decision is made collectively by the social system (Rogers, 2003). An example of this can be seen in mobile phones today. Nobody is technically forced to have a mobile phone, but it is part of the collective understanding that everyone is to have one. The final form of innovation decision is the authority innovation decision. This is when the authority, a small and influential part of the social system, enforces the adaptation of an innovation (Rogers, 2003). An example of this was seen in 2020 when the Norwegian government made heating through the burning of mineral oils illegal in housing, forcing its inhabitants to adopt a different solution to heating in their homes (Enova, 2020). This show that multiple factors determine the level of diffusion of the innovations. It is essential to see the total of all these factors to understand what is promoting or potentially hindering the diffusion.

Rogers (2003) assume that diffusion is happening in a non-linear way, where the adoption of the innovation starts slowly. The escalation then speeds up after a

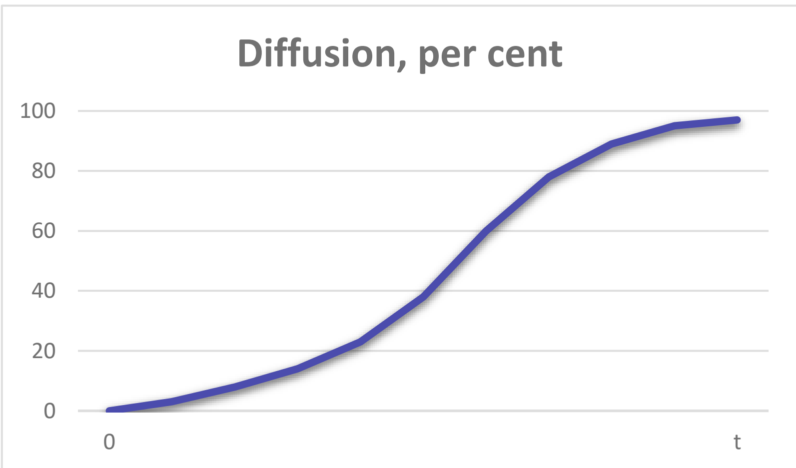

Figure 1: Diffusion of Innovation.

Note: Diffusion relates to the spread in a social system, and t is time.

Source: Own illustration based on (Rogers, 2003) while before slowing down when closing in on complete diffusion. This is typically presented in an S-curve that relates to the spread in a social system over time (Figure 1). The total market for diffusion is normally distributed and split into five categories: Innovators, early adopters, early majority, late majority, and laggards. The first 2.5 per cent of the adopters of the innovation is the innovators. They are followed by the early adopters, who comprise the next 13.5 per cent of the market. This is where the speed is starting to escalate. The fastest adoption is happening in the early- and late majority, with 34 per cent of the market each. When the market is starting to be capped, the laggards are slowly adopting the innovation. These comprise the last 16 per cent of the market (dos Santos et al., 2018; Rogers, 2003).

For this analysis, the focus will be on the potential diffusion of the innovation of RPV and different variables that is assumed to have a relationship to this potential. This potential diffusion is the total utilisation of the documented RPV potential by GEIE for the cities included in this analysis.

2.2 Previous Research on Solar Panels

The radiation provided by the sun is considered the largest deposit of renewable energy (Ioannou et al., 2014). For this energy to be harvested, researchers have developed photocells for converting solar rays into electricity since the 1950s (Chapin et al., 1954; McFarland & Tang, 2003). These PVs were the first to use solar rays for electricity and not just for heating, and they were doing so by introducing silicone to the panels (Chapin et al., 1954). From that time on, research in the area has focused a lot on increasing the conversion rate of PVs. In 2019 an average module efficiency of 20.3 per cent was reported, with predictions of this to increase to more than 22 per cent by 2030 (Victoria et al., 2021). This is a relatively low efficiency, meaning that there is almost 80 per cent unused potential in solar rays with today’s technology. One reason for this is the not ideal properties of silicone, even though this is still the primarily used material in PVs (Goetzberger & Hebling, 2000). Silicone types have, however, been improved to reduce the need for resources and cost optimising the production line (Victoria et al., 2021). Despite the relatively low efficiency, solar energy generation is seen as one of the most promising energy production sources for residential consumers (dos Santos et al., 2018)

To differentiate between the different fields of research available on PVs, it is here chosen to split the research into four categories. These include the technological direction, the financial direction, the social direction, and the environmental direction. The technological direction focuses a lot on improving the efficiency of the PVs (Chapin et al., 1954; Victoria et al., 2021; Barbón et al., 2022). However, there is also evidence on how PVs can be implemented in a way that optimises the output of electricity (Barbón et al., 2022; Ghazali et al., 2017). This includes the tilt angles of the panels (Mehleri et al., 2010), how RPVs are structured on the roof (Barbón et al., 2022), as well as how the panels are made (McFarland & Tang, 2003).

Another crucial technological challenge of solar energy is the time aspect. The time of production is most effective in the middle of the day (Richardson & Harvey, 2015). This might be optimal for companies that have their operations in the daytime. Still, it is less ideal for residential usage since the need for electricity is generally higher in the mornings and evenings when production is typically lower (Richardson & Harvey, 2015). It is therefore undertaken extensive research on energy storage from solar power (Agnew & Dargusch, 2015), methods of calculating optimal placements for maximising production throughout the day (Hong et al., 2017), and alternatives such as residential prosumers (Balta-Ozkan et al., 2015; Shahid et al., 2022), or using solar energy to produce other energy sources, such as hydrogen (Balat, 2008). It is also important to note that for a prosumer solution to work, the grid needs to be adjusted to account for this energy coming into the grid. This is also heavily researched, and how this could be optimised for more adoption of solar energy in residential zones (Ioannou et al., 2014; Jacobson, 2021).

The second direction of research found concerning PVs is the social direction. This part of the research focuses on the interaction between end users and PVs (Wolske et al., 2020) and how customers perceive PVs (Faiers & Neame, 2006; Simpson & Clifton, 2017). It can be seen that the interactions between people significantly impact the levels of diffusion of PVs (Barton-Henry et al., 2021). Barnes et al. (2022) found that word of mouth is highly effective in the early stages of diffusion to motivate early adopters. Environmental benefits and technophilia typically encourage these early adopters (Palm, 2020). However, more than word of mouth is needed to reach higher levels of diffusion, so other tactics are required to get later adopters to install RPVs

(Barnes et al., 2022). Since most later adopters are financially motivated, these measures should focus on how to inform potential customers of the financial benefits of adopting PVs (Palm, 2020).

Regarding socio-economic research, a sub-category to the social branch of PV research can be made. This includes how cities are designed, both in terms of social suitability but also for economic structures of society. From this research, there seems to be a difference between lower-rising and high-rise buildings in how suited they are for adopting PVs (Ghazali et al., 2017). This is explained by different energy needs in the different types of buildings and through the opportunity to adopt vertically integrated PVs on walls and rooftop-mounted PVs on high-rise buildings (Ghazali et al., 2017). Additionally, Balta-Ozkan et al. (2021) suggest a more detailed approach, including household size, house density, availability of roof space, and population density, amongst other variables as determinants of PV adoption. Furthermore, population density is also used as a variable in additional RPV-related research (Balta-Ozkan et al., 2015; Müller & Rode, 2013). This implies that the different types of buildings and different ways of living in them have varying potential for PV production. Therefore, population density is added as a variable in the analysis to explore this further.

The financial direction of research focuses mainly on the balance between cost and benefit (Benis et al., 2018; Elshurafa et al., 2018) and installation location for optimising solar ray absorption for the best return on investment. These articles are mostly suitability analyses (Stachura et al., 2022), cost-benefit analyses (Benis et al., 2018), and case studies (Dutt, 2020). It is concluded that most common forms of solar power generation are plausible and profitable with today's technology, even in low solar areas, such as Canada (Asaee et al., 2017), and in challenging terrains, such as mountain ranges (Stachura et al., 2022). IPCC (2022) have also concluded that the lowered PV prices, combined with its improved efficiency, will likely boost their adoption. This is a promising find regarding scalability and reaching the later stages of diffusion since the later adopters are financially motivated (Palm, 2020). Rural areas are also found to be able to produce more electricity than they need themselves through a combination of renewable energy sources, including solar energy (Poggi et al., 2018). Poggi et al. (2018) and Simpson & Clifton (2015) also highlight the importance of local governance interference to minimise land-use conflict. These findings imply that there might be differences in land characteristics that are more suited for PVs, and some countries might be more suited too. This motivates using dummy variables for countries and topography in this analysis.

The fourth and final direction of research on PVs is the environmentally focused articles. These focus primarily on how solar energy, as one of the multiple renewable energy sources, can help reduce the emission of greenhouse gasses (Khoie et al., 2019; Raksakulkarn et al., 2023; Shafiullah et al., 2012) and how they can help provide for the rising need of electricity in the world (Sakti et al., 2022). Environmental aspects like this, alongside technophilia, are seen as the primary motivators of early adopters of PVs (Palm, 2020). Previous research supports the need for PV installation on a small scale, such as for private housing (Lou et al., 2022). It is also found that adding greenery and alteration of transport emissions can help reduce carbon emissions in these residential areas (Lou et al., 2022). One of the ways alterations of transport can help reduce greenhouse gas emissions is through public transportation (Paulsson et al., 2018). This allows people to travel together, rather than having one car each. Solar power has also been found to be a good combination with hydrogen to provide the energy needed to produce hydrogen sustainably and allow for further emission cuts through the transportation sector (Balat, 2008). It would therefore be interesting to look at variables such as tree coverage and public transportation systems to evaluate the RPV offset potential. In this analysis, public mass transportation is added as a variable.

Research specifically on RPV seems to be focused mainly on two directions: How to meet the rising need for electricity in the world, especially in urban areas, and how to do so without destroying food-production fields, wildlife and natural areas, or other productive land areas, especially in rural areas (Calvert & Mabee, 2015; Poggi et al., 2018). This indicates a conflict between areas of high- and low population while there at the same time are indications of an increasing conflict over land use (Benis et al., 2018). Most research regarding land use concludes that RPV power production is an excellent way to produce the electricity needed by the building itself (Calvert & Mabee, 2015). It is also suitable for providing daytime electricity for other buildings through the grid or storing the surplus in large lithium batteries for later use at the building with RPVs (Richardson & Harvey, 2015). Improving the grid to handle the unstable electricity production is also a part of previous research on this topic (Zander et al., 2019).

One of the main benefits of RPVs is that there is no need for new land to make them. Even so, the growth in the usage of RPVs has been relatively low until recent years. This has been blamed on low availability and high investment costs (Shahid et al., 2022). However, PVs are now becoming more affordable, turning into a more desired option for a broader range of businesses and the general public as a result (Corbett et al., 2022; Elshurafa et al., 2018). The increased electricity prices due to the energy crisis have also been presented as a driver of investments in solar (Troeger, 2023).

RPVs are not the only potential usage of rooftops. Some rooftops, especially flat ones in cities, could also be used for food production (Benis et al., 2018). There seem to be different results based on what countries are included in the analysis. In Mediterranean climates, it has been found that food production might be more suitable than PVs (Benis et al., 2018). Even so, there seems to be a broad agreement on the benefits of RPVs (Asaee et al., 2017; Balta-Ozkan et al., 2015; Calvert & Mabee, 2015). Using rooftops for energy production would also allow more farmland to continue to be productive for food production or biofuels (Calvert & Mabee, 2015).

2.3 Potential Diffusion of Rooftop Solar Panels

When combining the findings from the existing research with the diffusion of innovation theory, it can seem as if there is a somewhat split on what to focus on. There is extensive research on the first element of diffusion, innovation. This is regarding both PVs in general, as well as RPVs. The focus is to improve the innovative solutions to optimise the product and in turn, convince the adoption of PVs. Research regarding the financial aspects of PVs is also heavily invested into this goal and attempts to reach later adopters through financial gains rather than technological or environmental persuasion (Palm, 2020).

The last three elements of diffusion, communication channel, time, and social system, are all found in the field of social research on PVs. These are all closely related to human interaction, how the customer perceives the PVs, and how different levels of government react to PVs. In addition to this, the environmental direction of research on PVs can be found in the social system element and the communication channel of the diffusion of innovation theory (Barton-Henry et al., 2021). This is also because the government highly controls this. Therefore, much of the research is done on how governments react to PVs as a tool to combat environmental challenges and how the general public communicates with each other about PVs (Balta-Ozkan et al., 2015; Balta-Ozkan et al., 2021; Barnes et al., 2022).

For this analysis, the dependent variable is the potential for RPVs to offset transport emissions of a city (potential RPV offset ratio). This is measured in tones of CO^2 emissions per year (tCO^2e/yr). The potential RPV offset ratio is calculated by dividing transport emissions by the offset potential of RPV and is therefore measured in percentages. This variable is then analysed using the relationship to population density, a continuous independent variable, as the main determinant. The goal is then to see if population density relates to the potential RPV offset ratio and if this is different in cities of lower population density, aka rural cities, than in cities of higher population density, aka urban cities. Additionally, various dummy variables will be used as control variables for this relationship. These include country, year, public mass transportation, and topography.

The cities will be the represented social system, and the results will mainly be aimed towards governments in the different cities. OECD (2020) defines a *city* as an area with a high population density that exceeds 50.000 inhabitants. However, this study uses the term *city* in a broader sense, including some regions and smaller parts of cities with different administrative boundaries. These boundaries are defined by Google Maps for GEIE and their calculations (GEIE, n.d.b).

Finally, the diffusion of innovation theory will be used to attempt to determine where in the diffusion process RPVs are today and what the potential diffusion might be in the future.

Given the literature and that the primary purpose of this study is to investigate aspects of importance for the RPV offset potential in a large group of cities in Australia, Canada, the United Kingdom, and the United States, the following hypothesis can be formulated:

H1: Population density is related to the potential RPV offset ratio.

In addition to the main hypothesis, three additional hypotheses regarding the relationship between the potential RPV offset ratio and the control variables are articulated.

H2: The potential RPV offset ratio varies across countries.

H3: The availability of public mass transportation systems is related to the potential RPV offset ratio.

H4: The topography of a city is related to the potential RPV offset ratio.

3 Empirical Method

For the analysis of the potential of RPVs to offset transport emissions, multivariate linear regression analysis is employed (Gordon, 2015; Wooldridge, 2012). It is common to quantify the capacity of renewable energy sources, and the UN regularly use numerical determinants to explore the progress of different societal challenges. Examples of this are found in the SDGs (United Nations, 2015). SDG 7 measures numerical determinants such as what share of consumed energy is from renewable sources and the number of people living without access to electricity (United Nations, n.d.b). Increasing the proportion of renewable energy sources is considered a significant pillar in the green transition (Potrč et al., 2021; Wigington et al., 2010). The use of large numerical data sets and multivariate regression models allow general conclusions to be drawn about empirical relationships (Stockemer, 2019; Wooldridge, 2012).

The linear regression analysis, often in the form of Ordinary Least Squares (OLS), is commonly used (Gordon, 2015). This method assumes that the relationship between the dependent and independent variables are linear and that a change in the dependent variable, Y, reacts with a set rate for each independent variable, X (Gordon, 2015). In addition, a constant, α, and an error term, ε, are included in the model. The constant reflects the predicted value of Y when all the X-es are zero, while the error term accounts for all unobserved factors relating to the dependent variable (Wooldridge, 2012). Linear regression analyses are used in previous research on RPVs (Balta-Ozkan et al., 2021; Lemay et al., 2023). This estimation approach is suitable for continuous dependent variables such as levels, ratios, or growth rates (Gordon, 2015).

In this analysis, the dependent variable used is the potential RPV offset ratio of a city. Based on the available literature, as highlighted in Chapter 2, Conceptual Background, population density is the main independent variable, while different dummy variables function as control variables. While population density is a continuous variable, the control variables are dummy variables. One of these dummy variables indicates the availability of public mass transportation. In addition, tree groups of dummy variables are included. These are country, topography, and year. First, the country variables define three of the four countries included in the analysis: Australia, the United Kingdom, and the United States, with Canada as the reference category. Next, two dummy variables representing topography are included. These are inland and coast, with mountain as the reference category. The final group of dummy variables is the three years 2019 to 2021, with 2018 as the reference category. All variables are described in closer detail in Chapter 4, Data Sources and Descriptive Statistics.

The relationship between the dependent and independent variables can be illustrated through the function: $Y_{it}=f(X_{it})$, where

Y_{it}= Potential RPV Offset Ratio, continuous variable.

X_{1it} = Population Density (PopDen) in each city, inhabitants per square kilometres, continuous variable.

X_{2it} = Country, three dummy variables: Australia, the United Kingdom, and the United States (reference category Canada).

X_{3it} = Public Mass Transportation (PMT), dummy variable equal to 1 if public mass transportation is available.

X_{4it} = Topography, two dummy variables: inland and coast (reference category mountain.

λ_t=Year, time effects measured by year (reference 2018).

where:

i = Each individual city, with i=1….88

t = Each individual year, dummy variable for each year.

This leads to the function:

$PotentialRPVOffsetRatio = f(PopDen_{1iy}, Country_{2iy}, PMT_{3iy}, Topography_{4iy}, Year_t)$

Since this specification will be used for a linear regression model, OLS, a constant and an error term is added, leading to the following equation (Equation 1):

$$PotentialRPVOffsetRatio_{it} = \alpha + \beta_1 PopDen_{it} + \beta_2 Country_{it} + \beta_3 PublMassTransp_{it} + \beta_4 Topography_{it} + \lambda_t + \varepsilon_{it} \qquad \text{Equation 1}$$

In addition, a robustness check will investigate whether there is a non-linear relationship between population density and the potential RPV offset ratio. To account for this, a fifth independent variable is introduced to test the population density variable in its squared form:

$$PotentialRPVOffsetRatio_{it} = \alpha + \beta_1 PopDen_{it} + \beta_2 Country_{it} + \beta_3 PublMassTransp_{it} + \beta_4 Topography_{it} + \beta_5 PopDen_{it}^2 + \lambda_t + \varepsilon_{it} \qquad \text{Equation 2}$$

Where X_{5it}= $PopDen_{it}^2$ (population density squared).

The OLS regression with robust standard errors is the starting point. Linear regression models assume that the variance of the error term is constant across all observation points. If this is not the case, the error term is heteroskedastic and may lead to a misspecification of the model. The remedy to this problem is to control for the possible appearance of heteroskedasticity in the estimation of the model (Wooldridge, 2012). A stepwise linear regression analysis is employed (Wooldridge, 2012). Even if this is a good starting point for empirical data analyses, it has limitations. One of these is that the findings might be somewhat misleading if the dataset has outliers or the dependent variable is not normally distributed (Rousseeuw & Leroy, 2005). Non-normality would then also appear in the error term, which goes against an essential assumption for the OLS (Rousseeuw & Leroy, 2005; Wooldridge, 2012). To reduce this presumptive problem, robust linear regression analysis is carried out (Huber, 1964; Huber, 1981). Robust regression still analyses the mean values of the dataset, but it gives a lower weight to the outliers of the dataset and can therefore give a more realistic image of the data (Huber, 1964; Huber, 1981; Wooldridge, 2012)

If there is an apparent discrepancy between the median and mean values of the dependent variable, a quantile regression analysis might be needed that focuses on the median Q(0.5) instead of the mean (Wooldridge, 2012). In this case, the representative offsetting potential is analysed rather than the average city. Median regression is also robust to non-normality and outliers in the dependent variable and the error term (Buchinsky, 1998).

Despite the fact that the dataset available for analysis consists of four years, panel data estimators cannot be used, both because of the short time span and since some of the independent variables are time-invariant, as seen in the following chapter (Wooldridge, 2012). The variables estimated will each be interpreted under the condition that everything else is held constant.

4 Data Sources and Descriptive Statistics

This chapter describes the data retrieval process and the different variables in detail. All the data used in this analysis is publicly available online, does not relate to specific individuals, and is thus not registered at SIKT (Sikt, n.d.). The data originate from the following sources: Google Environmental Insights Explorer (GEIE), Australian Burau of Statistics, Statistics Canada, Time and Date, United Nations Environment Programme (UNEP), United States Census Burau, and World Topographic Map (ABS, 2022; GEIE, n.d.a; Statistics Canada, 2023; Time and Date, n.d.; UNEP WCMC, 2002; USCB, n.d.; World Topographic Map, 2023).

4.1 Data retrieval

The GEIE is a new and experimental database still in development. It presents calculations on rooftop space available for PVs, including detailed complementary information across countries and continents. At the time of the data retrieval in January and February 2023, the database consists of 663 cities and regions, hereafter called cities. However, not all these observations include complete information on both RPV offset potential and transport emissions (GEIE, n.d.a). Since this is the denominator of the dependent variable in this study, some of the available cities are therefore eliminated from the analysis.

GEIE calculates the RPV offset potential using multiple big data sources processed through a trained machine learning algorithm, including images from satellites, 3D modelling, and shade calculations that Google provides (GEIE, n.d.b). The availability of sunlight is calculated using weather data provided by the National Renewable Energy Laboratory (GEIE, n.d.b). For a roof area to qualify to be included in the estimations, it must receive a minimum of 75 per cent of the available sunlight annually. The PVs are also expected to have an efficiency of 15.3 per cent (GEIE, n.d.b). The estimations may be lower than the actual potential because previous literature reports over 20 per cent efficiency and expects this to increase (Victoria et al., 2021). Additionally, GEIE calculates the RPV offset potential by assuming that all panels are installed flat on the roof, even on flat rooftops (GEIE, n.d.b). The available literature supports a higher actual potential if optimal tilt angles are used (Mehleri et al., 2010). Finally, obstacles such as chimneys or ventilation systems are accounted for, and the potential installation size is limited to between 2-1,000 kW (GEIE, n.d.b).

The dataset for the analysis is built manually by retrieving information about each observation one at a time. In this case, countries with a broader coverage are chosen for the analysis. This leaves information for Australia, Canada, the United Kingdom, and the United States (GEIE, n.d.a). These countries, in addition to New Zealand, also make up the core anglosphere (Dickens et al., 2022). This is, therefore, the area of research, and New Zealand was left out due to a lack of available data from the GEIE (GEIE, n.d.a).

Data available from the GEIE is the RPV potential, transport emissions over each year from 2018 to 2021, building emissions, size of the city, the population for each of the years 2018 to 2020, whether the city have a public mass transportation system or not, tree canopy coverage, and what country the city is located in (GEIE, n.d.a).

Since population data for 2021 is lacking at the GEIE (GEIE, n.d.a), this information is obtained from the official statistical offices in each country. This includes the United States Census Burau (USCB, n.d.), the Office for National Statistics (Office for National Statistics, 2022), Statistics Canada (Statistics Canada, 2023), and the Australian Burau of Statistics (ABS, 2022). Regrettably, some of the cities in the dataset are too small to be included in the data from the statistical offices, or the borders are not clearly defined by the statistical offices. In addition, the data from the statistical offices and the GEIE regarding the years 2018 to 2020 do not perfectly align. As a result, an alternative method is developed. To minimise the risk of misleading data, the numbers collected from the statistical offices are used to create the growth rate between 2020 and 2021. This growth rate is then applied to the 2020 data provided by the GEIE to generate the 2021 data.

The total amount of observations achieved by this specific retrieval method is 159. Regrettably, some observations turned out to be fully or partly overlapping. These observations are removed from the dataset (Wooldridge, 2012). This leads to the removal of five observations in the United Kingdom and the United States, as well as four cities in Australia. An example of this is the region of West Sussex overlapping both the Adur District and the city of Worthing. In this case, the region of West Sussex is removed from the dataset to optimise the number of available observations. Random sampling is used in cases where one observation overlaps with just one other observation, such as the region of Kent and the city of Canterbury.

The data retrieval is finished when all observations are ensured to be exclusive with no overlap. To ensure comparable results, all countries are represented with an equal number of observations (Wooldridge, 2012), leading the analysis to have a total of 88 observations from the four different countries. The United Kingdom, the country with the fewest number of suitable observations in the GEIE dataset, is used to determine the number of observations per country. All its 22 available observations are included in the analysis.

A randomised sampling procedure is used to select observations for the three remaining countries (Wooldridge, 2012). To ensure a good geographical spread within each country, all observations are grouped together using the available time zones (Time and Date, n.d.). All three countries consist of six different time zones.

In Australia, the collected observations are spread across four of the time zones in the country. These are spread in the following way: two observations in AEST, 20 observations in AEDT, 13 observations in ACED, and 13 observations in AWST (GEIE, n.d.b; Time and Date, n.d.). To ensure a well-balanced selection, the two observations from the AEST time zone are included, alongside six randomly chosen observations from each of the three other time zones, for a total of 20 observations. Finally, the last two needed observations are chosen at random from the remaining 27 observations.

For Canada, the 36 available observations are spread across five time zones. The spread of these is as follows: one observation in CST, 17 in PST, two in MST, 14 in EST and two in AST (GEIE, n.d.b; Time and Date, n.d.). First, all five observations in CST, MST and AST are included in the analysis to ensure the representation of all these. Next, the remaining 17 needed observations for the analysis are selected by randomly selecting eight observations from each of the two time zones, PST and EST. Finally, the final observation needed is selected at random from the remaining 15 observations.

In the sampling of the United States, the 45 observations are divided between four time zones. The observations are divided as follows: 10 observations in CST, 14 in EST, three in MST, and 18 in PST (GEIE, n.d.b; Time and Date, n.d.). All three observations within MST area are included in the analysis to optimise the representation of the time zones. The remaining 19 observations needed for the analysis are randomly selected from the three remaining time zones by randomly sampling six observations from each of them. The final observation is selected from the remaining 24 observations at random.

Both main variables in the dataset, potential RPV offset ratio and population density, are panel data. This is because they are collected over multiple years (Wooldridge, 2012). Since the data collected is from 2018 to 2021, there is a need to control for possible variations over time. Because of this, a group of dummy variables representing year is added to the dataset. This brings the total number of observations in the dataset to 352 from 88 cities.

The variables included in the analysis are briefly summarised (Table 1) before the following sections go into more detail about their characteristics and descriptive statistics.

Table 1: Different Variables Described

	Description	Measure
Potential RPV Offset Ratio	This shows the potential for RPV to offset the transport emissions of a city. The potential RPV offset ratio is found by dividing transport emissions (tCO^2e/yr) by the offset potential of RPV (tCO^2/yr).	0-1, where 1 equals 100 per cent.
Population Density	Population density measures how densely inhabitants live within a square kilometre. It is a continuous variable that is calculated by dividing the population of the city by the size of the city (PopDen=Pop/Size).	Whole numbers.
Country	A set of dummy variables defining which of the four countries each observation is located in.	0 or 1
Year	A set of dummy variables defining which of the four years each observation is from.	0 or 1
Public Mass-Transportation	A dummy variable defines whether a city has an internal public mass-transportation system or not.	0 or 1
Topography	A set of dummy variables defining which of the three kinds of land structure the observation has.	0 or 1

4.2 Main variables

4.2.1 Dependent Variable: Potential RPV Offset Ratio

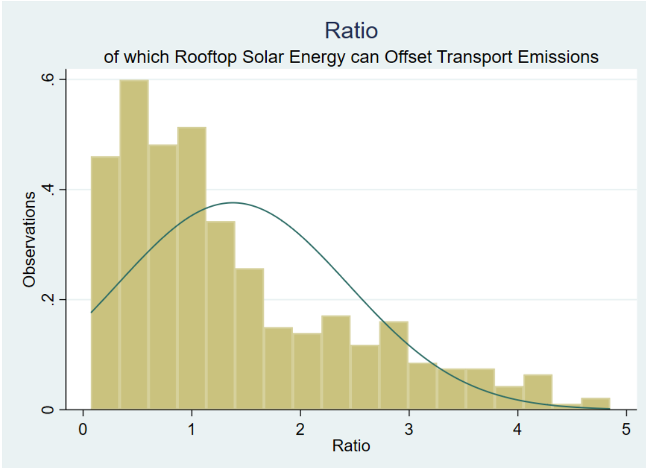

Figure 2: Potential RPV Offset Ratio.

Source: Own calculations based on (ABS, 2022; GEIE, n.d.a; Statistics Canada, 2023; Time and Date, n.d.; UNEP WCMC, 2002; USCB, n.d.; World Topographic Map, 2023).

Stata command: hist

The potential RPV offset ratio is the dependent variable in this analysis. It combines the collected data from the GEIE database on the offsetting potential of RPV, divided on the transport emissions for the same city. Both the offsetting potential of RPV and transport emissions are registered in tonnes of CO^2 emissions (tCO^2e), and the ratio is in percentage points. Therefore, this variable describes the extent to which the RPV installations are able to offset the transport emissions of the city. Their relationship is visualised in a histogram (Figure 2).

The highest concentration of cities in the collected dataset is between 0-1. This means that many cities included in the analysis have the potential to offset between 0-100 per cent of their transport emission by utilising the potential of RPV in their area (Figure 2). What is perhaps even more interesting is that there are champion cities in the observations that have the potential of offsetting almost 500 per cent of their transport emissions through RPV. This indicates that there is a skewed distribution of the observations in the potential RPV offset ratio. It also implies that there might be scope for offsetting more emissions than those created by transportation.

Since the dependent variable has a skewed distribution, the mean value must be investigated. The mean value of the potential RPV offset ratio is therefore displayed in a box plot (Figure 3). This box plot shows that the mean value of the dataset is slightly higher than one. From the circles at the top of the box plot, it is clear that there are champion cities that are outliers at the higher end of the dataset. These are all later found to be Australian cities (Table 10). To summarise, it is indicated that if all the cities included in the dataset fully utilise their RPV offsetting potential, their combined efforts could fully offset their total transport emissions and still have the potential to offset additional emissions from other sources.

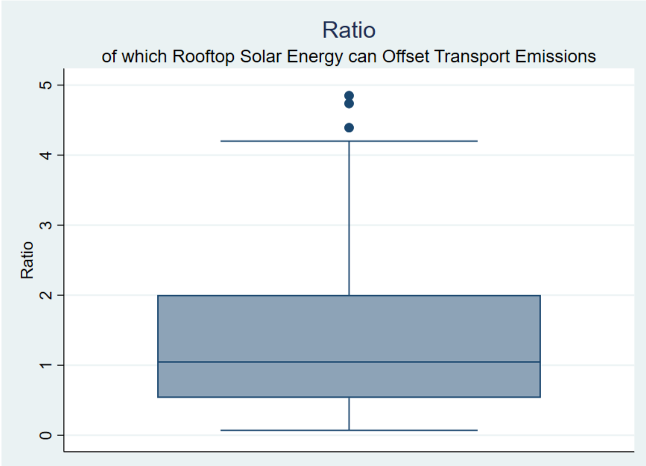

Figure 3: Ratio of which Rooftop Solar Energy can Offset Transport Emissions.
Source: Own calculations based on (ABS, 2022; GEIE, n.d.a; Statistics Canada, 2023; Time and Date, n.d.; UNEP WCMC, 2002; USCB, n.d.; World Topographic Map, 2023).
Stata commands: graph box

4.2.2 Main Independent Variable: Population Density

Population density is the primary independent variable of interest. It reflects the number of inhabitants per square kilometre. The collected data from the GEIE includes the population of the city and the size of the city in square kilometres (GEIE, n.d.a). The population density is then calculated by dividing the population of the city by the size of the city (PopDen=Pop/Size). This is previously found to have a negative impact on the RPV potential (Müller & Rode, 2013). As this is one of the two elements determining the potential RPV offset ratio, it is also expected to have a negative relationship to the dependent variable of this analysis.

The data is put into a histogram to visualise how the population density is represented in the dataset (Figure 4). A large part of the observations in the dataset is below 2.000 inhabitants per square kilometre. This is supported by the mean value of the dataset being 1,961.49 (Table 10). However, it also seems that the data is somewhat skewed (Figure 4).

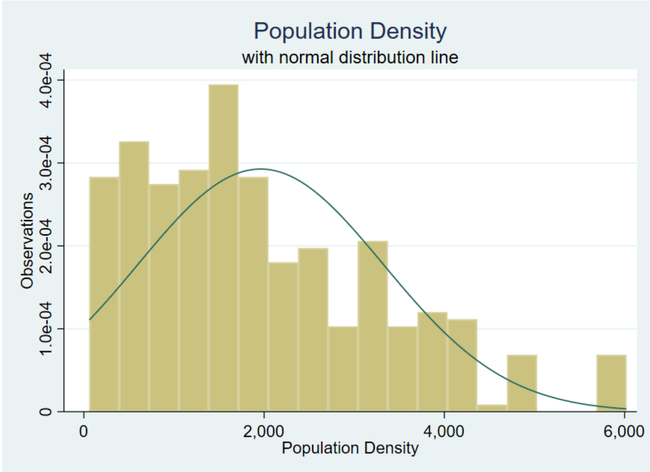

Figure 4: Population density.
Source: Own calculations based on (ABS, 2022; GEIE, n.d.a; Statistics Canada, 2023; Time and Date, n.d.; UNEP WCMC, 2002; USCB, n.d.; World Topographic Map, 2023).
Stata commands: hist

To get a first indication of the relationship between population density and the potential RPV offset ratio, the bivariate Pearson correlation coefficient is calculated (Wooldridge, 2012, p. 34)(Table 2).

Table 2: Pearson Correlations to Potential RPV Offset Ratio			
	Correlation		Observations
Population Density	-0.15	***	352

Note: The asterisks ***, **, and * represent a significance level of 1, 5, and 10 per cent, respectively.
Source: Own calculations based on (ABS, 2022; GEIE, n.d.a; Statistics Canada, 2023; Time and Date, n.d.; UNEP WCMC, 2002; USCB, n.d.; World Topographic Map, 2023).
Stata command: pwcorr

The correlation coefficient reveals that there is a negative correlation between the two variables. The results are also significant at a 1 per cent level. This correlation indicates, given that nothing else affects the relationship, that an increase in the population density reduces the RPV offsetting potential.

4.3 Additional Independent Variables

In addition to the main independent variable, population density, the potential RPV offset ratio is also controlled for by a set of additional independent variables. These variables are public mass transportation, country, topography, and year. They are all presented in the following sections.

4.3.1 Public Mass Transportation

Public mass transportation is a dummy variable used to differentiate between the cities with such a system and those without. The cities with a public mass transportation system are represented with a 1, and those without are given a 0. The number of observations with a public mass transportation system is 17, and 71 observations without.

The GEIE dataset provides detailed information on transportation emissions and what form of transportation the emissions stem from (GEIE, n.d.a). This data is used to determine whether a city has a public mass transportation system or not. All buses and trains are categorised as non-mass-transportation systems in this analysis. This is because buses are too small, and trains are connected to cross-country systems of transportation, and as a result, they are not a local transportation system. Transportation methods that are categorised as public mass transportation in this analysis are, therefore, subways, trams, and equivalent systems.

To explore the potential relationship between the public mass transportation variable and the potential RPV offset ratio, they are visualised in a box plot (Figure 5). It here becomes visible that there is a difference between the cities that have a public mass transportation system and those that do not. It appears that cities without a public mass transportation system have a higher chance of having a higher offsetting potential of transport emissions by the use of RPV than cities with a public mass-transportation system.

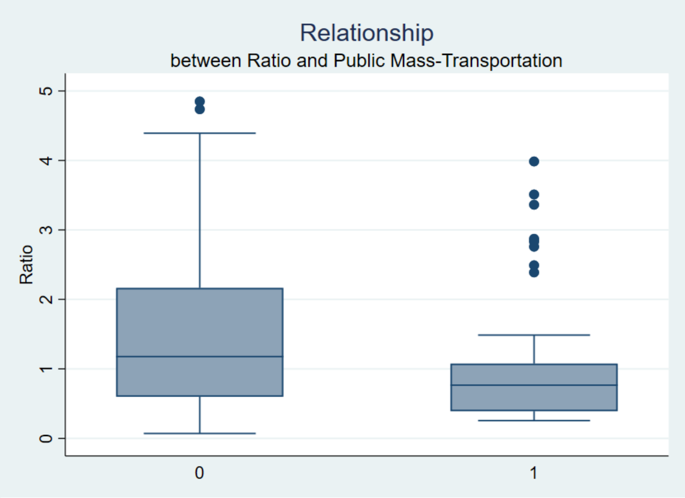

Figure 5: Relationship to Public Mass-Transportation.

Source: Own calculations based on (ABS, 2022; GEIE, n.d.a; Statistics Canada, 2023; Time and Date, n.d.; UNEP WCMC, 2002; USCB, n.d.; World Topographic Map, 2023).

Stata Commands: graph box

To test if there is a significant difference in the potential RPV offset ratio based on whether a city has public mass transportation systems or not, a two-sample t-test is conducted (Table 3) (Longest, 2020). The t-test shows that cities without a public mass transportation system have the potential to offset more than 147 per cent of their transport emissions. For comparison, the cities with such a transportation system only have the potential to offset almost 98 per cent of their transport emissions. The null hypothesis also implies a significant difference at the 1 per cent level between the cities with a public mass transportation system and those without. This is the same result for the null hypothesis regarding the difference being larger than 0. From this, it is indicated that there is a significant difference in whether a city has a public mass transportation system or not. It also indicates that cities without such a system are more likely to have a higher potential RPV offset ratio than those that do.

Table 3: T-test of Public Mass Transportation System on Potential RPV Offset Ratio

Reg.	Obs.	Mean	Std. Dev	95% conf. interval		Diff < 0		Diff !=0		Diff > 0	
				Lower	Upper	Pr(T < t)		Pr(|T| > |t|)		Pr(T > t)	
0	284	1.474	1.087	1.347	1.601		1.00	***	0.00	***	0.00
1	68	0.975	0.838	0.772	1.177						

Note: The asterisks ***, **, and * represent a significance level of 1, 5, and 10 per cent, respectively.

Source: Own calculations based on (ABS, 2022; GEIE, n.d.a; Statistics Canada, 2023; Time and Date, n.d.; UNEP WCMC, 2002; USCB, n.d.; World Topographic Map, 2023).

Stata command: ttest

4.3.2 Country

The country variable is collected from the GEIE database and is divided into four different dummy variables for the analysis (GEIE, n.d.a). These variables are one for each of the countries included in the analysis, Australia, Canada, the United Kingdom, and the United States. All observations are given a 1 for the country they belong to and a 0 for the three other countries. These dummy variables are intended to explore if there is a significant difference in the potential RPV offset ratio across countries and continents.

To get an understanding of how the potential RPV offset ratio is in the different countries, they are displayed in a pie chart (Figure 8). There is a clear leader in terms of what country in the dataset that have the largest potential RPV offset ratio. Australia, with 25 per cent of the observations, has almost 50 per cent of the total potential RPV offset ratio of the dataset. In contrast, Canada has the lowest potential RPV offset ratio, at only 6.42 per cent. This is less than half of the potential of the second lowest country, the United Kingdom that have a potential of 18.25 per cent offset of their transport emissions through RPV.

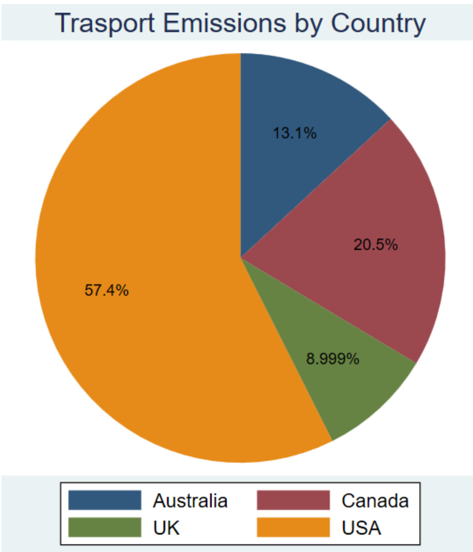

Figure 6: Transport Emissions by Country.
Source: Own calculations based on (ABS, 2022; GEIE, n.d.a; Statistics Canada, 2023; Time and Date, n.d.; UNEP WCMC, 2002; USCB, n.d.; World Topographic Map, 2023).
Stata command: graph pie

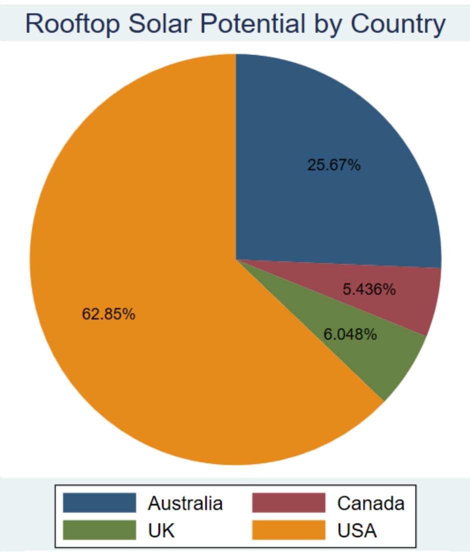

Figure 7: RPV Potential by Country.
Source: Own calculations based on (ABS, 2022; GEIE, n.d.a; Statistics Canada, 2023; Time and Date, n.d.; UNEP WCMC, 2002; USCB, n.d.; World Topographic Map, 2023).
Stata command: graph pie

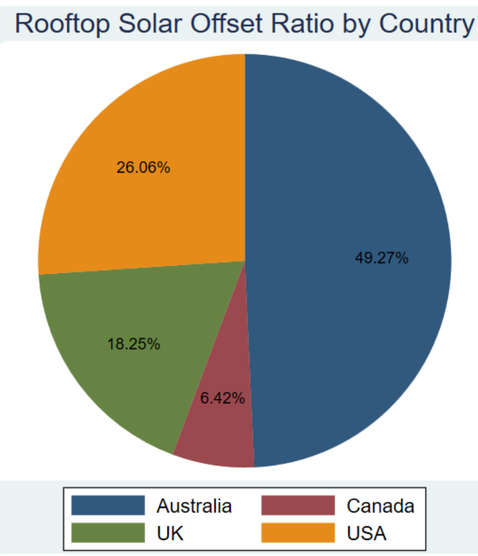

Figure 8: Potential RPV Offset Ratio by Country.
Source: Own calculations based on (ABS, 2022; GEIE, n.d.a; Statistics Canada, 2023; Time and Date, n.d.; UNEP WCMC, 2002; USCB, n.d.; World Topographic Map, 2023).
Stata command: graph pie

It is important to note that although Australia has the largest total potential RPV offset ratio, this does not mean that they have the largest potential for RPV power production in general. This is because the potential RPV offset ratio is in per cent of transport emissions. When looking at only the raw potential of RPV power production (Figure 7), the country in this dataset with the best potential is the United States, with an impressive 62.85 per cent of the potential recorded in the dataset. The reason they do not manage to continue this lead is that they have almost equally large transport emissions (Figure 6). The reasons for this could be many and are most likely a combination of multiple factors such as the population in the area, the size of the cities, and other qualities of the cities included in the dataset.

To further explore the properties of the country variable in the dataset, the mean, minimum, and maximum values of the countries are displayed (Table 4). It here becomes clear that all the outlier observations of the potential RPV offset ratio are registered for Australia. This is because the highest registration in any other city is in the United States, with 3.41 units, while Australia's highest registration is at 4.85 units. It is also interesting to note that all countries have observations that do not fully offset their transport emissions. Furthermore, from the lowest observations of each country, only the Australian observation can offset more than 50 per cent of its transport emissions through its RPV potential. Canada not only has the lowest potential RPV offset ratio, but it also has the city with the lowest potential RPV offset ratio in the dataset at only 7 per cent. This is seen in all values, mean, minimum, and maximum observations (Table 4).

Table 4: Potential RPV Offset Ratio per Country

	Mean	Min	Max
United Kingdom	1.01	0.50	1.90
United States	1.44	0.43	3.41
Australia	2.72	0.62	4.85
Canada	0.35	0.07	0.78

Source: Own calculations based on (ABS, 2022; GEIE, n.d.a; Statistics Canada, 2023; Time and Date, n.d.; UNEP WCMC, 2002; USCB, n.d.; World Topographic Map, 2023).

Stata command: (sum Ratio if UK), (sum Rato if USA)…. Etc.

Lastly, it is tested if the difference between the mean values of the different countries is of significant levels. This is undertaken by a multivariate test of means using Wilks' lambda (Stata, n.d.). The result shows that the null hypothesis should be rejected and that there is a significant difference between the mean values across countries (Table 5).

Table 5: Multivariate test of Means on Country

	Statistic	Prob>F	
Wilks' lambda	0.3366	0.0000	***

Note: The asterisks ***, **, and * represent a significance level of 1, 5, and 10 per cent, respectively.

Source: Own calculations based on (ABS, 2022; GEIE, n.d.a; Statistics Canada, 2023; Time and Date, n.d.; UNEP WCMC, 2002; USCB, n.d.; World Topographic Map, 2023).

Stata command: gen country="UK" if UK==1

```
replace country="Australia" if Australia==1
replace country="Canada" if Canada==1
replace country="USA" if USA==1
mvtest means Ratio, by(country)
```

4.3.3 Topography

Another group of dummy variables used in this analysis is topography. It is divided into three categories, where each observation is given a 0 or a 1 depending on which of the three categories they fall into. These three categories are coast, mountain, and inland. Every city in the dataset is only given one of the three categories. For cities that span over multiple categories, they will be given the most fitting one. For example, if a city is mountainous, it does not matter if it is coastal or inland, it will be given mountain as its category. And for cities being so large that they can qualify for both inland and coast, they will be put in the coastal category.

To determine which of these categories a city fall within, Google Maps has been used (Google Maps, n.d.). In addition to this, an interactive online topographic map is used (World Topographic Map, 2023). Cities that have a coastline to an ocean or are within 2 km of one (Barros et al., 2023) are given 1 for coast and 0 for mountain and inland. Rivers and lakes, regardless of size, are not included in the definition of ocean in this analysis. If a city does not fall into the coast category and does not consist mainly of mountains, the city is given 1 for inland and 0 for coast and mountain. For a city to be given 1 for mountain, and 0 for coast and inland, the majority of the city must be mountains. A mountain is here defined as an elevated part of the crust of the earth, of a minimum 300-meter height, with a minimum 300-meter increase in height compared to its relatively close surroundings (UNEP WCMC, 2002).

In this dataset, inland is the most observed topography with 176 observations, while coast has 120, and mountain has the lowest number of observations with only 56 observations (Barros et al., 2023; GEIE, n.d.a; Google Maps, n.d.; UNEP WCMC, 2002; World Topographic Map, 2023). Since these are observations spanning over four years, this means that there are 44 inland cities, 30 coastal cities, and 14 mountainous cities in the dataset.

To get an understanding of the relationship each variable has to the potential RPV offset ratio, a summary of the mean, minimum, and maximum registrations is created (Table 6). There seems to be some difference in the mean value of the variables, but it is not as large as the ones observed in the country variable. The minimum and maximum values of the dataset also seem to be more similar in this variable.

Table 6: Potential RPV Offset Ratio per Topographical Variable				
	Obs.	**Mean**	**Min**	**Max**
Inland	176	1.362	0.241	4.737
Mountain	56	1.143	0.070	3.612
Coast	120	1.510	0.244	4.849
Source: Own calculations based on (ABS, 2022; GEIE, n.d.a; Statistics Canada, 2023; Time and Date, n.d.; UNEP WCMC, 2002; USCB, n.d.; World Topographic Map, 2023). Stata command: (sum Ratio if Inland), (sum Rato if Mountain)…. Etc.				

To further examine the topography variable, a multivariate test of means is conducted using Wilks' lambda (Stata, n.d.). It can seem as if the null hypothesis should be rejected since there seems to be a difference between the three variables. Even so, the difference is only significant at a 10 per cent significance level. This implies that its strength might deteriorate further when additional variables are accounted for in the estimations.

Table 7: Multivariate test of Means on Topography			
	Statistic	**Prob>F**	
Wilks' lambda	0.9868	0.0980	*
Note: The asterisks ***, **, and * represent a significance level of 1, 5, and 10 per cent, respectively. Source: Own calculations based on (ABS, 2022; GEIE, n.d.a; Statistics Canada, 2023; Time and Date, n.d.; UNEP WCMC, 2002; USCB, n.d.; World Topographic Map, 2023). Stata command: gen topography="Inland" if Inland==1 replace country="Coast" if Coast==1 replace country="Mountain" if Mountain==1 mvtest means Ratio, by (Topography)			

4.3.4 Year

Since the analysis uses panel data that change over time, there needs to be a differentiation on what year the data represent (Wooldridge, 2012). Because of this, a third group of dummy variables are created to account for this. Each observation is then registered with data on all four years in the dataset in the transport emission and population variables.

Table 8: Potential RPV Offset Ratio per Year			
	Mean	Min	Max
2018	1.240	0.071	4.125
2019	1.223	0.070	4.074
2020	1.666	0.089	4.849
2021	1.381	0.076	4.200

Source: Own calculations based on (ABS, 2022; GEIE, n.d.a; Statistics Canada, 2023; Time and Date, n.d.; UNEP WCMC, 2002; USCB, n.d.; World Topographic Map, 2023).

Stata command: (sum Ratio if Year_1), (sum Rato if Year_2)…. Etc.

To map out the potential RPV offset ratio per year, the mean, minimum, and maximum observations are found (Table 8). The three years, 2018, 2019, and 2021 are relatively similar across mean, minimum, and maximum values. On the other hand, 2020 seems to have somewhat different results. This is most likely related to events during the first year of the Covid-19 pandemic, where mobility is heavily restricted, implying that the denominator of the potential RPV offset ratio is affected (Ajanovic, 2022). To test this, a multivariate test of means using Wilks' lambda is carried out (Stata, n.d.). This test support that there is a difference between the year variables at a 5 per cent significance level (Table 9).

Table 9: Multivariate test of Means on Year			
	Statistic	**Prob>F**	
Wilks' lambda	0.9719	0.0192	**

Note: The asterisks ***, **, and * represent a significance level of 1, 5, and 10 per cent, respectively.

Source: Own calculations based on (ABS, 2022; GEIE, n.d.a; Statistics Canada, 2023; Time and Date, n.d.; UNEP WCMC, 2002; USCB, n.d.; World Topographic Map, 2023).

Stata command: gen year="2018" if 2018==1
replace country="2019" if 2019==1
replace country="2020" if 2020==1
replace country="2021" if 2021==1
mvtest means Ratio, by(Year)

4.4 Data summary

The data and descriptive statistics show that there is bivariate significance in all variables. The most significant relationships to the potential RPV offset ratio seem to be with population density, public mass transportation, and country since they all are significant at a 1 per cent significance level (Tables 2, 3, & 5). The variable with the weakest relationship to the potential RPV offset ratio seems to be topography. It is, however, essential to note that these relationships might change when accounting for other variables in a multivariate regression analysis. This will be highlighted in Chapter 5, Empirical Methods. To conclude the data chapter, the characteristics of the dataset available for the estimations are presented (Table 10).

Table 10: Summary Statistics for the Estimation Dataset (2018 to 2021)

Variable	Median	Mean	Std. dev.	Min	Max
Potential RPV Offset Ratio (per cent)	1.05	1.38	1.06	0.07	4.85
RPV Offset Pot. (tCO^2e in 1000s)	248.50	834.75	1,751.40	6.33	11,800.00
Transport Emissions (tCO^2e in 1000s)	222.00	653.43	1,224.54	37.10	9,760.00
Building Emissions (tCO^2e in 1000s)	778.50	1,866.88	2,901.24	78.70	17,600.00
Population (number of inhabitants)	131,556.5	294,560.40	399,214.80	25,117	2,557,091
Size (km^2)	98.5	309.15	489.17	10.00	2,358.00
Population Density (inhabitants/km^2)	1,625.67	1,961.49	1,363.12	60.24	6,021.10
Public Mass-Transp.		19%		0	1
United Kingdom		25%		0	1
United States		25%		0	1
Australia		25%		0	1
Canada		25%		0	1
Inland		50%		0	1
Coast		34%		0	1
Mountain		16%		0	1

Source: Own calculations based on (ABS, 2022; GEIE, n.d.a; Statistics Canada, 2023; Time and Date, n.d.; UNEP WCMC, 2002; USCB, n.d.; World Topographic Map, 2023).
Stata command: summarize, detail

Both the median and the mean value of the potential RPV offset ratio are higher than 1 (Table 10). This show that if this potential is used fully, RPVs can offset all transport emissions in the cities included in this dataset. This could support the work needed to limit the temperature rise below two degrees Celsius from the Paris Agreement (United Nations, n.d.a) while simultaneously supporting SDG 7 by providing affordable and renewable energy (United Nations, 2015).

Despite this, there is a large difference between the city with the highest potential, 485 per cent, and the lowest potential, with only 7 per cent. This, and the fact that the median is 1.05, emphasise the skewness of the dataset. As a result, an OLS linear regression alone might overestimate the relationship (Wooldridge, 2012). This indicates the need for methods that handle outliers, such as robust- or quantile regression analysis.

There is a large span in the population density in the different cities included in the dataset (Table 10). Seeing as the city with the lowest population density only have 60.24 inhabitants per square kilometre, while the city with the highest population density has 6,021.10 inhabitants per square kilometre, there is implied a very different community structure in these cities. Similarly to the potential RPV offset ratio, the population density has a relatively large difference between the mean and median values. This, too, supports the use of alternative regression methods (Wooldridge, 2012).

5 Results

The quantile (Q 0.5) estimations (Table 13) reveal that the potential RPV offset ratio is significantly and negatively related to population density. This means that H1 can not be rejected. Additionally, H2 can also not be rejected since all three countries are found to be significantly different from the reference country Canada. In this case, their offsetting potential is significantly higher than that of Canada. Furthermore, the availability of public mass transportation is found to have a negative relationship to the potential RPV offset ratio, supporting H3. However, these findings should be interpreted with care due to the low number of cities in the dataset with such systems. Lastly, H4 can not be verified since the topography seems to not be related to the potential RPV offset ratio.

Following the introduction of the main results, this chapter continues by reporting the different steps taken in the empirical analysis in more detail. Given that the dataset holds a dependent variable with a skewed distribution and that there is an apparent discrepancy between the mean and median values, the pooled OLS estimation is followed by both robust and quantile (Q 0.5) regressions. Interpretation of magnitudes and discussion of results will mainly focus on the quantile regression. Robustness checks are then conducted to test if the relationship between population density and the potential RPV offset ratio is non-linear. Finally, this chapter closes with a discussion where the results are considered in relation to the contextual background and the diffusion of innovation theory (Rogers, 2003), which in this case, is used for a potential diffusion rather than an actual diffusion of RPVs.

5.1 Regression Analysis Results in Detail

The pooled OLS analysis is estimated in three steps to investigate whether the bivariate significances from Chapter 4, Data Sources and Descriptive Statistics hold in a multivariate situation (Table 11) (Gordon, 2015).

Table 11: Pooled OLS Estimations. Dependent Variable: Potential RPV Offset Ratio									
	Specification (i)			Specification (ii)			Specification (iii)		
	Coeff.		t-stat	Coeff.		t-stat	Coeff.		t-stat
Population Density	-0.0002	***	-3.94	-0.0001	***	-3.25	-0.0001	***	-3.29
United Kingdom (ref. Canada)	0.943	***	11.59	0.930	***	10.82	0.878	***	10.60
United States	1.061	***	14.66	1.043	***	14.52	1.072	***	14.97
Australia	2.427	***	24.97	2.407	***	24.54	2.461	***	25.98
2019 (ref. 2018)	-0.015		-0.19	-0.015		-0.19	-0.015		-0.20
2020	0.431	***	4.75	0.430	***	4.76	0.430	***	4.84
2021	0.143	*	1.74	0.143	*	1.75	0.143	*	1.78
Public Mass Transp.				-0.148	*	-1.83	-0.132	*	-1.68
Inland (ref. Mountain)							0.072		0.86
Coast							-0.185	**	-1.99
R-squared	0.716			0.718			0.729		
Observations	352			352			352		

Note: The asterisks ***, **, and * represent a significance level of 1, 5, and 10 per cent, respectively.

Source: Own calculations based on (ABS, 2022; GEIE, n.d.a; Statistics Canada, 2023; Time and Date, n.d.; UNEP WCMC, 2002; USCB, n.d.; World Topographic Map, 2023).

Stata command: regress with robust standard error.

The first step of the OLS regression includes variables for population density, country, and year (Table 11, Specification i). Population density, as well as country, are significant at the 1 per cent level, with the former exhibiting a negative relationship and the latter a positive one. Australia is found to be the country with the largest potential to offset its transport emissions through RPVs. The year 2020 stands out with a particularly strong and significant positive relationship to the potential RPV offset ratio. This is also the first year of the Covid-19 pandemic.

When the availability of public mass transportation (Table 11, Specifications ii) and topography (Table 11, Specifications iii) is added to the model, the initial variables are only marginally changed. Public mass transportation is significantly weakly related to the potential RPV offset ratio while with a negative sign. The variable coastal cities also exhibit a negative link to the potential RPV offset ratio at the 5 per cent significance level.

Lastly, in specification iii, where all variables are included, the R-squared indicates that almost 73 per cent of the variation in the dependent variable can be explained by the determinants. It is also important to note that the R-squared value increase throughout the different specifications as more variables are added to the linear regression analysis. This indicates that all the variables add to the understanding of the potential RPV offset ratio and that they hold some importance for the dependent variable.

As illustrated in Chapter 4, Data Sources and Descriptive Statistics, the dependent variable potential RPV offset ratio has a skewed distribution, which might give misleading results with the OLS estimator. Therefore, the second step in the analysis is using robust regression methods (Huber, 1964; Huber, 1981).

Table 12: Robust Regression based on Pooled Data. Dependent Variable: Potential RPV Offset Ratio

	Coefficient		t-stat
Population Density	0.00001		0.52
United Kingdom (ref. Canada)	0.610	***	8.68
United States	0.917	***	15.63
Australia	2.449	***	40.33
2019 (ref. 2018)	-0.016		-0.28
2020	0.324	***	5.60
2021	0.110	*	1.90
Public Mass Transportation	-0.137	**	-2.48
Inland (ref. Mountain)	0.080		1.23
Coast	-0.008		-0.11

Note: The asterisks ***, **, and * represent a significance level of 1, 5, and 10 per cent, respectively.

Source: Own calculations based on (ABS, 2022; GEIE, n.d.a; Statistics Canada, 2023; Time and Date, n.d.; UNEP WCMC, 2002; USCB, n.d.; World Topographic Map, 2023).

Stata command: rreg

In the robust regression analysis, the population density variable is no longer significantly different from zero. The topography variables, inland and coast, also become insignificant when the presumptive outliers are down-prioritised. On the other hand, the robust regression analysis enhances the significance of public mass transportation from being significant at a 10 per cent level in the OLS estimation to being significant at a 5 per cent level. It is also interesting to note that neither the country nor the year dummy variables appear with major differences compared with the OLS estimations (Table 12).

As apparent from the summary statistics (Chapter 4, Data Sources and Descriptive Statistics, Table 10), there is a clear difference between the mean and median values of the dependent variable. Therefore, a median regression (Q 0.5) analysis is expected to be more suited to prevent misleading estimation results. (Wooldridge, 2012).

Table 13: Quantile (Q 0.5) Estimations on Pooled Data. Dependent Variable: Potential RPV Offset Ratio

	Coefficient		t-stat
Population Density	-0.00007	***	-2.82
United Kingdom (ref. Canada)	0.750	***	15.23
United States	1.022	***	15.90
Australia	2.357	***	14.62
2019 (ref. 2018)	-0.006		-0.16
2020	0.361	***	4.95
2021	0.099	**	2.52
Public Mass-Transportation	-0.863	**	-2.07
Inland (ref. Mountain)	0.036		0.64
Coast	-0.055		-0.87

Note: The asterisks ***, **, and * represent a significance level of 1, 5, and 10 per cent, respectively.

Pseudo R2 = 0.536.

Source: Own calculations based on (ABS, 2022; GEIE, n.d.a; Statistics Canada, 2023; Time and Date, n.d.; UNEP WCMC, 2002; USCB, n.d.; World Topographic Map, 2023).

Stata commands: bsqreg with quantile (.5) and reps (100)

The third step in the analysis is, therefore, the median regression (Q 0.5). Here, the results in population density are significant at the 1 per cent level with a negative sign, similar to the OLS regression, but more robust. An increase of 1,000 individuals per square kilometre is used as an example to get an increased understanding of the magnitude of this relationship. For each increase of the population density with 1,000 individuals per square kilometre, the potential RPV offset ratio decreases by 0.07. This means that the city can offset seven percentage points less of its transport emissions if the population density increases by 1,000.

The findings related to public mass transportation coincide more with the robust regression analysis, and public mass transportation is significant at a 5 per cent level. The quantile regression (Q 0.5) also shows that the year 2020 is significant at a 1 per cent level, while 2021 is significant at a 5 per cent level. The positive coefficients of both 2020 and 2021 reveal that these years have a higher potential RPV offset ratio than 2018. It also demonstrates that the potential RPV offset ratio is as much as 36 percentage points higher in 2020 than in 2018, while 2021 has almost ten percentage points higher potential RPV offset ratio than 2018. Interestingly, the topography variables are also non-significant in the quantile regression analysis, much like they were in the robust regression analysis. Lastly, the pseudo-R squared indicates that more than 53 per cent of the variation in the dependent variable can be explained by the determinants.

5.1.1 Robustness Check

The variation in significance levels of the population density across the estimation methods used can indicate that there is a non-linearity in the link to the potential RPV offset ratio (Wooldridge, 2012). As a robustness test of the results and the fourth step in the analysis, population density in its squared format is therefore added to the quantile regression analysis (Table 14).

Table 14: Robustness Check: Quantile (Q 0.5) Estimations on Pooled Data. Dependent Variable: Potential RPV Offset Ratio			
	Coefficient		t-stat
Population Density	0.0003	***	3.13
Population Density^2 (Squared)	0.00000002	***	-4.07
United Kingdom (ref. Canada)	0.608	***	9.29
United States	0.966	***	10.25
Australia	2.412	***	19.21
2019 (ref. 2018)	-0.013		-0.40
2020	0.352	***	5.43
2021	0.098	**	2.51
Public Mass Transportation	-0.099	**	-2.38
Inland (ref. Mountain)	0.102	**	1.97
Coast	-0.035		-0.57

Note: The asterisks ***, **, and * represent a significance level of 1, 5, and 10 per cent, respectively.

Pseudo R2 = 0.56.

Source: Own calculations based on (ABS, 2022; GEIE, n.d.a; Statistics Canada, 2023; Time and Date, n.d.; UNEP WCMC, 2002; USCB, n.d.; World Topographic Map, 2023).

Stata commands: bsqreg with quantile (.5) and reps (100)

The robustness-check regression clearly shows that the squared variable is also significant at the 1 per cent level. This indicates that the relationship between population density and the potential RPV offset ratio is curved and has a turning point (Wooldridge, 2012). A margins plot is made to illustrate the point where the significance of the population density changes (Figure 9). This shows the significance across the continuous distribution of the population density. The relationship is significant when the 95 per cent confidence interval does not cross the zero line. This means that the relationship between population density and the potential RPV offset ratio in areas with low population density is significantly positive. Meanwhile, between 1,000 and approximately 2,000 inhabitants per square kilometre, the relationship is non-significant. A turning point in significance appears shortly after 2,000 inhabitants per square kilometre, from where the relationship is clearly negative (Figure 9).

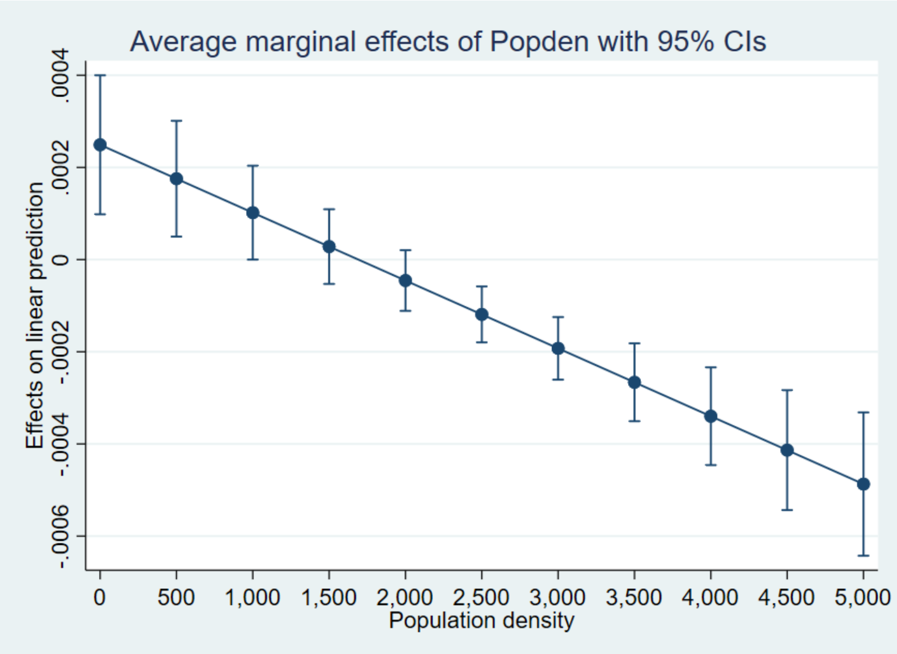

Figure 9: Average Marginal Effects of Population Density

Source: Own calculations based on (ABS, 2022; GEIE, n.d.a; Statistics Canada, 2023; Time and Date, n.d.; UNEP WCMC, 2002; USCB, n.d.; World Topographic Map, 2023).

Stata commands: marginsplot

This could be a result of multiple things, but it is expected that the availability of land to build new housing on is one of them. Cities with a higher population density are probably more likely to have more people living in high-rise buildings or at least more than one family per house. Building high-rise buildings allows a city to house more people without having to use more land (Ghazali et al., 2017). This does, however, not provide more room for RPV installations. A single-family house covering the same amount of land as a 10-story building housing nine families will most likely have close to identical RPV potential.

As an additional robustness check, two potential control variables are explored. The first one is building height. It would be interesting to investigate the buildings themselves within the cities and if this altered the findings from the median quantile regression analysis since this was implied in previous research (Ghazali et al., 2017). Especially the height or other characteristics of the buildings would be crucial to investigate closer. This could potentially affect factors such as temperature, sun hours in a day, or the amount of shade covering nearby buildings. Unfortunately, information on building height is not available in the GEIE dataset. A different method is therefore tested.

A list of the 100 tallest fully completed buildings in the world, as of February 2023, is explored (Council of Tall Buildings and Urban Habitat, 2023). For the city to be awarded a 1 in the dataset, there must be one of these 100 buildings within the geographical limits of the city. If there are no observations of these buildings, the city is given a 0. Regrettably, none of the cities in the GEIE database overlaps with these buildings, even outside of the 88 observations sampled within this analysis. This dummy variable is, therefore, currently not included in the analysis.

The final variable that is desirable to use as a robustness check due to findings in previous research is the tree canopy variable (Lou et al., 2022). This variable is based on the collected data from the GEIE and is an estimation of how large a percentage of the city is covered by tree canopy (GEIE, n.d.b). Unfortunately, at the time of this paper being written, the GEIE does not have data on all cities for this. Regrettably, the majority of cities within the dataset used for this analysis do not include this data (GEIE, n.d.a). The usage of this variable would, therefore, not provide generalisable data and is therefore not included at this time.

5.2 Discussion

Methodologically, and given the characteristics of the dataset, the quantile regression seems to be the most solid alternative to describe the relationship between the potential RPV offset ratio and the independent variables. This is the case even though most variables appear with similar significances as in the OLS estimation, with the only exception being topography. Furthermore, the main independent variable is not significant in the robust regression, possibly because the skewness of the dataset does not relate to measurement errors which is an underlying assumption for choosing this model (Rousseeuw & Leroy, 2005).

From the quantile median regression analysis, it seems as though population density is significant when explaining the different variables having a relationship to the potential RPV offset ratio. This supports H1. Based on the lost significance of the variable in the robust regression analysis, this could indicate that there is a certain level of population density that is the optimal density to maximise the potential RPV offset ratio. This is tested in the robustness check, and it is found that the relationship is on a curve and that the turning point is slightly higher than 2,000 inhabitants per square kilometre. It is also found that the population density is significant at a 1 per cent level even when squared.

Since H1 can not be discarded, and the quantile median regression analysis finds the variable significant at a 1 per cent significance level, there is little doubt that population density is an important variable when describing the potential RPV offset ratio. This can be a result of many features of the variable, such as how houses are built in higher-density urban cities and lower-density rural cities (Ghazali et al., 2017) or how land is used in rural versus urban cities (Poggi et al., 2018).

When considering the found relationship in combination with the diffusion of innovation theory (Rogers, 2003), there seems to be potential for the future diffusion of RPVs. However, even countries with high adoption rates of RPVs, such as Australia, where 20 per cent of the population have residential solar (Zander et al., 2019), are at a relatively low level of diffusion. This is based on the assumption that the diffusion is developing along an s-curve (Figure 10) and that the early majority of adopters is between the first 16 to 50 per cent of the population to adopt the innovation (dos Santos et al., 2018; Rogers, 2003). Therefore, since solar power generation is still at its low levels of diffusion, there is a lot of unused potential for further diffusion of this method of energy production.

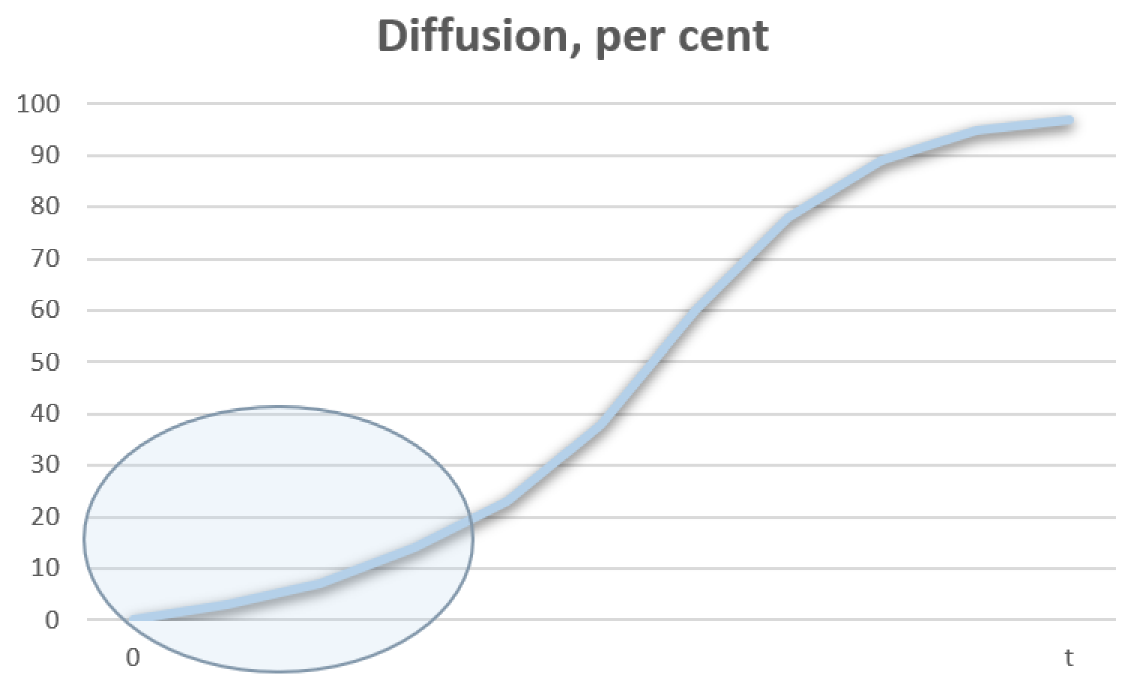

Figure 10: Current Diffusion of RPV

Source: Own illustration based on (Rogers, 2003)

For the potential diffusion of RPV to be exploited at a larger rate, it is important to note that there could be certain hurdles to this. These are not the focus of this paper but features like the social systems made up of the people living in the house could potentially hinder the adoption of RPV. This is due to the fact that when only one family live in a house, they fully own themselves, they are the primary decision-makers. If a family want to adopt RPV for their home, but they live in a high-rise building in a large city, this is most likely more complicated since everyone in the social system of the building has a say in the decision. It is also not unlikely that this could affect the time needed to make the decision to adopt RPVs. This will, however, not affect the potential RPV offset ratio but just the actual diffusion of RPVs.

As seen from the quantile (Q 0.5) regression, all three countries in the dataset have significantly different potential RPV offset ratios to the reference country Canada (Table 13). This also reveals that they are all different to each other. For example, Australia, being the country with the largest potential to offset their transport emissions through RPV, has more than 2.3 times as high a potential RPV offset ratio as Canada, ceteris paribus. This supports H2 in the assumption that the potential RPV offset ratio varies across countries.

The reasons for this could be many and complex. Environmental impacts such as how many hours of sun is available in a country are perhaps one of the more critical factors to the difference between the countries. This is, though, not something a country can change. A factor that could, over time, be optimised to fit RPV is the shape and direction of rooftops. Both hours of sunlight and rooftop shape and -direction are factors used by the GEIE to estimate the potential offset that can be provided by RPVs (GEIE, n.d.b). Seeing as the tilt angle is highly relevant for the efficiency of PVs in general (Mehleri et al., 2010) and that the GEIE uses flat RPVs on the rooftops in their estimations (GEIE, n.d.b), it is likely that optimising this on RPVs will also provide a larger potential for RPVs to offset transport emissions than what is shown in this analysis.

Even though the potential RPV offset ratio is not directly connected to the actual diffusion of RPVs, it is relevant to note that Australia has a very high diffusion of RPV compared to the world in general (Zander et al., 2019). This is partly found to be due to the support and influence of the government to adopt RPVs in residential housing, but also from a wish to provide local renewable energy for their residents (Zander et al., 2019). This, in turn, motivates a higher diffusion of RPVs since people communicate with each other, and they see others having PVs too (Barnes et al., 2022). Furthermore, since the government is supporting citizens in the initial financial cost of installing the RPVs, this also motivates the later adopters to get on board since these are financially motivated (Palm, 2020). It can therefore seem that the involvement from the government, local or national, is important for the potential diffusion of RPVs to be converted to actual diffusion (Poggi et al., 2018) and, in turn, provide offset potential for transport emissions.

From the quantile (Q 0.5) regression, it is seen that the presence of public mass transportation is an important factor when analysing the potential RPV offset ratio since this dummy variable is significant at a 5 per cent level. According to the findings, cities without a public mass transportation system have a more than 86 percentage points higher potential RPV offset ratio than cities with such a system (Table 13). What is important to note about these findings, however, is that only 19 per cent of the cities in the dataset have a public mass transportation system (Table 10). This means that as much as 81 per cent of the cities does not have such a system. As a result, the findings are interpreted with care. Even though a significant relationship is indicated in this analysis, further research on this variable is needed to draw more general conclusions. It is possible that there are some other characteristics that the cities with a public mass transportation system share that are resulting in this.

One of the primary reasons why public mass transportation is included in this analysis is that it is found to reduce transport emissions (Paulsson et al., 2018). Since transport emissions is one of the two variables making up the dependent variable potential RPV offset ratio, it is assumed that there is a relationship between them. This highlights one of the main parts of this variable that has not been heavily discussed at this point in the paper. This is that there are two ways of improving the potential RPV offset ratio. One of the ways is to improve the offset potential of RPVs by making more rooftops suitable for RPVs. The other way to improve the potential of a city to offset its transport emissions through RPVs is to reduce their transport emissions. This is what happened in 2020, and the after-effects of this can also be seen in 2021 on a smaller scale (Table 13). Since the pandemic was global, it influenced all cities and countries in the dataset. The pandemic led to lockdowns, people being forced to work from home, and travel less (Ajanovic, 2022). As a result, transport emissions fell (R. Zhang & J. Zhang, 2021).

The quantile (Q 0.5) regression analysis shows that the year 2020 had a positive relationship to the potential RPV offset ratio and that it is significant at a 1 per cent level. From the reference year of 2018, there is a 36.1 percentage points increase in the median value of the potential RPV offset ratio (Table 13). The fact that 2020 is significantly different from 2018 is important to show that factors that are not part of this research, such as the Covid 19 pandemic, are accounted for. The fact that 2021 is less significant than 2020 but still more significant than the pre-pandemic years implies that the pandemic might have altered the behaviours of people, even though lockdowns and restrictions are being removed (Ajanovic, 2022).

Since the RPV potential in this dataset is a constant number, the change in the potential RPV offset ratio comes from a lowered transport emission. This indicates that cities wanting to offset their transport emissions through their RPV potential could achieve faster results if this is done in combination with mitigation efforts towards transport emissions.

Electrical vehicles (EVs) are increasingly popular across the world, with China accounting for roughly 60 per cent of the current global market (IEA, 2023). For local governments wanting to boost their potential RPV offset ratio, or mitigate transport emissions in their city, investing in infrastructure for EVs is an effective measure (Q. Zhang et al., 2018). This and car-free downtown zones are the two main tips the GEIE give to their target group (GEIE, n.d.a). Both measures have the potential to reduce transport emissions in the city since EVs are considered emission-free vehicles (Ajanovic, 2022), and car-free zones will remove traffic from the area.

If measures like these are combined with efforts to motivate the use of RPVs, their effects could be even larger. As EVs will increase the need for electricity (IEA, 2023), RPV can also help provide local and renewable energy without needing more expensive land for energy production. Previous research also motivates that rural areas with a lower population density could play a vital part in providing urban cities with a higher population density with some much-needed renewable energy. This is because they have the potential to produce more renewable energy than they need and can therefore export their surplus to nearby urban cities in need of more energy (Balta-Ozkan et al., 2021; Poggi et al., 2018).

From hypothesis four, it was expected that topography would be a relevant variable when describing the potential RPV offset ratio. This seemed to be the case in scenario iii in the linear regression analysis. However, these findings are not coinciding with the quantile (Q 0.5) regression estimates, where the variables turned non-significant. Furthermore, it was expected that the mountainous cities would be less suited for RPV offsetting transport emissions due to the high altitude and potentially steep surroundings. Based on recent literature, this group of dummy variables is expected to be significant since land use is a large part of the debate on RPV (Balta-Ozkan et al., 2021; Benis et al., 2018; Poggi et al., 2018), although this is not the case. It is possible that this is important in other aspects of the potential of RPV, but it does not seem to be significant in terms of offsetting transport emissions. As a result, hypothesis four cannot be verified.

6 Conclusion

To reach the goals of the Paris Agreement and limit temperature rise from global warming to below two degrees Celsius, a rapid change away from fossil fuels is needed (United Nations, n.d.a; Wehrle et al., 2021). However, even though solar energy is considered the largest deposit of renewable energy, it is often seen as a support source of energy rather than a primary source (Ioannou et al., 2014). This could be due to the low efficiency rate of around 20 per cent or because it produces less energy compared to larger power plants options such as hydropower and wind (Potrč et al., 2021; Victoria et al., 2021). Previous literature finds that high investment costs and low efficiency are some of the causes of the low diffusion of RPV, but this trend is shifting due to sinking prizes and increasing efficiency (IPCC, 2022).

Estimation results from this analysis based on a novel experimental big dataset show that there is an opportunity to offset all transport emissions in a city by a complete diffusion of rooftop solar panels. There is even a surplus offsetting potential that can be used to offset other CO^2 emissions. These results partly contradict recent literature that focuses on the aspect that solar panels are not always the most efficient renewable energy source. If combined with mitigation efforts for transport emissions, such as investing in EVs, this surplus could cover some emissions from other sources, such as building emissions. The quantile (Q 0.5) regression analysis conducted in this study shows that population density has a negative relationship to the potential RPV offset ratio. Additionally, it shows that rural cities have a higher potential to offset their transport emissions than urban cities. The estimations also reveal that the potential RPV offset ratio varies across countries and that public mass transportation has a negative relationship to the potential RPV offset ratio. Lastly, the topography is found to not be a significant variable when discussing the potential RPV offset ratio.

Stakeholder implications from this study are varied. For building owners, regardless of if they are private, businesses, or government, they may relate to the willingness to invest in the technology. There is also a possibility of indirect implications if the government decides to utilise this potential to reach its goals of cutting emissions, encouraging, or forcing new building developments to either include RPV or, at the very least, optimise them for installation of RPV at a later stage. This is also one of the implications for the government and parliament. Since there is a potential to offset more than 100 per cent of transport emissions through RPV, this could be a good reason to make laws, create funding schemes, or in other ways motivate the installation of RPVs in different buildings. For landowners, implications of these findings could include a lowered pressure on land since the use of non-productive rooftops can free up land for other purposes such as farming, recreation, construction, and businesses, to name a few.

The primary limitation of this analysis is the data availability. The experimental dataset does not yet fully cover the continents or countries. This opens for future research on larger groups of cities and more countries when the database is expanded. Including variables presently unavailable, like building height, tree canopy, or building emissions, could also be highly interesting for future research. Seeing as public mass transportation is found to be significant in this analysis, it would also be interesting to make this the main determinant for the sampling of data. At the current state of the GEIE dataset, there are not enough cities to do this. However, as it continues to expand, it could provide exciting intel about this variable's relationship to the potential RPV offset ratio.

The deductive research method used in this study has its limitations. It is based on a set of à priori assumptions about causalities or relationships, and a break of these assumptions may distort the results. To avoid misspecification of the model due to data characteristics, different estimation methods are tested. In addition, a robustness check is undertaken where the main variable population density is estimated in its squared form. Results from this analysis indicate a turning point in the number of inhabitants per square kilometre, approximately 2.000 inhabitants, beyond which the negatively significant relationship appears. A methodological limitation is the short time series (four years) for the dependent variable and several independent variables that do not vary over time. This means that relationships, but not causal inferences can be drawn from the study. With longer time series and new measures, this is a topic for future research. A major advantage of empirical research is the opportunity to measure and quantify relationships and draw representative conclusions.

In total, the findings of this analysis support the role of RPV in the transition away from fossil fuels. It also highlights the need for cooperation between cities, regions, and countries since rural areas are more suited for RPVs than urban areas. And finally, even though there is potential to offset all the transport emissions through the utilisation of the potential of RPV, it is important to note that while doing so, the transport emissions themselves should also be lowered simultaneously. This is not an either-or situation, it is a “yes, please, both” situation.

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