From intention to actual adoption of green energy in households: a comparative study between Denmark and the Netherlands

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Summary

The Dutch Ministry of Economic Affairs and Climate Policy faces a significant challenge: the Netherlands lags behind Denmark and other European Union countries in renewable energy adoption. While Denmark has made impressive strides, the Netherlands remains heavily reliant on natural gas and fossil fuels, hindering its progress toward the EU's target of a 42.5% share of renewable energy by 2030 (European Parliament and Council of the European Union, 2023). Denmark's successful transition from fossil fuels to renewable energy, particularly wind power, contrasts with the Netherlands' challenges due to several reasons, including historical reliance on natural gas (NAM, n.d.), social resistance to renewable energy projects (Koelman et al., 2022) and complex and sometimes fragmented energy policies (Van Hoeve, 2010). It is clear that the Ministry needs to find ways to increase renewable energy adoption in the Netherlands. Understanding the factors influencing renewable energy adoption is crucial for replicating Denmark's success.

This study addresses gaps in the literature by investigating the relationship between households' intentions to adopt renewable energy through green energy suppliers and actual adoption in Denmark and the Netherlands, while also examining the associations with sociodemographic factors. The central research question is:

How are the intentions to adopt renewable energy, together with sociodemographic factors, associated with actual adoption of renewable energy on the household level in Denmark and the Netherlands from 2010 to 2020?

The sub-questions focus on the intention to adopt renewable energy, the association between intentions and sociodemographic factors and actual adoption, and the differences between the two countries.

A mixed-methods approach was employed, using Google Trends data to measure the intention to adopt renewable energy through green energy suppliers as a proxy for public interest. Linear regression models analyzed the relationship between intention and actual adoption rates, incorporating the sociodemographic factor of home ownership. Data from Eurostat and Google Trends focused on the period from 2010 to 2020.

Results showed higher and more consistent interest in renewable energy adoption in the Netherlands compared to Denmark. In Denmark, interest peaked around 2012 and stabilized, before increasing again in the latest years. In the Netherlands, interests showed a clear upward

trend, which suggests a growing intention among Dutch households to adopt renewable energy solutions.

Linear regression analysis indicated that intention, along with the sociodemographic factor home ownership, influenced actual adoption rates. In Denmark, intention and home ownership were negatively associated with renewable energy adoption in households. In the Netherlands, intention was positvely associated with adoption, and the association with home ownership was found to be not significant.

The study concludes that while the Netherlands shows a higher intention to adopt renewable energy, translating this intention into actual adoption could still remain challenging in the future. In the Netherlands, there was a positive association between the intention to adopt renewable energy and its actual adoption, indicating effective behavioral control where intentions can be translated into actions. Conversely, in Denmark, higher levels of interest did not consistently correlate with increased adoption rates and even showed declines, suggesting a more mature market where many households eager to adopt such technologies have already done so. The remaining households may encounter obstacles in behavioral control, or their attitudes and social norms may not fully align with their intentions to adopt.

To optimize the transition towards renewable energy, the Dutch Ministry of Economic Affairs and Climate Policy should enhance the visibility and appeal of green energy suppliers through targeted marketing and public endorsements. Additionally, the Ministry should offer tailored incentives to support households lacking behavioral control to prevent market saturation, as faced in Denmark, which can lead to a misalignment between intention and adoption, ensuring sustained growth in renewable energy adoption.

Future research should expand the dataset by including more years and countries, enabling more comprehensive models that can also include more factors. Conducting surveys to gather data on attitudes, social norms, and the percentage of households with green energy contracts would provide valuable insights. Additionally, investigating barriers to renewable energy adoption, particularly in saturated markets like Denmark, and examining how home ownership might negatively affect adoption rates in certain countries, would inform policy measures to enhance adoption.

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1 Introduction

The Dutch Ministry of Economic Affairs and Climate Policy confronts a significant issue: the Netherlands lags behind many of its European Union counterparts in renewable energy adoption, notably Denmark. This is not just a matter of national energy strategy, but it is also crucial in meeting the EU's ambitious renewable energy targets. The EU has set binding targets for its member states, aiming for a collective 42,5% share of renewable energy by 2030 (European Parliament and Council of the European Union, 2023). However, as of the latest data, the Netherlands is lagging, with only about 14% of its energy coming from renewable sources, in contrast to Denmark's impressive 43% (Ritchie et al., 2024). This gap is concerning, given the EU's efforts to combat climate change and promote sustainability. The Netherlands, traditionally reliant on natural gas and fossil fuels, faces the challenge of rapidly transforming its energy landscape. The country's goals, as outlined in its Integrated National Energy and Climate Plan, are ambitious and achieving them requires a significant shift in energy policy and practice. The country’s expected renewable energy adoption rate in 2030 is around 27%, far lower than the collective share the EU is aiming for (Ministry of Economic Affairs and Climate Policy, 2019). It is clear that the Ministry needs to find ways to increase renewable energy adoption in the Netherlands.

Denmark's triumph in renewable energy provides a stark contrast to the Netherlands' struggle. One would not necessarily expect this, considering the countries share similar geographic and climatic conditions (Worlddata, 2022), and are also culturally quite similar (Storm et al., 2019; HST Groep, 2020). In the Netherlands, there are several factors that could have impeded renewable energy adoption. Firstly, the Dutch economy's long-standing reliance on fossil fuels, particularly natural gas, poses a challenge. Since 1948, the Dutch have been using natural gas, and the fields in Groningen have long contributed to The Netherlands’ gas supply (NAM, n.d.). The existing infrastructure, designed for fossil fuel energy, requires substantial modifications to accommodate renewables, especially variable sources like solar or wind energy. In addition, public perception and societal acceptance of renewable energy infrastructure could also be a significant barrier in the Netherlands. There often is social resistance against renewable energy projects in the Netherlands. This resistance occurs particularly at the local level, such as from individual landowners, communities, and other stakeholders like governmental agencies, leading to a misalignment between national objectives and local implementation capabilities (Koelman et al., 2022). Another consideration is the effectiveness of regulatory and policy frameworks in the Netherlands. Complex and sometimes fragmented energy policies might have hindered the swift adoption of renewables. In terms of regulations, finances, and government involvement, there are such significant obstacles that investing in wind energy, for example, has hardly been worthwhile (Van Hoeve, 2010).

Denmark has successfully addressed challenges similar to those currently faced by the Netherlands. Initially dependent on oil and natural gas, Denmark shifted towards wind energy following the oil crises and environmental concerns of the 1980s (Krohn, 2002). Today, wind energy accounts for 54% of Denmark's electricity generation, compared to 18% in the Netherlands (International Energy Agency, 2024). This focused strategy has been crucial in achieving its high renewable energy rates (Pinson et al., 2017). One of the solutions in overcoming social resistance to renewable energy projects in Denmark has been the promotion of collective citizen ownership of wind energy projects (Van Est, 2022). Additionally, Denmark has maintained streamlined and supportive policies for renewable energy since the 1980s, which have stimulated the market and encouraged local community participation in renewable energy adoption (Van Hoeve, 2010). The Netherlands has the opportunity to follow suit by increasing the share of renewable energy in the energy mix as well. But replicating Denmark’s success in the Netherlands requires an understanding of the specific factors influencing renewable energy adoption.

While the existing literature provides insights into various factors influencing renewable energy adoption, including policy impacts (Woerter et al., 2017; Oosthuizen & Inglesi-Lotz, 2022), socio-demographic factors like studied by Bollino (2009) and Masrahi et al. (2021) among others, and social acceptance (Warren & McFadyen, 2010), notable gaps remain. Firstly, research often focuses on renewable energy adoption at the national level, neglecting the nuances of household adoption through green energy suppliers. Additionally, while many studies examine factors influencing the actual adoption of green energy or the willingness to pay for it, there is a gap in studies analyzing the intention to adopt renewable energy versus actual adoption. Lastly, there is a scarcity of comparative studies that explore the role of sociodemographic factors in the differences in green energy adoption across countries. This study aims to address these gaps by investigating the relationship between households' intentions to adopt renewable energy and actual adoption in Denmark and the Netherlands, while also examining the associations with sociodemographic factors. Therefore, this study contributes to the expansion of knowledge on renewable energy adoption, specifically focusing on household adoption through green energy suppliers and the translation from intention to actual adoption in different countries. Societally, these findings can inform policymakers, like the Dutch Ministry, to design targeted interventions (for specific sociodemographic groups) that promote higher adoption rates in households. Policymakers can design appropriate policies or campaigns to either address barriers or continue stimulating interest and support for the transition to renewable energy, therefore contributing to national and global sustainability goals.

Central to this study is the following research question:

How are the intentions to adopt renewable energy, together with sociodemographic factors, associated with actual adoption of renewable energy on the household level in Denmark and the Netherlands from 2010 to 2020?

To answer this question, the following sub-questions have been formed:

1. *What is the intention of adopting renewable energy at the household level in Denmark and the Netherlands from 2010 to 2020?*
2. *How are the intentions to adopt renewable energy, together with sociodemographic factors, associated with actual adoption of renewable energy on the household level in Denmark and the Netherlands?*
3. *To what extent do Denmark and the Netherlands differ in the association between the intention to adopt renewable energy and the actual adoption among households, and the role of sociodemographic factors on adoption?*

To address the research questions, this study employs a mixed-methods approach, using Google Trends to measure the intention of adopting renewable energy in households. Correlation analysis is then applied to analyze the association between this intention and actual adoption rates together with linear regression models, which also incorporate sociodemographic factors to find the associations and differences between the countries.

The remainder of this thesis is structured as follows. Section 2 provides theoretical and empirical background for the topic. Section 3 discusses the used data and conducted methodology. Section 4 provides the main results. Finally, Section 5 discusses the findings and concludes, thereby giving recommendations to the Ministry of Economic Affairs and Climate Policy in the Netherlands.

2 Theoretical Framework

This chapter presents the theoretical framework for this study by examining the energy mix in Denmark and the Netherlands, exploring how households can contribute to increasing renewable energy consumption, introducing the Theory of Planned Behavior, identifying key sociodemographic factors influencing renewable energy adoption, and outlining the conceptual model for this study.

2.1 (Renewable) energy comparison

Understanding the energy mix and consumption patterns of Denmark and the Netherlands is important for this research as it provides a contextual backdrop against which the adoption of renewable energy at the household level can be examined. Both countries have distinct energy profiles and dependencies that influence their potential and strategy for integrating renewable energy.

The Total Energy Supply (TES), as sourced from the International Energy Agency (2024) serves as an indicator of all the energy sources either produced within or imported into a country, after accounting for exports and storage. It includes both direct energy sources and those transformed into fuels or electricity for end users. In 2022, Denmark's TES was marked by reliance on oil (38%), biofuels (34%), and wind/solar energy (12.4%), highlighting a strong commitment to renewable energy as nearly half of the TES came from renewables. Conversely, the Netherlands heavily depended on oil (38%) and natural gas (37%), with a smaller proportion from biofuels (9.1%), reflecting a greater dependence on fossil fuels, particularly natural gas.

Different sectors dominate the energy consumption profiles in each country. In Denmark, residential (31%) and transport (29%) sectors led energy consumption in 2021, while in the Netherlands, the industry sector (24%) was predominant, followed by non-energy uses (23%), with a relatively smaller role for residential (18%) consumption (International Energy Agency, 2024).

Electricity generation methods also vary between the two countries. Denmark predominantly uses wind power, which accounted for 54% of its electricity generation in 2022 (International Energy Agency, 2024), with renewables making up 81.1% of electricity production, showing an increase of 423% since 2000 (International Energy Agency, 2022a). In contrast, the Netherlands still largely relies on natural gas for electricity (International Energy

Agency, 2024) but has also seen a significant increase in renewables' contribution to electricity generation, reaching 39.6% in 2022, with a remarkable growth of 1100% from 2000 (International Energy Agency, 2022a).

Finally, the share of renewables in energy consumption further illustrates the countries' energy strategies. Denmark had 39.7% of its energy consumption from renewables in 2020, a 270% growth from 2000, whereas the Netherlands, despite a lower share of 10.79% in the same year, demonstrated a commitment to enhancing this with a 524% growth over two decades (International Energy Agency, 2022b).

2.2 Increasing renewable energy share through household adoption

Increasing the share of renewable energy in overall energy consumption can be achieved by encouraging households to adopt green energy. For instance, investing in green energy technologies such as solar panels is one practical approach to boost household adoption of renewable energy. There is extensive literature available on the adoption of solar energy in households, including studies by Lan et al. (2020), Poier (2021), and Mohandes et al. (2019). However, there remains a research gap in understanding how households adopt renewable energy specifically through green energy suppliers. This is also how the use of wind energy, which has been actively promoted in Denmark, could be stimulated. According to Milieu Centraal (n.d.), while small wind turbines for home use exist, they often do not provide the environmental or economic benefits one might expect, leading to their limited use. They suggest that promoting the adoption of wind energy through energy suppliers could be a more effective and impactful strategy for integrating renewable energy at the household level. In this study, the intention to adopt renewable energy in households specifically refers to the adoption through green energy suppliers.

2.3 Theory of planned behavior

This study looks at the intention of adopting renewable energy versus the actual adoption. It is important to know that intention does not always have to lead to actual behavior. In this research, the Theory of Planned Behavior serves as the overarching framework due to its widespread application in analyzing consumer adoption patterns, including in the context of energy-efficient technology (Claudy et al., 2013; Wolske et al., 2017). As explained by Ajzen (1991), the Theory of Planned Behavior posits that an individual's intention to engage in various behaviors can be effectively forecasted through the interplay of three critical components. These components include attitudes towards the behavior, influenced by beliefs about the outcomes of the behavior and the probability of these outcomes occurring; societal norms, which relate to the perceived approval or disapproval by others of the behavior; and perceived behavioral control, which assesses an individual's perceived capacity to perform the behavior. It's important to distinguish between perceived and actual ability in this context. Often, there may be a discrepancy between what individuals believe they can do and what they are actually capable of doing. This discrepancy can significantly affect their intention to act. Specifically, if individuals underestimate their actual capabilities, their intention to engage in the behavior might be limited. To the extent that it is an accurate reflection of actual behavioral control, perceived behavioral control can, together with intention, be used to predict behavior. Figure 1 shows these relationships.

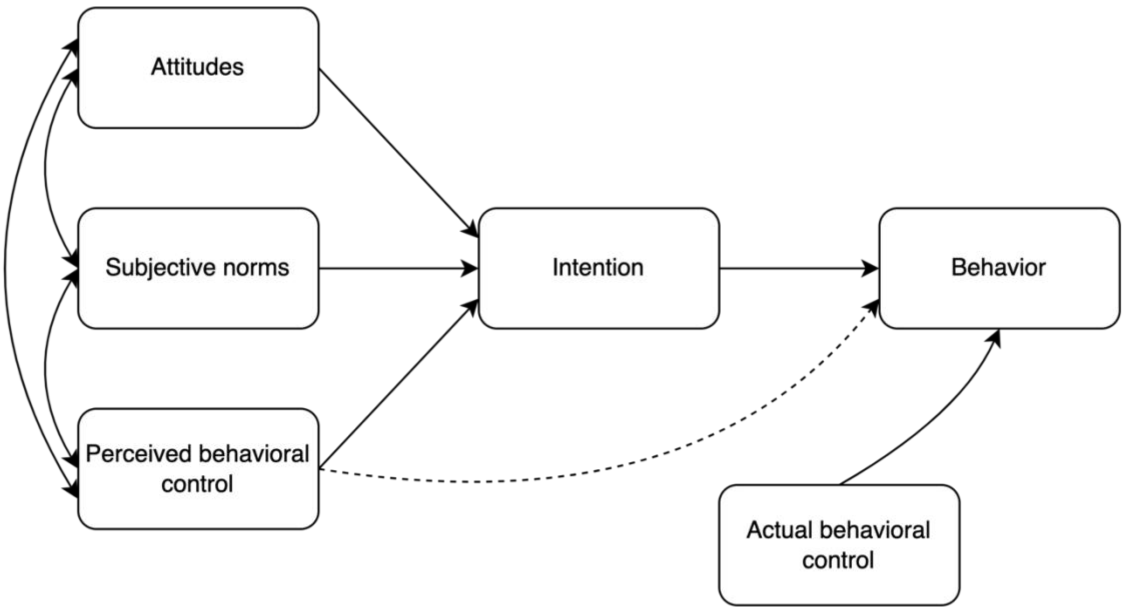

Figure 1*: Theory of Planned Behavior*

In this study, the Theory of Planned Behavior is employed to analyze the relationship between intention and adoption (behavior) in both countries. When intentions successfully translate into adoption, it suggests that behavioral controls are well-aligned with the intentions to adopt. Conversely, if intentions fail to result in actual adoption, this discrepancy may indicate a misalignment between intentions and the behavioral controls in place.

2.4 Relevant sociodemographic factors

Next to the association between intention and adoption of renewable energy in households, this study also takes sociodemographic factors into account. While literature regarding adoption through green energy suppliers is limited, there is literature available focusing on the sociodemographic factors influencing renewable energy adoption (in households) in general, which can also include renewable energy technologies. From the relevant literature, three key sociodemographic factors have been identified as having the strongest influence on the renewable energy adoption. These factors are *home ownership, household income* and *higher education levels,* and they will be taken into the analysis as sociodemographic factors.

Home ownership has been found to be a factor influencing renewable energy adoption in households. Bollino (2009) investigates the willingness to pay for renewable energy in Italy with socio-demographic determinants. The study finds that income and home ownership have a positive effect on respondents' willingness to pay for renewable energy. Fredriks et al. (2015) also find that homeowners tend to make larger capital investments in energy conservation measures (e.g., household improvements to increase energy efficiency, purchase of new technology and energy-saving devices) than those living in rental housing. Results from a study by Gu et al. (2019) also show that households that own a house are more inclined to invest in solar panels or heat pumps. An interesting finding is that of Ameli & Brandt (2015), who, next to observing that homeowners are more likely to invest in clean energy technologies, also find that the investment probability for light bulbs, heat thermostats, thermal insulation and energy-efficient windows depends negatively on the time that households have already spent in their place. This could indicate that households are more likely to invest in energy upgrades when they first move into their home.

Higher household income has also been found to positively affect the adoption of renewable energy. Masrahi et al. (2021) explore the factors influencing consumers' behavioral intentions to purchase renewable energy in the U.S., including demographic factors. The findings showed that the average household income in the residential sector has an important effect on consumers' intentions to use renewable energy. A study by Zografakis et al. (2009) also finds this. Larger willingness to pay for renewable energy sources was reported by those with high family income. Twumasi et al. (2022) also find household income as a significant factor influencing renewable energy adoption in households.

Lastly, studies find that education levels are associated with renewable energy adoption. Rahut et al. (2015) find that a higher level of education of the household head is strongly related to a switch to the use of clean energy. This is also supported by Ma et al. (2018), who find that higher education levels are positively associated with higher spendings on clean energy. Twumasi et al. (2022) also revealed that that household heads with higher education are 0.049 percent more likely to adopt renewable energy compared to household heads with no or low levels of education.

2.5 Conceptual model

The conceptual model for this study, as seen in Figure 2, focuses on analyzing the relationship between intention and adoption, alongside the influence of sociodemographic factors, on adoption. In this research, the three components of intention defined in the Theory of Planned Behavior—attitude, subjective norms, and perceived behavioral control—will not be examined individually, since the focus of this study is more on the translation of intention to adoption rather than the factors influencing intention. Thus, this study will explore the direct effect of intention on adoption. Sociodemographic factors such as income, home ownership, and higher education levels are considered as partial determinants of actual behavioral control, as they can enhance the capacity to adopt green energy according to literature, though they do not encompass all aspects of control. To conclude, this study looks at the effect of intention (through green energy suppliers) on adoption in Denmark and the Netherlands, together with the effect of socio-demographic factors (as some aspects of actual behavioral control).

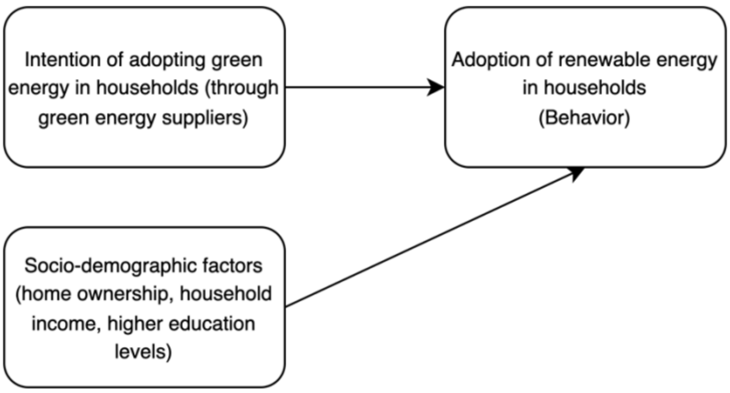

***Figure 2**: Conceptual model for this study*

3 Methodology

This chapter outlines the methodology of this research, detailing the research design, time horizon and sample selection, data collection methods, data analysis procedures, and validation and verification processes.

3.1 Research design and motivation behind methods

This study employed a quantitative research design, focusing on numerical data collection and statistical analysis to examine the relationship between the intention to adopt renewable energy and the actual adoption rates in households, while also controlling for socio-demographic factors. Specifically, this study used Google Trends data and Eurostat data. Google Trends provides data on public interest, while Eurostat offers sociodemographic data and renewable energy adoption statistics.

In order to study the research questions, Google Trends analysis, correlation analysis and linear models were used. Google Trends data was utilized to measure public interest in renewable energy providers, serving as a proxy for the intention of adopting green energy in households. Stocka & Matsa (2017) explain that the kinds of searches that users perform can be a good proxy for the public's interests, concerns or intentions, and Google Trends search data has also been used as a proxy for intention in other studies like that of Chan et al. (2022). Google Trends is a powerful tool for measuring public interest and intention, a key element of this research. It tells us what people are searching for, from 2004 all the way to now. This data can be used to measure search interest in a particular topic, in a particular place, and at a particular time (Google News Initiative, n.d.). The tool allows us to capture a wide spectrum of societal interest and intention in adopting green energy through green energy suppliers by analyzing specific search terms. As per Rogers (2016), Google Trends data reflects relative search interest, normalized to the highest point on the chart for the selected region and time. Each data point is divided by the total searches of the geography and time range it represents, ensuring that the data is comparable across different time periods and regions. The result is a score between 0-100, where a score of zero means that there was not enough data and a score of 100 means that the search interest for the search term was the highest in that timeframe. This feature makes Google Trends a powerful tool for understanding trends in public interest and intention over time, especially when examining the intention to adopt renewable energy technologies. Perju-Mitran et al. (2018, 2022) have already demonstrated the use of Google

Trends to analyze public opinion on solar and wind energy, which shows the potential of search data in understanding public interest in renewable energy.

Correlation analysis was employed to identify the direction and strength between the intention and actual adoption in both countries. This statistical method was a good first step to see if there were any associations between the variables before moving on to the regression analysis.

Linear models were used to perform a regression analysis in the programming environment R, the most popular statistical programming language in the world, which data scientists rank as their top option (Kamel et al., 2023). Regression analysis was chosen for its efficacy in quantifying relationships between multiple variables, a necessity for answering our research questions. This method allows us to statistically analyze the impact of identified independent variables (interest scores and sociodemographic factors) on the dependent variable (renewable energy adoption rates) (Sarstedt & Mooi, 2019). By including two separate models, the differences in effects for both countries could be analyzed.

3.2 Time horizon and sample selection

A specific time horizon and sample selection of green energy suppliers was chosen for the analysis.

3.2.1 Time horizon

For this study, a time horizon from 2010 to 2020 was selected. This choice was driven by several factors. First, renewable energy adoption rates in households, as sourced from Eurostat, were available up to 2020. Second, the analysis of interest in specific green energy companies through Google Trends required a sufficient amount of data. As explained in the Data collection section, it was determined that starting from 2010 provided adequate data for the analysis. Earlier years lacked sufficient data, likely because many green energy suppliers had not been established for long. Starting from a later year would lead to less observations, which is not preferable for our research.

3.2.2 Sample selection of green energy suppliers for Google Trends analysis

As mentioned before, to find the intention of adopting renewable energy in households, a Google Trends analysis was performed. The intention was measured as the search interest in green energy suppliers, together with a more general search interest in renewable energy companies, which will be explained later in this chapter. To analyze search interest in renewable energy suppliers, a sample of specific companies had to be selected.

For the Netherlands, the sample of specific companies was chosen based on annual research about the sustainability of energy suppliers in the Netherlands (Consumentenbond et al., 2014, 2015, 2016, 2017, 2018, 2019, 2020). In short, the research evaluates investments, purchasing, and electricity delivery to provide a complete view of the sustainability of Dutch energy suppliers. Using these aspects, a score is given to each company and a ranking follows. The ranking distinguishes suppliers in three categories. Suppliers scoring 8 or higher actively contribute to the transition to sustainable energy. They sometimes produce renewable energy themselves or purchase it directly from green electricity producers, supporting investments in sustainable generation. A large part of their electricity supply consists of wind energy, solar energy, and sustainable biomass. Scores between 5.5 and 8 indicate a sufficient level of sustainability. Scores below 5.5 are considered insufficient. Using this ranking for the years 2014 to 2020, the suppliers scoring 8 or higher were first selected and can be seen in Table 1 below. Some suppliers, namely Windunie, Huismerk Energie and Qurrent with Greenchoice, and Raedthuys with Pure Energie, were merged in the analysis. This is because those suppliers later moved on to merge with Greenchoice (WISE, n.d.; Greenchoice, 2018) or Pure Energie (Pure Energie, n.d.), or started supplying energy to one of these companies (Windunie, n.d.).

Table 1: *Energy suppliers scoring 8 or higher in the Netherlands*

Year	**Energy suppliers scoring 8 or higher**
2014	- Windunie (10) & Huismerk Energie (10) & Qurrent (9,9) (Greenchoice) - Raedthuys (10) (Pure Energie)
2015	- DE Unie (10) - Pure Energie (10) - Qurrent (10) (Greenchoice) - Vandebron (9,3)
2016	- DE Unie (10) - Pure Energie (10) - Qurrent (10) (Greenchoice) & Greenchoice (8,4) - Vandebron (9,6)
2017	- Pure Energie (10) - Greenchoice (8,5) & Qurrent (10) & Huismerk Energie (8,6) (Greenchoice) - om | nieuwe energie (10) - Vandebron (9,6) - Powerpeers (9)

Year	Energy suppliers scoring 8 or higher
2018	- easyEnergy (10) - Energie VanOns (10) - om | nieuwe energie (10) - Pure Energie (10) - Greenchoice (8,7) & Qurrent (10) & Huismerk Energie (8,5) (Greenchoice) - Vrijopnaam (10) - Powerpeers (9,4) - Vandebron (9,0) - Qwint (8,4)
2019	- easyEnergy (10) - Energie VanOns (10) - om | nieuwe energie (10) - Pure Energie (10) - Vrijopnaam (10) - Powerpeers (9,9) - HVC Energie (9,8) - Vandebron (9,7) - Greenchoice (9,1) & Huismerk Energie (8,7) (Greenchoice) - Qwint (8,5)
2020	- Pure Energie (10) - Vrijopnaam (10) - Energie VanOns (10) - om | nieuwe energie (10) - Powerpeers (10) - HVC energie (9,9) - Energy Zero (9,8) - easyEnergy (9,6) - Vandebron (9,5) - Greenchoice (8,2) - Eneco (8,1)

Since the analysis runs from 2010 to 2020, the companies that yielded enough search data in a longer period were selected for the Google Trends analysis of this research. Those suppliers were Greenchoice (and the companies that merged with them), Pure Energie (together with Raedthuys) and Vandebron. Greenchoice and Pure Energie were founded before 2010 (Greenchoice, n.d.; Pure Energie, n.d.) and could therefore be analyzed from this year. Vandebron joined the ranking of suppliers scoring 8 or higher in 2015 and was founded in 2013 (Consumentenbond, n.d.). To take out the popularity effect of a new founded supplier and to make sure the supplier could be marked as a renewable energy supplier, Vandebron was taken into the analysis from 2015. The energy suppliers that were not taken into the analysis were either founded too late for a proper analysis or did not yield enough search data, possibly due to being smaller companies.

A yearly conducted study, similar to the one used for the Netherlands, was not available for Denmark as far as I know. In order to find out what specific energy suppliers could be labeled as ‘green’, the energy supplier comparison website ‘Elpris’ was used (Elpris, n.d.). The Danish Utility Regulator is behind Elpris, and energy suppliers that sell electricity to Danish customers are obliged to publish their current prices on Elpris.dk (Elpris, n.d.). To compare energy suppliers, it was needed to enter a postcode. The postcode 1050 was entered to compare energy suppliers in Copenhagen: the largest city in Denmark. It was assumed that the largest city would offer the most energy suppliers. The energy suppliers that solely offer electricity from 100% renewable sources were selected. In total, 17 energy suppliers were found for further analysis. The names of the energy suppliers can be found in Table 2.

Table 2: *Green energy suppliers in Copenhagen*

Number	Name of energy supplier
1	Energidrift
2	iWatt
3	Vindstød
4	Grøn el forsyning
5	b.energy
6	Velkommen
7	Gasel
8	OK
9	Jysk Energi
10	Nordisk Energi
11	Samstrom
12	NRGI
13	Bornholms
14	Andel Energi
15	Verdo
16	Elg
17	Edison

Once again, only the green energy suppliers that yielded enough search data in a long enough period of time were selected for the Google Trends analysis of this research. Those suppliers were Andel Energi, Vindstød and Jysk Energi. Andel Energi used to have the name SEAS-NVE since 2005 (Politiken, 2004) and changed their name in 2020 (Via Ritzau, 2020), which was accounted for in the analysis. Vindstød started in 2012 (Crunchbase, n.d.). To use a similar approach as for Vandebron in the Netherlands, 2014 was used as the start year for the Google Trends analysis. Jysk Energi was founded way before 2010 and used to have the name NOE, before changing the name to Jysk Energi in 2013 (Jysk Energi, n.d.). Since NOE is also the name of a network company right now (NOE Net A/S, n.d.), it was decided to only use the name Jysk Energi and start in 2013, instead of combining the names and starting from 2010. The energy suppliers that were not taken into the analysis were either founded too late for a proper analysis or did not yield enough search data, possibly due to being smaller companies.

3.2.3 How Google Trends provides samples

Google Trends provides two types of data samples: real-time and non-realtime. Real-time data covers searches from the past seven days, while non-realtime data spans from 2004 up to 72 hours before the search. In this research, non-realtime data was used from 2010 to 2020. Although Google only uses a sample of searches, this is sufficient due to the vast number of searches conducted daily. Handling the entire dataset would be impractical for quick processing. By sampling, Google Trends offers a representative dataset that allows for timely insights into search trends (Google Support, n.d.-a).

3.3 Data collection

Data was collected through Google Trends and Eurostat. Google Trends provides data on public interest, while Eurostat offers sociodemographic data and renewable energy adoption statistics.

3.3.1 Google Trends data

Two types of interest data were collected through Google Trends to understand the intention to adopt renewable energy: specific interest in green energy suppliers and a more general interest in green energy companies. The reason for this was to essentially control for some limitations in the specific interest. Since the specific interest is based on the searches of three green energy suppliers, it is logical to assume that not all interest in green energy suppliers is captured through these searches alone. Next to this, searches in specific green energy suppliers might capture a popularity effect due to other factors rather than intention to adopt green energy through this specific supplier. For example, a news article about the supplier could lead to a higher search volume. In order to 'control' for this, a more general search interest in green energy companies was also analyzed through search data.

For the specific interest in green energy suppliers, the method of data collection was as follows. For each renewable energy supplier, search terms were set up that captured the interest in this supplier. These search terms included alternative spellings, previous names of the company or other green energy suppliers that were later merged with the company. The search terms for each supplier were then grouped together using the '+' operator, which allows the results to include searches for each of the words (Google Support, n.d.-b). Table 3 shows the specific search terms that were used to capture interest in the selected renewable energy suppliers. For each green energy supplier, a separate Google Trends analysis was performed, allowing for the time frame to be adjusted for each specific supplier. Google Trends offers the option to add a category to a search to control for double meanings of words. This was only used for the analysis of Jysk, since this is also the name of a widely known home furniture retailer. For the analysis of Jysk, the category of 'energy and electricity companies' was selected. The data was then downloaded as a csv file for each supplier, and included the year, month and normalized interest score (between 0-100).

Table 3*: Search terms and time frame used for Google Trends analysis of green energy supplier*

Country	Name of energy supplier	Search terms used	Time frame
Netherlands	Greenchoice	Greenchoice + Windunie + Huismerk Energie + Qurrent + Qurrent Nederland B.V. + Qurrent Nederland BV	2010-2020
Netherlands	Pure Energie	Pure Energie + Raedthuys + Raedthuys Energie B.V. + Raedthuys Energie BV	2010-2020
Netherlands	Vandebron	Vandebron + Vandebron energie + Vandebron Energie B.V. + Vandebron Energie BV	2015-2020
Denmark	Andel Energi	Andel Energi + seas-nve + seas-nve energi + seas-nve el + andel el	2010-2020
Denmark	Jysk	jysk + jysk energi + jysk el + jysk energi a/s	2013-2020

Country	Name of energy supplier	Search terms used	Time frame
Denmark	Vindstød	Vindstød + Vindstød Energi + Vindstoed + Vindstoed energi + Vindstød el + Vindstoed el	2014-2020

For the general interest in green energy companies, data collection was easier. Since Google Trends allows the option to select a certain category without including any search terms, the category of ‘Renewable and alternative energy companies’ was selected by first clicking on ‘Categories’, then ‘Business & Industry’, then ‘Energy & Utilities’, and lastly ‘Renewable and alternative energy’. What followed was the general search trend for renewable and alternative energy companies in both countries. It is important to note that it is not clear what search terms Google uses for these categories and that renewable energy companies could also include companies that are not private energy suppliers. However, this data could show a more general trend in order to control for biases in the specific interest data. Once again, this data was downloaded as a csv file for both countries and included the year, month and normalized interest score (between 0-100).

3.3.2 Eurostat data

Eurostat was used for data on sociodemographic factors and renewable energy adoption rates. For home ownership, Eurostat’s data on tenure status was used (Eurostat, 2024c). The metadata (Eurostat, 2024f) tells us that this data is part of the European Union Statistics on Income and Living Conditions (EU-SILC) survey. It describes that the survey is designed to gather timely and comparable cross-sectional and longitudinal data on income, poverty, social exclusion, and living conditions. Denmark and the Netherlands both participate in EU-SILC, which uses a random sampling method to ensure representative data for the entire population. The survey includes data from private households and individuals within those households. The dataset from Eurostat shows the distribution of the population by tenure status, type of household and income group. The dataset was first customized by selecting Denmark and the Netherlands as geographical entities, the years 2010 to 2020 as time, and the tenure status to ‘Owner’. Then, the data was downloaded as a csv file.

To collect data on higher education levels, Eurostat's data on tertiary education was used (Eurostat, 2024g). The metadata (Eurostat, 2024d) tells us that this data is sourced from the EU Labour Force Survey (EU-LFS). The survey covers the highest level of education successfully completed by individuals in the population, classified according to the International Standard Classification of Education (ISCED). Data includes annual averages and adjustments for missing values or main breaks in the series. The survey samples the total population, excluding those in collective or institutional households, and is updated quarterly. The dataset from Eurostat shows the population by educational attainment level, sex and age. Once again, the dataset was customized by selecting Denmark and the Netherlands as geographical entities and the years 2010 to 2020 as time. Next to this, tertiary education (levels 5-8) was selected, and the data was filtered for the ages 25-74 years. This age filter was chosen because it ensures that only people with a completed tertiary education, as well as people that can make household decisions, are considered in the tertiary education data. The data was then downloaded as a csv file.

Eurostat's data for adjusted gross disposable income of households per capita was used to collect data on household income (Eurostat, 2024a). The metadata (Eurostat, 2024b) tells us that this data is sourced from the European Statistical System (ESS). This system collects data reported by the countries, ensuring high-level quality standards of European Statistics. The data is updated annually and disseminated within a year after the reference year. Once again, the dataset was customized by selecting Denmark and the Netherlands as geographical entities and the years 2010 to 2020 as time. Then, the data was downloaded as a csv file.

The renewable energy adoption data was sourced via DBnomics (DBnomics, 2022a, 2022b), a free platform to aggregate publicly available economic data provided by national and international statistical institutions, but also by researchers and private companies (DBnomics, n.d.). The platform uses a dataset by Eurostat, which was discontinued and therefore not available anymore on the Eurostat site itself (Eurostat, 2024e). For Denmark, the original energy statistics data, including household energy consumption, are collected primarily through surveys conducted by the Danish Energy Agency (Eurostat, 2022a). For the Netherlands, a similar approach is taken where energy statistics data are collected by Statistics Netherlands (CBS) and other agencies through surveys and administrative sources. These data collections include residential energy consumption, with data sourced from surveys and mandatory reporting from energy providers (Eurostat, 2022b). The data on renewable energy adoption shows the renewables and biofuels in the final energy consumption mix of households from 1990 to 2020 as a share of the total residential fuel consumption. This was used as the adoption of renewable energy in households. The data was then downloaded for each country as a csv file.

3.4 Data analysis methods

Data was analyzed using descriptive statistics, boxplots, correlation analysis and regression analysis.

3.4.1 Data preparation

Before all downloaded data could be analyzed, it was needed to prepare the data. For the Google Trends analysis, this was as follows. First, all data regarding interest in a specific supplier or general interest needed to be averaged by year. This way, the average interest scores per year for each supplier for each country, and the general interest per year for each country, were formed. After this, the average specific interest was calculated by taking the average score of the three specific suppliers each year per country. Missing values were not taken into account. So, if a year only had two values, the average of those two years was taken.

Then, to combine the average specific and average general interest into one score, a weighted average between the two interest scores was formed. In order to estimate the weight for the specific and general interest score, the following method was used. For the Netherlands, the total green energy suppliers for the years 2014 to 2020 were known. For each year, a rate was calculated that showed how many suppliers were taken into the analysis for that year and how many total suppliers were labeled as 'green' for that year, to essentially see how much of the specific interest was captured. Since only the most 'popular' suppliers could be chosen based on available data, it was assumed that those suppliers reflected the specific interest well. Equation 1 shows the rate that was calculated each year.

$$Green\ rate\ per\ year = \frac{green\ energy\ suppliers\ taken\ into\ analysis}{total\ green\ energy\ suppliers} \tag{1}$$

Since our analysis runs from 2010, it was assumed that the suppliers that were labeled as 'green' in 2014 were also the providers that were 'green' from 2010 to 2014. This was assumed because the number of green energy suppliers was way less in earlier years. Also, the suppliers that were labeled as 'green' in 2014 were some of the bigger companies and all taken into analysis, and those suppliers were formed way before 2014 and 2010 which means they existed in 2010 and were well established. The rates that were calculated can be seen in Table 4. Then, the average green rate over all years was calculated and was 0.72.

Table 4*: Green rate per year*

Year	Energy suppliers scoring 8 or higher	Green rate
2010	- **Greenchoice** - **Pure Energie**	1
2011	- **Greenchoice** - **Pure Energie**	1
2012	- **Greenchoice** - **Pure Energie**	1
2013	- **Greenchoice** - **Pure Energie**	1
2014	- **Windunie (10) & Huismerk Energie (10) & Qurrent (9,9) (Greenchoice)** - **Raedthuys (10) (Pure Energie)**	1
2015	- DE Unie (10) - **Pure Energie (10)** - **Qurrent (10) (Greenchoice)** - **Vandebron (9,3)**	3/4
2016	- DE Unie (10) - **Pure Energie (10)** - **Qurrent (10) (Greenchoice) & Greenchoice (8,4)** - **Vandebron (9,6)**	3/4
2017	- **Pure Energie (10)** - **Greenchoice (8,5) & Qurrent (10) & Huismerk Energie (8,6) (Greenchoice)** - om | nieuwe energie (10) - **Vandebron (9,6)** - Powerpeers (9)	3/5
2018	- easyEnergy (10) - Energie VanOns (10) - om | nieuwe energie (10) - **Pure Energie (10)** - **Greenchoice (8,7) & Qurrent (10) & Huismerk Energie (8,5) (Greenchoice)** - Vrijopnaam (10) - Powerpeers (9,4) - **Vandebron (9,0)** - Qwint (8,4)	3/9
2019	- easyEnergy (10) - Energie VanOns (10)	3/10

Year	Energy suppliers scoring 8 or higher	Green rate
	- om | nieuwe energie (10) - **Pure Energie (10)** - Vrijopnaam (10) - Powerpeers (9,9) - HVC Energie (9,8) - **Vandebron (9,7)** - **Greenchoice (9,1) & Huismerk Energie (8,7) (Greenchoice)** - Qwint (8,5)	
2020	- **Pure Energie (10)** - Vrijopnaam (10) - Energie VanOns (10) - om | nieuwe energie (10) - Powerpeers (10) - HVC energie (9,9) - Energy Zero (9,8) - easyEnergy (9,6) - **Vandebron (9,5)** - **Greenchoice (8,2)** - Eneco (8,1)	3/11

Since I did not have this specific data per year for Denmark, but again three suppliers had been chosen based on available data (and therefore were some of the most ‘popular’ suppliers), it was assumed that for Denmark the same amount of specific interest was initially captured. Therefore, the average green rate was also assumed to be 0.72 for Denmark.

The Netherlands and Denmark both have different starting times for specific green energy suppliers in the analysis. It was assumed that the average specific interest would be most reliable if the interest scores were captured from 2010 to 2020. In order to essentially control for energy suppliers that were taken into the analysis at a later time, and therefore made the average specific interest less reliable, a ‘penalty’ was calculated for the weight of the specific interest. First, the average start year for the analysis for specific interest for both countries was calculated by adding the start years of the three specific suppliers in each country together and dividing this by the number of companies (three):

$$average\ start\ year\ DK = \frac{2010 + 2013 + 2014}{3} = 2012.33 \tag{2}$$

$$average\ start\ year\ NL = \frac{2010 + 2010 + 2015}{3} = 2011.67 \tag{3}$$

Then, the difference between the average start year and the year 2010 was calculated for both countries:

$$start\ time\ difference\ DK = 2012.33 - 2010 = 2.33 \tag{4}$$

$$start\ time\ difference\ NL = 2011.67 - 2010 = 1.67 \tag{5}$$

The initial specific weight per year was calculated as follows:

$$initial\ specific\ weight\ per\ year = \frac{average\ green\ rate}{amount\ of\ years} = \frac{0.72}{11} = 0.066 \tag{6}$$

Then, the weight penalty for both countries was calculated with the following equations:

$$weight\ penalty\ DK = initial\ specific\ weight\ per\ year * start\ time\ difference\ DK \approx 0.15 \tag{7}$$

$$weight\ penalty\ NL = initial\ specific\ weight\ per\ year * start\ time\ difference\ NL \approx 0.11 \tag{8}$$

The weight penalties were subtracted from the initial weights for the specific interest, and the actual specific weights for both countries were calculated:

$$specific\ weight\ DK = green\ rate - weight\ penalty\ DK \approx 0.57 \tag{9}$$

$$specific\ weight\ NL = green\ rate - weight\ penalty\ NL \approx 0.62 \tag{10}$$

The weights for the general interest were then calculated as follows:

$$general\ weight\ DK = 1 - 0.57 = 0.43 \tag{11}$$

$$general\ weight\ NL = 1 - 0.62 = 0.38 \tag{12}$$

After calculating the weights, the weighted interest scores per year could then be calculated with the following formula:

$$weighted\ interest = general\ interest * general\ weight + specific\ interest * specific\ weight \tag{13}$$

A sensitivity interval for the weighted interest was also calculated by adjusting the weights to create lower and upper bounds in order to account for variability in the weighting factors, therefore providing a more robust Google Trends and correlation analysis. The upper bound was determined by increasing the weight of the specific interest by 10 percentage points and decreasing the weight of the general interest by the same amount. Conversely, the lower bound was established by decreasing the weight of the specific interest by 10 percentage points and increasing the weight of the general interest by 10 percentage points. The interest scores for all specific suppliers, along with the average specific, general, and weighted interest (including the lower and upper bounds) per year for each country, were then compiled into a single dataset using R and saved as a CSV file.

Then, the renewable energy adoption rates and sociodemographic factors, sourced from Eurostat, were added to a new dataset manually by selecting the factors and adding them to the database in Excel. The specific, general and weighted interest scores per year per country were then also added to this dataset. The dataset was ordered by year and country, and two separate subsets were created that included the data per country. For Denmark, to limit biased estimates, the row for year 2010 was deleted due to the residual being an outlier after visually inspecting the *Weighted Interest* vs *Renewable Energy Adoption Percentage* plots. For easy comparison, the variables were also standardized using the scale() function in R and these standardized variables were also added to the dataset. The datasets were then ready for further data analysis.

3.4.2 Operationalization

Table 5 shows the operationalization for the concepts of this study. It includes the variables that were (initially) created for the linear models. It is important to note that *Weighted_Interest* was taken as the intention to adopt renewable energy, as it represents the specific and general interest.

Table 5: *Operationalization of concepts in this study*

Concept	Variable	Indicator	Unit of measure before standardizing	Data source
Intention to adopt renewable energy	Weighted_Interest (+ Weighted_Interest_Lower & Weighted_Interest_Upper)	Normalized search interest of renewable energy suppliers/companies per year, consisting of the specific and general interest	Normalized score between 0-100	Google Trends

Concept	Variable	Indicator	Unit of measure before standardizing	Data source
	Specific_Interest	*Normalized search interest of specific green energy suppliers per year*	*Normalized score between 0-100*	*Google Trends*
	General_Interest	*Normalized search interest of general renewable energy companies per year*	*Normalized score between 0-100*	*Google Trends*
Adoption of renewable energy in households	RE_Adoption_Percentage	Share of renewables and biofuels in final energy consumption mix of households per year	Percentage between 0-100%	Eurostat (DBnomics)
Socio-demographic factors	Home_Ownership_Percentage	Share of tenure status = 'Owner' in population aged 16 and older	Percentage between 0-100%	Eurostat
	Higher_Education_Percentage	Share of tertiary education (levels 5-8) in population aged 25-74	Percentage between 0-100%	Eurostat
	Household_Income	Adjusted gross disposable income of households per capita	Purchasing power standard (PPS) per inhabitant	Eurostat

3.4.3 Data analysis for the intention to adopt green energy

The Google Trends interest data was analyzed through boxplots and descriptive statistics, and by plotting the interest trends over time. By using the 'summary()' function in R, the minimum, 1st quartile, median, mean, 3rd quartile, and maximum values of the variables were analyzed. These variables consisted of the specific, general, and weighted interest scores. The boxplots and interests over time were plotted in R using the 'ggplot2' package. By using descriptive statistics and boxplots, the intention could be measured, and by plotting, the intention trend over time could be analyzed.

3.4.4 Data analysis for the relation between intention, home ownership, and adoption

To find the relationship between intention and adoption, and controlling for socio-demographic factors, a correlation analysis and regression analysis were used. First, a correlation analysis was performed to find the strength and magnitude between the intention and adoption relation. For this, the specific, general, and weighted interests were correlated against the renewable energy adoption rates for both countries using the ‘rcorr()’ function from the ‘Hmisc’ package in R. This way, the correlation coefficients and p-values could be analyzed.

Second, a linear regression model was used per country to analyze the relationship between renewable energy adoption rates and weighted interest and socio-demographic factors. An ARIMAX model, which combines Autoregressive Integrated Moving Average (ARIMA) with exogenous variables, was also considered to account for potential autocorrelation from the data being a time-series. However, preliminary tests indicated that the ARIMAX models selected (0,0,0) parameters, essentially reducing it to a linear regression model with no significant autocorrelation. Given the complexity of implementing ARIMAX without substantial additional benefits and the straightforward nature of the linear regression approach, together with the fact that autocorrelation tests did not find significant autocorrelation, linear regression models were chosen for their simplicity and interpretability. The linear models were estimated using the renewable energy adoption percentage as a dependent factor and using the weighted interest and all socio-demographic factors as independent factors. Variables were checked for multicollinearity using Variance Inflation Factor (VIF). Variables with high VIF values, indicating multicollinearity, were excluded one by one to improve model stability and interpretability. What was also considered when removing variables was the low number of observations. Since the number of observations is low (11 per country), model simplicity is preferred to avoid overfitting. Therefore, the final linear models excluded *Household_Income* and *Higher_Education_Percentage*. The multicollinearity between these variables could theoretically also be well explained since higher education levels are typically associated with higher incomes.

The final linear regression model per country used *RE_Adoption_Percentage* as a dependent variable, and *Weighted_Interest* and *Home_Ownership_Percentage* were used as independent variables. The following linear regression model was specified per country using the standardized variables from the data subsets:

$$RE\ Adoption\ Percentage_i = \beta 0_i + \beta 1_i * Standardized\ Weighted\ Interest_i + \beta 2_i * Standardized\ Home\ Ownership\ Percentage_i + \varepsilon_i \tag{14}$$

where:

$RE\ Adoption\ Percentage_i$ represents the percentage of renewable energy adoption in households for country *i*

$\beta 0_i$ is the intercept of the model for country *i*

$\beta 1_i$ is the coefficient for the standardized weighted interest, which measures the intention to adopt renewable energy through green energy suppliers for country *i*
$\beta 2_i$ is the coefficient for the standardized home ownership percentage, representing the sociodemographic factor of home ownership for country *i*
ε_i is the standard error term of the model for country *i*

The linear regression models were estimated using the 'lm()' function in R. The significance of each predictor was assessed using the t-test, and the overall model fit was evaluated using the F-test. This was all done by using the 'summary()' function R.

3.5 Validation/verification

Residual diagnostics were performed to ensure the assumptions of the linear regression models were met. These included tests for linearity, autocorrelation, normality, and heteroskedasticity. Fitted values vs residuals plots were used to check for linearity, Durbin-Watson test was used to check for autocorrelation, Q-Q plots for normality, and the Breusch-Pagan test for heteroskedasticity. The results of these diagnostic checks are detailed in Appendix A. While these tests provided important insights into the data, the primary focus of the models was on exploring associations rather than making predictions. Consequently, given the small sample size and the exploratory nature of the study, the emphasis was placed on the overall patterns observed rather than strict adherence to diagnostic criteria.

Models that included one of the other sociodemographic variables were also considered but did not improve the model fit or give more significant results. Models were also estimated for the lower and upper bounds of the weighted interest to verify the stability of the results. These alternative models did not significantly alter the strength, direction, or significance levels of the associations observed. Given that our focus is on understanding associations rather than making predictions, the standard model was deemed sufficient for identifying these associations.

4 Results

In this chapter the results are presented, giving answers to the formulated research questions.

4.1 Intention to adopt renewable energy

To answer the first research question, the results of the Google Trends analysis will be given.

4.1.1 Descriptive statistics

The minimum, 1st quartile, median, mean, 3rd quartile, and maximum values for the specific, general, and weighted interest scores were calculated to understand the distribution and central tendencies of the interest data. Table 6 summarizes these statistics for both countries.

Table 6*: Descriptive statistics of interest scores*

Statistic	Specific Interest (DK)	General Interest (DK)	Weighted Interest (DK)	Specific Interest (NL)	General Interest (NL)	Weighted Interest (NL)
Min	14.58	38.33	31.50	27.17	62.67	43.09
1st Quart.	33.15	40.00	38.05	42.54	69.17	54.27
Median	35.81	43.08	40.70	49.08	70.25	56.75
Mean	38.35	49.07	42.96	48.69	73.38	58.07
3rd Quart.	46.17	52.62	48.22	56.92	79.08	63.85
Max	58.94	82.75	62.56	63.83	84.92	70.83

The results of this analysis were plotted using boxplots, as can be seen in Figure 3, and revealed several key insights. In Denmark, the average specific interest scores for renewable energy suppliers ranged from a minimum of 14.58 to a maximum of 58.94, with a median value of 35.81. The mean specific interest score was 38.35, indicating a moderate level of interest over the observed period. In the Netherlands, the specific interest scores exhibited a higher range, from a minimum of 27.17 to a maximum of 63.83, with a mean value of 48.69 and a median of 49.08. The general interest scores, representing a broader interest in renewable energy, ranged from 38.33 to 82.75 in Denmark, with a mean value of 49.07 and a median of 43.08. In the Netherlands, these general interest scores were also higher compared to Denmark, ranging from 62.67 to 84.92, with a mean of 73.38 and a median of 70.25. The weighted interest scores, calculated as a combination of specific and general interest scores, showed a range from

31.50 to 62.56 in Denmark, with a mean of 42.96 and a median of 40.70. The weighted interest scores in the Netherlands ranged from 43.09 to 70.83, with a mean of 58.07 and a median of 56.75, again exhibiting a higher interest than Denmark.

Even though Google Trends scores are normalized and relative to country and time, these results showed that in the Netherlands, the interest in green energy suppliers (relative to all other searches), which was used as a proxy for intention, was higher than in Denmark, suggesting a stronger intention to adopt green energy solutions compared to Denmark.

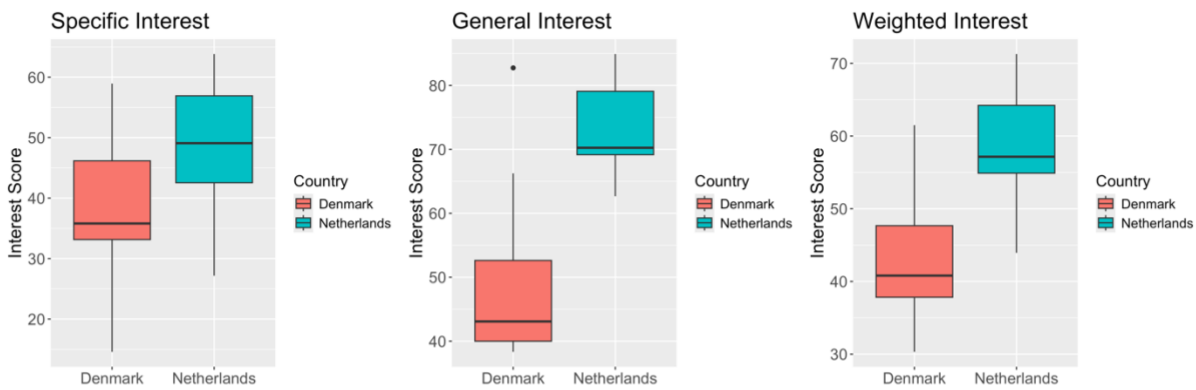

Figure 3: *Boxplots showing distribution and central tendencies of interests in renewable energy (suppliers)*

4.1.2 Trend analysis

The trend analysis for Denmark, as illustrated in Figure 4, reveals several patterns in the interest scores over the period from 2010 to 2020.

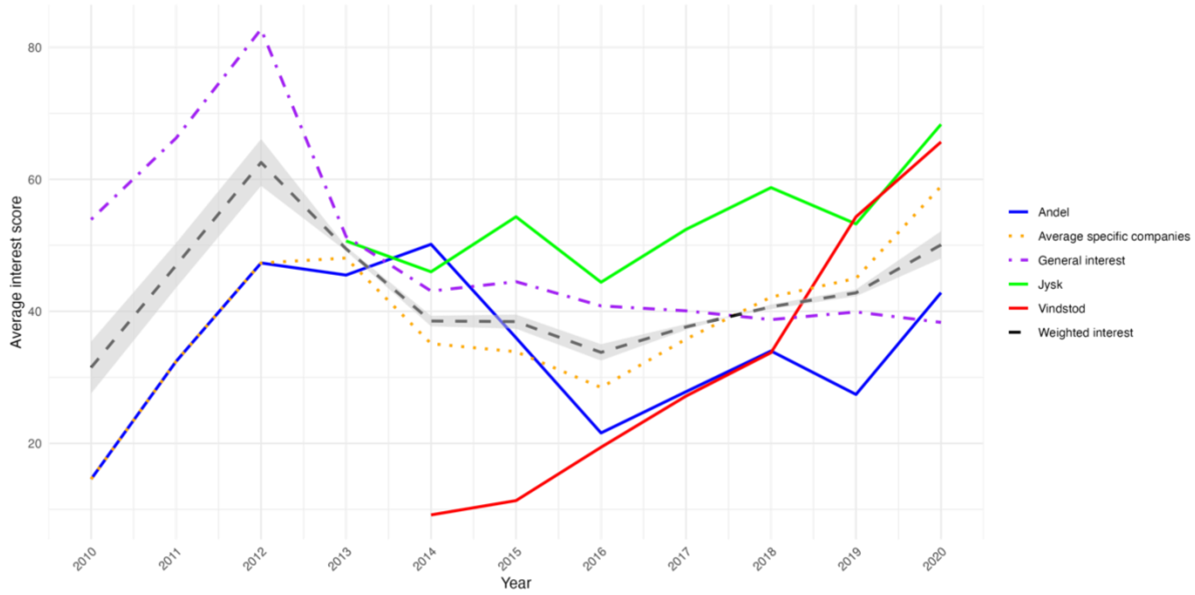

Figure 4: *Average interest scores per year for green energy companies in Denmark*

The general interest scores, represented by the purple dashed line, showed fluctuations throughout the observed period. General interest peaked around 2012, reaching its highest point before declining and stabilizing towards 2020 at a normalized score of around 40.

The average interest in specific companies, represented by the yellow dotted line, showed an initial increase in interest up to 2013, followed by a decline until 2016. In contrast to the general interest, the specific interest increased again towards 2020, reaching a peak in that year. This specific interest is an average interest score of three specific suppliers. Represented by the blue line, Andel's interest increased up to 2014, then declined until 2016, and slightly increased up to 2020. Represented by the green line, Jysk maintained a relatively stable interest level with some fluctuations, showing a slight increase towards the latter part of the observed period. Represented by the red line, Vindstød exhibited a clear upward trend since its start in 2014.

The weighted interest scores, represented by the gray dashed line, provide a measure combining both specific and general interests. The weighted interest peaked around 2012, mirroring the general interest trend, then showed a gradual decline followed by stabilization towards the end of the period. After 2016, the weighted interest increased slightly. The shaded area around the weighted interest line reflects the lower and upper bound of the weighted interest, reflecting possible variations in the interest score due to changes in the weighting factors.

Overall, while the general interest indicated a peak in 2012 followed by a decline and stabilization, the specific interest initially followed the same trend but increased again in later years. Combining these trends into a weighted interest trend shows that interest in green energy suppliers or companies, used as a proxy for intention to adopt green energy through green energy suppliers, peaked in 2012, then declined and stabilized before rising slightly again from 2016 to 2020.

The trend analysis for the Netherlands, as illustrated in Figure 5, reveals several patterns in the interest scores over the period from 2010 to 2020 as well.

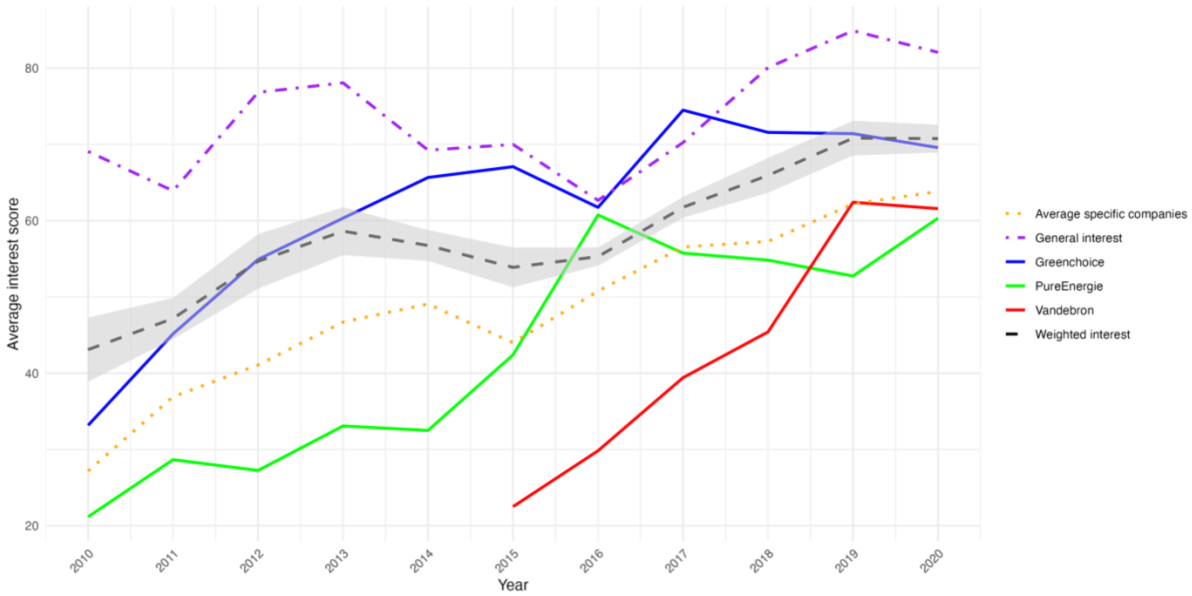

Figure 5*: Average interest scores per year for green energy companies in the Netherlands*

General interest remained high and relatively stable with slight variations, reaching its highest points around 2013 and again in 2019, stabilizing around the normalized score of 80.

The average interest in specific companies, represented by the yellow dotted line, showed a consistent upward trend throughout the observed period. This indicates a growing interest in specific renewable energy suppliers in the Netherlands over time. This specific interest is an average interest score of three specific suppliers. Represented by the blue line, Greenchoice's interest first showed a steady increase and stabilized in the last years. Represented by the green line, Pure Energie's interest generally increased over the entire period. Represented by the red line, Vandebron exhibited a clear upward trend since its start in 2014, showing a sharp increase in interest.

The weighted interest scores, represented by the gray dashed line, provide a measure combining both specific and general interests. The weighted interest showed a steady increase over the period, reflecting the combined effect of rising specific interest and stable general interest. The shaded area around the weighted interest line reflects the lower and upper bound of the weighted interest, reflecting possible variations in the interest score due to changes in the weighting factors.

Overall, the general interest indicated stable and high levels of interest in renewable energy over the period, while the specific interest demonstrated a clear and consistent upward trend. Combining these trends into a weighted interest trend shows that interest in green energy suppliers or companies, used as a proxy for intention to adopt green energy through green energy suppliers, steadily increased from 2010 to 2020. This suggests a growing intention among Dutch consumers to adopt green energy solutions over time.

These results indicate that the intention to adopt renewable energy at the household level was stronger and more consistent in the Netherlands compared to Denmark, as can be seen in the comparison in Figure 6. This result aligns with the theoretical framework, which indicates that the Netherlands exhibited a higher trend over time in renewable energy consumption and renewable electricity generation compared to Denmark. The weighted interest trend in the Netherlands showed a continuous increase, reflecting a growing intention to adopt green energy solutions over time, whereas Denmark's weighted interest trend revealed more variability with an initial peak, subsequent decline, and a slight rise towards the end of the period. Thus, the analysis answers the first research sub-question by demonstrating that from 2010 to 2020, the intention to adopt renewable energy at the household level was higher and steadily increasing in the Netherlands, while in Denmark, the interest peaked early in the decade and exhibited a declining trend after with an increase in recent years.

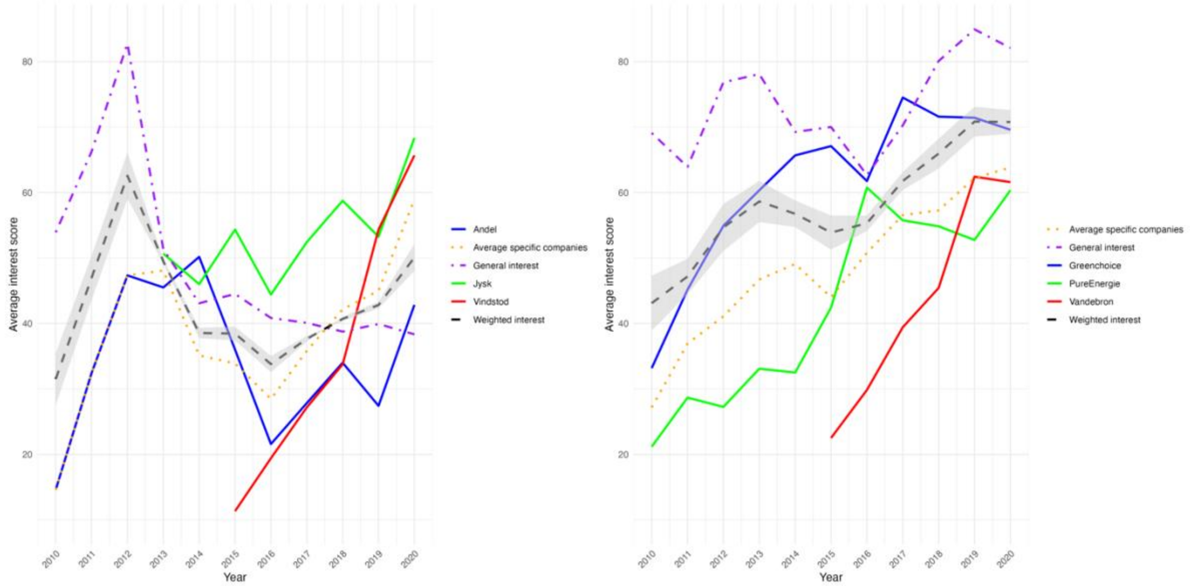

Figure 6*: Comparison between interests in renewable energy companies in Denmark (left) and the Netherlands (right)*

4.2 Correlation between intention and adoption

The correlation analysis results provided insights into the strength and direction of the relationships between the intention to adopt renewable energy, as measured by Google Trends interest scores, and the actual adoption rates of renewable energy at the household level in Denmark and the Netherlands from 2010 to 2020. The results are summarized in Table 7.

Table 7*: Correlation analysis between interest and adoption rates*

Variable	RE_Adoption_Percentage (Denmark)	RE_Adoption_Percentage (Netherlands)
Specific_Interest	0.09 (0.782)	0.89 (0.0003)***
General_Interest	-0.76 (0.006)**	0.43 (0.184)
Weighted_Interest	-0.45 (0.166)	0.83 (0.0016)**
Weighted_Interest_Lower	-0.57 (0.069)	0.80 (0.0034)**
Weighted_Interest_Upper	-0.31 (0.353)	0.85 (0.0008)***

Note. p-value placed in parentheses. Significant codes: 0.001’***” 0.01 ‘**’ 0.05 ‘*’

In Denmark, the correlation coefficients indicated that there was almost no correlation between specific interest and renewable energy adoption rates, with a correlation coefficient of 0.09 and a p-value of 0.7819, suggesting that this relationship was not statistically significant. The general interest scores, however, showed a strong negative correlation with renewable energy adoption rates, with a correlation coefficient of -0.76 and a p-value of 0.0062, indicating a significant inverse relationship. This suggests that higher general interest scores were associated with lower adoption rates. The weighted interest scores exhibited a moderate negative correlation with adoption rates, with a correlation coefficient of -0.45 and a p-value of 0.1658, which was not statistically significant. The lower bound of the weighted interest showed a stronger negative correlation with a coefficient of -0.57 and a p-value of 0.0687, approaching significance. The upper bound of the weighted interest had a weaker negative correlation with a coefficient of -0.31 and a p-value of 0.3534, which was not significant. Overall, these results show that weighted and specific interest do not have a significant correlation with adoption rates in Denmark, although the lower bound of the weighted interest is close to being significant.

In the Netherlands, the specific interest scores were strongly positively correlated with renewable energy adoption rates, with a correlation coefficient of 0.89 and a p-value of 0.0003, indicating a significant and strong positive relationship. This suggests that higher specific interest scores were associated with higher adoption rates. The general interest scores showed a moderate positive correlation with adoption rates, with a correlation coefficient of 0.43 and a p-value of 0.1839, indicating that this relationship was not statistically significant. The weighted interest scores displayed a strong positive correlation with adoption rates, with a correlation coefficient of 0.83 and a p-value of 0.0016, indicating a significant positive relationship. The lower bound of the weighted interest also showed a strong positive correlation with a coefficient of 0.80 and a p-value of 0.0034, and the upper bound of the weighted interest exhibited a strong positive correlation with a coefficient of 0.85 and a p-value of 0.0008, both indicating significant positive relationships.

These results suggest that in Denmark, higher general interest in renewable energy was associated with lower actual adoption rates, while in the Netherlands, higher specific and weighted interest scores were significantly associated with higher adoption rates. This indicates that the intention to adopt renewable energy, as measured by specific interest in green energy suppliers, played a more crucial role in influencing actual adoption rates in the Netherlands compared to Denmark. Because of the low significance of these correlations in Denmark, it could mean that intention is not necessarily translating into adoption. Based on the Theory of Planned Behavior, this could suggest the presence of barriers in behavioral control. Next to this, the correlations in Denmark were mostly negative while in the Netherlands, they were positive. This shows that there might be a difference in direction of the relationship between the countries.

4.3.1 Relation between intention, home ownership and adoption

The analysis of the linear regression models for Denmark and the Netherlands provides insights into how intentions to adopt renewable energy relate to actual adoption rates among households and highlights the role sociodemographic factors play in this relationship. Together with the correlation analysis, this answers the second and third research sub-questions.

For Denmark, the model summary is shown in Table 8.

Table 8: *Regression coefficients for linear model for Denmark*

Predictor	Estimate	Standard error	t value	p-value	Fit	F-statistic
Intercept	23.6680	0.2118	111.772	<.001		
Standardized Weighted Interest	-0.9679	0.2449	-3.952	.006		
Standardized Home Ownership	-0.8378	0.2449	-3.421	.011		
					Multiple R^2:0.8686 Adjusted R^2:0.8311	23.14 on 2 and 7 DF, (p-value<0.001)

The linear model for Denmark explains a significant portion of the variance in renewable energy adoption, with an adjusted R-squared of 0.8311, indicating a strong model fit. The coefficient for standardized weighted interest is notably negative and statistically significant ($\beta = -0.9679$, $p = 0.00552$), suggesting that an increase of one standard deviation in the standardized weighted interest in renewable energy is associated with a decrease of 0.9679 standard deviations in the adoption percentage of renewable energy among Danish households. This essentially means that higher search interest is linked to a decrease in adoption of renewable energy in homes. Additionally, an increase of one standard deviation in home ownership percentage is linked to a decrease of 0.8378 standard deviations in renewable energy adoption ($p = 0.01112$). This indicates that higher rates of home ownership are associated with lower adoption rates in Denmark.

Conversely, the regression model for the Netherlands, which explains about 62.77% of the variance (adjusted R-squared = 0.6277), shows a different relationship. The summary for this linear model can be found in Table 9.

***Table 9**: Summary of linear model for the Netherlands including regression coefficients*

Predictor	Estimate	Standard error	t value	p-value	Fit	F-statistic
Intercept	4.7682	0.1234	38.629	<.001		
Standardized Weighted Interest	0.4769	0.1829	2.607	.031		
Standardized Home Ownership	0.1127	0.1829	0.616	.554		
					Multiple R^2:0.7022 Adjusted R^2:0.6277	9.432 on 2 and 8 DF, (p-value=0.008)

Here, an increase of one standard deviation in the standardized weighted interest leads to an increase of 0.4769 standard deviations in the adoption of renewable energy ($p = 0.0313$). This positive relationship suggests that in the Netherlands, increased interest in renewable energy is effectively translated into higher adoption rates. However, the effect of home ownership on renewable energy adoption is not statistically significant ($\beta = 0.1127$, $p = 0.5549$), indicating that unlike Denmark, home ownership in the Netherlands does not significantly influence the adoption rates of renewable energy in the residential sector.

Comparatively, the findings illustrate national differences in how intentions to adopt renewable energy and sociodemographic factors relate to actual adoption rates. While both countries show a significant relationship between interest and adoption, the direction and magnitude of these relationships vary, with Denmark exhibiting a negative association and the Netherlands a positive one. Additionally, the impact of home ownership differs between the two countries. In Denmark, there is a significant negative association, whereas in the Netherlands, the association is positive but not significant. This contrasts with studies such as Bollino (2009) and Gu et al. (2019), who find a positive significant association.

5 Conclusion and discussion

This thesis explored the dynamics between the intention to adopt renewable energy and its actual adoption at the household level in Denmark and the Netherlands over a decade (2010-2020). Using Google Trends data as a proxy for public interest and intention, the study analyzed how this intention corresponds to actual renewable energy consumption patterns in households, while also analyzing the association with home ownership.

The analysis revealed that intentions, as measured by Google Trends, vary significantly between Denmark and the Netherlands. Interest in renewable energy in the Netherlands has been consistently higher and rising, in contrast to Denmark, where interest reached its highest point early in the decade, followed by a decline and eventual stabilization, with a slight uptick in recent years. This variance could stem from the Netherlands having a relatively lower baseline of renewable energy adoption, suggesting a greater potential for growth in interest and intention. Conversely, Denmark's higher baseline indicates a more mature market where a larger proportion of households have already incorporated green energy solutions. As a result, interest in green energy suppliers surged earlier and is now gradually stabilizing due to this market saturation.

In the Netherlands, there was a positive association between the intention to adopt renewable energy and its actual adoption, indicating that increased interest among households leads to greater adoption. This pattern aligns with the Theory of Planned Behavior, suggesting effective behavioral control where intentions can be readily translated into actions. This translation is likely facilitated by supportive policies and a market context where enough households still possess the necessary behavioral controls to actualize their intentions into concrete behaviors. In contrast, Denmark exhibited a more intricate relationship between intention and adoption. Higher levels of interest did not consistently correlate with increased adoption rates, and the linear model showed that higher interest even corresponded with declines in adoption. This phenomenon may once again be attributed to Denmark's more mature renewable energy market, where many households eager to adopt such technologies have already done so. The remaining households that have yet to adopt renewable energy may encounter obstacles in behavioral control, or their attitudes and social norms may not fully align with their intentions to adopt.

Home ownership played a differential role in the two countries. In Denmark, higher rates of home ownership were associated with lower adoption rates: something that is not supported by literature and that needs further investigation. In the Netherlands, home ownership did not significantly impact renewable energy adoption, which might indicate either a balanced market where renters and homeowners are equally likely to adopt renewable energy or effective policies that encourage renewable adoption irrespective of ownership status.

Thus, this study demonstrates that in the Netherlands, there is a positive association between the intention to adopt renewable energy and its actual adoption in households. Conversely, in Denmark, despite high initial interest, the relationship between intention and actual adoption is negative, likely due to market saturation where most interested households have already adopted renewable energy solutions. Additionally, higher rates of home ownership in Denmark are associated with lower adoption rates, suggesting barriers related to property ownership that do not significantly impact adoption rates in the Netherlands.

To optimize the transition towards renewable energy adoption, the Dutch Ministry of Economic Affairs and Climate Policy should leverage the existing positive association between the intention to adopt and actual adoption rates, while proactively addressing potential challenges that could arise from market saturation, as might be observed in Denmark. The Ministry should maintain the momentum by enhancing the visibility and appeal of green energy (suppliers) through targeted marketing campaigns and public endorsements. Additionally, to prevent the potential negative impact of market saturation seen in Denmark, the Ministry should focus on ensuring that households, particularly those that may lack behavioral control, receive substantial support. This could be achieved by offering tailored incentives for adopting solutions from green energy suppliers, such as reduced tariffs for energy produced by renewable sources. By ensuring these supports are in place, the Ministry can facilitate a smoother transition for all households, particularly those that are currently less engaged or face greater barriers, thus avoiding the pitfalls of market saturation and ensuring sustained growth in renewable energy adoption.

The findings of this study have to be seen in light of some limitations. Firstly, only one sociodemographic factor, home ownership, was included in the linear models. While this factor provided valuable insights, other sociodemographic factors could have further enriched the analysis and provided a more comprehensive understanding of the factors influencing residential renewable energy adoption. Additionally, the study had a small sample size, with only 11 years of data per country, which reduces the statistical power of the analysis and restricts the ability to include more variables.

Another limitation is the use of Google Trends data to measure the intention to adopt renewable energy through green energy suppliers. While Google Trends can provide insights into public interest and is an innovative approach, it does not necessarily always measure intention, and the reasons behind search term popularity can vary widely. This study also did not account for attitudes and social norms, key components of the Theory of Planned Behavior, which can significantly influence the intention to adopt renewable energy.

Furthermore, some evidence of heteroskedasticity in the data may have led to biased or inflated results, affecting the reliability of the regression coefficients. However, since this study was not about predicting future adoption rates, this was of less importance.

To address these limitations, future research should consider increasing the number of observations by including more years and additional countries. A larger dataset would allow for more comprehensive models that capture a wider range of factors influencing renewable energy adoption. With a larger dataset that includes multiple countries and years, a panel data structure could be employed, and a fixed effects or random effects model could be estimated.

Next to this, conducting surveys to gather data on attitudes and social norms related to the intention to adopt renewable energy in households would provide valuable insights regarding the intention. Surveys can also capture information on the percentage of households with green energy contracts in both countries, which was not readily available in this study.

Future research should also investigate the barriers households face in adopting renewable energy, particularly in countries like Denmark where market saturation may be an issue. Understanding these barriers and how policies can influence behavioral control would be valuable for developing strategies to increase adoption rates.

Moreover, it would be beneficial to study how home ownership affects renewable energy adoption in households. This study found that higher rates of home ownership in Denmark were associated with lower adoption rates, an interesting finding that warrants further investigation. Understanding why home ownership leads to a decrease in renewable energy adoption in Denmark could uncover important insights into the barriers faced by homeowners and inform policy measures to address these challenges.

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Appendix A Diagnostic tests for linear models

In this appendix, I present the results and interpretation of the diagnostic tests conducted to validate the linear regression models for Denmark and the Netherlands.

The Breusch-Pagan test was conducted to assess heteroskedasticity in the residuals. For Denmark, the test result was BP = 0.59353, df = 2, p-value = 0.7432. A p-value greater than 0.05 indicates no evidence of heteroskedasticity, suggesting the assumption of homoskedasticity is not violated. For the Netherlands, the test result was BP = 7.1191, df = 2, p-value = 0.02845. A p-value less than 0.05 indicates the presence of heteroskedasticity, suggesting that the variability of the residuals is not constant across all levels of the independent variables, potentially leading to biased estimates of the coefficients' standard errors.

The Durbin-Watson test was used to check for autocorrelation in the residuals. For Denmark, the test result was a DW Statistic of 1.845803 with a p-value of 0.376. A p-value greater than 0.05 indicates no significant autocorrelation, suggesting the residuals are independent. For the Netherlands, the test result was a DW Statistic of 2.102369 with a p-value of 0.616. Again, a p-value greater than 0.05 indicates no significant autocorrelation, suggesting the residuals are independent.

Q-Q plots were generated to assess the normality of residuals, as can be seen in Figure A1. For Denmark, the residuals align well with the 45-degree reference line, suggesting they are approximately normally distributed. Similarly, the Q-Q plot for the Netherlands shows that the residuals align well with the reference line, indicating approximate normality, especially considering the small sample sizes.

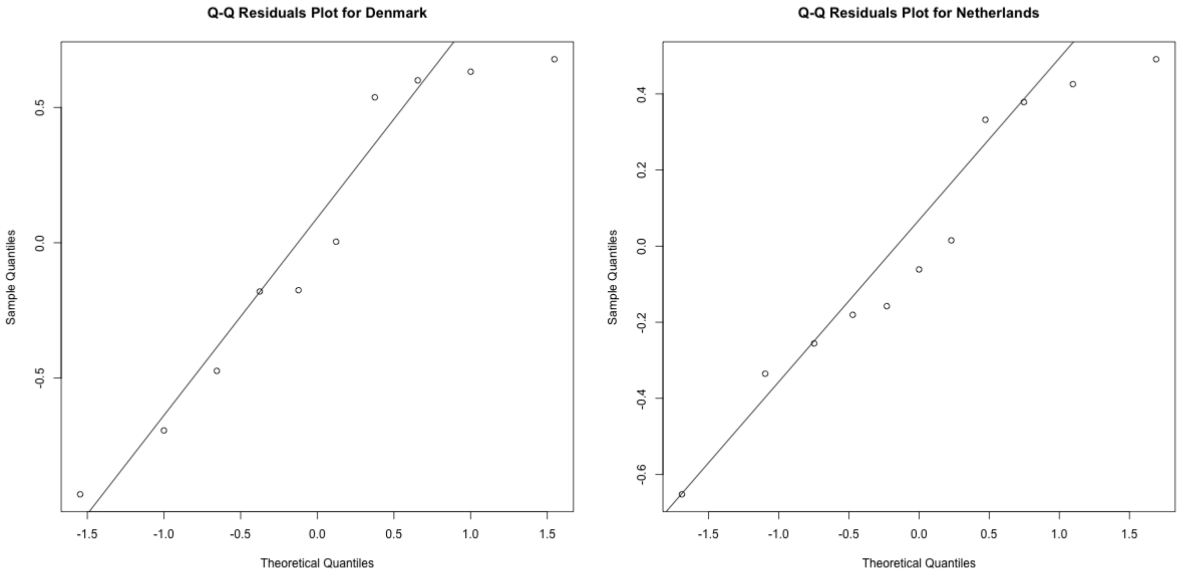

***Figure A1**: Q-Q Residuals plots for Denmark and the Netherlands*

The residuals vs fitted values plots for Denmark and the Netherlands, as shown in Figure A2, help diagnose potential issues with the linearity assumption in our regression models. Ideally, residuals should be randomly scattered around the horizontal line at zero, indicating a good fit. While the plots show some deviations, these are not necessarily problematic given the context. In Denmark's plot, a slight U-shaped pattern suggests some non-linearity, which could also be due to the small sample size rather than a fundamental issue with the model. The Netherlands' residuals are a bit more scattered, indicating variability but generally aligning with the expected distribution. Given the limited sample size of 11 observations per country, these plots should be interpreted cautiously. While they suggest areas for improvement, they do not necessarily undermine the overall validity of the model. The results should be seen as indicative rather than definitive, providing a useful exploratory analysis for understanding the association between the variables.

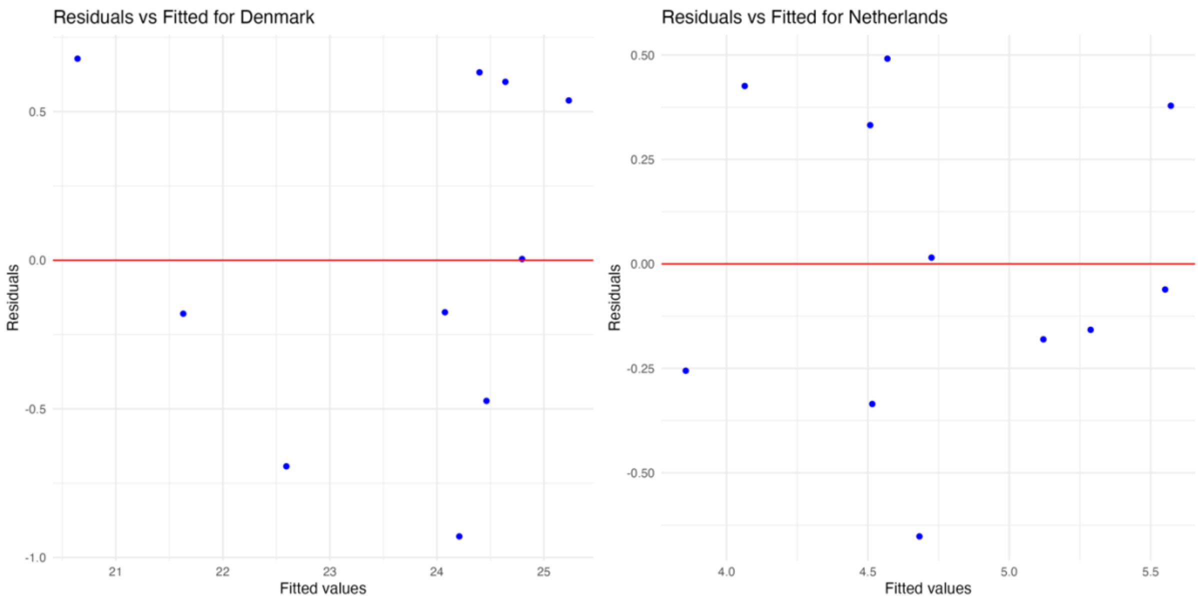

Figure A2: *Residuals vs fitted values plots for Denmark and the Netherlands*

Overall, the diagnostic tests indicate that the assumptions of homoskedasticity and normality are met for the Danish model, while the Dutch model exhibits heteroskedasticity. Despite this, the normality and autocorrelation assumptions are satisfied for both models. The linearity plots do show some deviations, which could also be due to the small sample size. Given the primary goal of examining associations rather than predictions and the limited sample size, these results provide a reasonable basis for the conclusions drawn in this study.