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Diffusion of photovoltaic systems and electric vehicles among Dutch consumers: implications for the energy transition

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Abstract

A key issue in smart grid visions is the integration of the energy and mobility systems. Electric vehicles (EVs) can be charged with renewable photovoltaic (PV) solar power, and contribute to the integration of solar power in the electricity network via vehicle-to-grid systems. In such systems the role of consumers becomes crucial as they both generate and store energy. We investigate differences between PV and EV adopter groups and the implications of these differences for the transition to smart energy systems. We study how socio-demographic characteristics of the consumer base influence regional diffusion patterns. In turn, we build scenarios to explore the influence of diffusion patterns on the viability of regional EV-PV integration in terms of energy use and regional self-consumption. The results point out large differences in the spatial diffusion patterns between EV and PV. These differences have implications for the transition to smart sustainable grids; vehicle-to-grid systems may not be viable for certain regions.

Main text

1. Introduction

Visions of a sustainable future couple the widespread diffusion of electric vehicles to energy supply from renewable sources [1]. In these visions, electric vehicles (EVs) act both as a source of demand [2] and a storage option for excess renewable energy in vehicle-to-grid (V2G) systems [3]. The adoption and use of renewable energy technologies and electric vehicles by consumers will determine the characteristics of the future electricity grid. Independent micro-grids are a likely outcome when the same consumers adopt both technologies [4]. But if the two technologies appeal to different groups of consumers in different regions, national (super-) grids may be needed to interconnect local grids [4][5]. Understanding these interactions requires a co-adoption perspective [6], as well as taking into account consumer heterogeneity and spatial diffusion patterns. We study the early market development of different clean energy technologies to gain insights in which solutions for integrating these technologies in the existing infrastructure are viable and what their potential contribution to a future more sustainable energy and mobility system is.

More specifically, in this paper, we compare and link the adoption of photovoltaic (PV) solar power and electric vehicles (EVs) by using unique micro-level diffusion data. As a case study we focus on the Netherlands. Our empirical work consists of two parts. First, we analyse the recent diffusion of PV and EV in the Netherlands, and characterize the adopters of these technologies, by linking diffusion data to neighbourhood characteristics via a regression
model. This provides insights in the potential for co-adoption and a profile of the early adopters. Using the Bass model of diffusion [7], we estimate future diffusion of PV and EV for different regions of the Netherlands. We use PV self-consumption as a central concept to link these two technologies. PV self-consumption refers to how much electrical energy is consumed by the loads supplied by the local PV solar panels [8]. Higher levels of PV self-consumption will result in decreased stress on the electricity grid and therefore easier integration of PV solar panels in the existing infrastructure. Several countries including China, Japan and Italy have policies in place to increase PV self-consumption of households [9]. PV self-consumption can be increased by energy storage and demand side management (DSM) [9]. EVs can contribute to load balancing via smart charging and V2G [10]. Combining adopter profiles with scenario analysis enables us to investigate the viability of V2G systems and come to policy recommendations.

Our study offers a new approach for taking users into account in energy systems modelling, using a variety of modelling techniques. Hereby, we quantitatively demonstrate the large impact users have on the viability of the EV-PV combination in a future energy system. Our model estimates the viability of V2G systems for different energy scenarios and contributes to the larger effort of integrating insights from social sciences with energy science [11]–[13]. The remainder of the paper is structured as follows. Section 2 discusses the background of our study, section 3 our methodology and section 4 the results. In section 5 we discuss the main contributions, limitations and policy implications of our study and section 6 concludes the paper.

2. Background
The European Union has the ambition to increase adoption levels of both PV solar panels and EVs. Recently, the European Parliament has voted to ensure that by 2030, half of electricity demand should be produced by wind, solar and biomass [14]. Furthermore, the European Commission has put forward legislative measures that should support energy consumers to become prosumers with PV solar panels [15]. EVs are regarded as having the potential benefits of reduced oil consumption and reduced emissions of CO\textsubscript{2} and other pollutants [16]. The European Commission supports a European wide electromobility initiative called Green eMotion\textsuperscript{1}, aiming to facilitate EV market roll-out.

In the Netherlands, PV and EV adoption sharply increased in recent years. In 2016, installed PV capacity rose to 2.1 GWp [17]. In 2015, the Netherlands ranked 4th in installed PV capacity and 9th in cumulative installed PV capacity for the EU-28 [18]. The number of registered battery electric vehicles (BEVs) increased by 40% to 13,105 in 2016, and the number of registered plug-in hybrid EVs (PHEVs) increased by 27% to 9,8903 [19]. In 2015, 9.7% of newly registered cars were EVs, and the Netherlands had the most EV sales within the EU [20]. Both technologies have large potential for growth, since less than 6% of household rooftops have solar panels, in total providing less than 1% of total annual electricity production, and BEVs and PHEVs combined amount to less than 2% of the total car fleet in the Netherlands. The broadly supported National Action Plan on PV power states a target of 10 GWp in 2023 [21]. The Dutch government has the ambition that by 2030 all new vehicles sold in the Netherlands are zero-emission vehicles [22].

There is both a daily and seasonal mismatch between household electricity demand and PV production. Most PV power is produced around midday, when demand is low. Demand is

\footnote{See \url{http://www.greenemotion-project.eu/} for program website}
high in the winter and low in the summer, as the Netherlands has cool summers and moderate winters. To address the imbalance between PV power supply and household demand several Dutch on-going projects aim at developing smart charging of EVs and V2G [23]. Combined with being a front-runner in EV deployment, this makes the Netherlands a good case for studying the integration of PV and EV.

The uptake of new technologies usually follows an S-curved pattern where diffusion is initially slow, followed by a take-off phase of fast diffusion before the diffusion levels off and the market is saturated. Rogers [24] explains this S-curve from social processes where different groups, with different socio-demographic characteristics, decide to adopt the innovation at different points in time, starting with adoption by innovators followed by early adopters, early majority, late majority and laggards. Following Rogers’ classification, the diffusion of PV is in the early adoption stage and the diffusion of EV is in the innovator stage in the Netherlands. Insight in the characteristics of innovators and early adopters is pivotal as these are key groups in the diffusion process and shape the early market.

There is a growing body of literature focusing on the drivers and barriers of both PV adoption and EV adoption. In the case of PV adoption, studies have focussed on the role of costs [25]–[30], environmental attitudes [25], policy incentives [31], [32], business models [33]–[35], and peer effects [36]–[39]. Several studies on PV diffusion identify socio-demographic factors drive unique diffusion patterns [25], [39]–[47]. Factors consistently found to have a positive effect on PV adoption are the proportion of middle-aged residents [25], [39], [41] and education level [39], [41], [43]. Interestingly, the effect of income differs among these studies, with some studies finding a positive effect [30], [40], [41], [47] and others finding a negative effect [28], [39], [44], [46]. Other factors found to have an influence are political preferences [41], [47], ethnicity [41], lifestyle [43], housing density [38], [40], [41], and house ownership [25], [42]. Research on factors affecting EV adoption has mostly focused on the role of costs, charging infrastructure and individual factors such as range anxiety, emotions, attitude towards the environment and symbolic attributes of EVs [48]–[50]. Furthermore, several studies stress the influence of socio-demographic factors on EV diffusion [51]–[54]. A notable difference between these studies and studies on PV adoption mentioned earlier [39]–[43] is that in studies on EV adoption the socio-demographic factors are usually discussed as input for a diffusion model and not the key focus of the research. Factors found to have an effect on EV adoption are income [51]–[53], size of the local car fleet [52], education level [51], family composition [51], [54], and political preferences [55].

The scientific literature on the influence of socio-demographic factors on PV and EV diffusion patterns allows for indirect comparison of PV and EV adopter groups. In this study we directly compare the socio-demographic characteristics of EV and PV adopters on a neighbourhood level to get insight in the general profiles of both EV and PV adopters.

We complement these profiles with estimations of future diffusion of PV and EV to investigate its impact on the energy system and come to overall conclusions and policy recommendations. Several approaches to diffusion forecast modelling exist, with varying aspects of focus and levels of refinement [56], [57]. Models used for forecasting PV diffusion include the Bass model [31], [58], [59], which has its roots in the diffusion of innovation theory formulated by Rogers [24] and agent based models (ABMs) [43], [60], [61]. ABMs are a popular tool for forecasting EV [53], [54], [62]–[68]. Other studies base their forecasts on methods using s-curves, such as the Fisher-Pry model [52], pearl curves [69], and the Bass model [70]. In the latter study, the Bass model is combined with discrete choice models and
system dynamics. S-curve approaches such as the Bass model offer less flexibility than ABMs, since these are basically an extrapolation of current trends. S-curves are often used as forecasting tools rather than as tools to perform ex-ante policy evaluation. One of the major advantages of ABMs is that such models offer a flexible environment allowing the inclusion of a wide variety of factors such as social networks, subsidy schemes, and information campaigns, while at the same time enabling the use of theoretical models such as the Bass model. A main application of agent-based diffusion models is ex-ante comparison of policies aimed at stimulating diffusion.

We use the Bass model of diffusion to estimate the future diffusion of both technologies. The Bass model of diffusion uses Rogers’ classification of adopters; innovators can decide to adopt an innovation at any point time, while the timing of adoption for all other groups depends on the decisions of other members in the social system. In this epidemic model of diffusion, adoption patterns are ultimately determined by the spread of information amongst consumers. The Bass model is well suited for application on micro-level diffusion data as available in the present study, and has been applied before for both PV diffusion [31], [58], [59] and EV diffusion [70], as well as for analysing differences in diffusion among regions within a country [71]. We prefer to use the Bass model over other formulations of s-curves since, in contrast to for instance the Fisher-Pry model, its parameters can be directly linked to concepts from innovation diffusion theory, such as the spread of information and heterogeneous consumer groups.

3. Methods
This section discusses our data sources and methodology. Our methodology consists of two parts. First, we link PV and EV adoption levels to neighbourhood characteristics via a regression model. This will allow us to contrast and compare the adopter groups for these technologies, using country level data. Second, we investigate the implications of the differences between these adopter groups by estimating future diffusion of PV and EV via the Bass model of diffusion, and link these estimates to the energy systems. Section 3.1 presents our data sources, section 3.2 presents our method for the regression analysis and section 3.3 introduces the Bass model of diffusion. Finally, we present our method to link the diffusion of PV and EV to the energy system in section 3.4.

3.1 Data
We use a variety of datasets coming from different sources, most of them starting from the year 2005. The data comprise number of PV installations, the number of electric vehicles and public charging stations, open data from distribution grid operators, solar irradiation, socio-demographic data, cadastral maps, number of voters of GroenLinks political party (left-wing, green party), number of municipal council members belonging to GroenLinks. Table 1 presents specifications of the datasets we have used in our analysis. Most of our data is available at four-digit postal code level (PC4). The Netherlands is divided in 4052 four-digit postal codes with an average of 4160 inhabitants (s.d. = 4134).
| Dataset                          | Source                                           | Description                                                                 | Spatial resolution | Years       |
|---------------------------------|--------------------------------------------------|-----------------------------------------------------------------------------|--------------------|-------------|
| PV installations                | Production installation register                 | PV adoption data including date of placement and nominal power              | PC4                | 1968-2015   |
| Electric vehicles               | Netherlands Vehicle Authority                    | EV adoption data including date of first admission                          | PC4                | 1904-2016   |
| Public charging stations        | Netherlands Vehicle Authority                    | Public charging stations                                                   | PC4                | 2014        |
| Open data distribution grid     | Lander, Stedin, Enexis, Enduris                  | Data on energy use of households                                           | PC6                | 2009-2015   |
| Solar irradiation data          | Royal Netherlands Meteorological Institute        | Solar irradiation in de Bilt, available per hour for 2014                  | -                 | 2014        |
| Socio-demographic data          | Central Bureau of Statistics of the Netherlands   | Population and housing characteristics, car fleet                          | PC4                | 2009-2014   |
| Cadastral map                   | The Netherlands’ Cadastre, Land Registry and Mapping Agency | Building characteristics                                                   | m²                 | 2015        |
| GreenLeft voters                | Stichting Politieke Academie                     | Number and percentage of GroenLinks voters for the national election 2010 in polling places within neighbourhood | PC4                | 2010        |
| GreenLeft municipal council      | Groenlinks                                       | Number of municipal council members affiliated with GroenLinks              | Municipality       | 1994-2014   |

**PV installations**
In the Netherlands PV installations are registered in the production installation register (PIR), an initiative by the Dutch grid operators. The register contains information on the address of installations, the date of instalment and the nominal power. In the version of the dataset available to us the information on address is aggregated to PC4-level. For installations registered before the 1st of April 2014 we know the date of instalment. For installations registered between the 1st of April 2014 and the third of July 2015 we only have the year of installation. In total 277,373 installations are included in the register.

**Electric vehicles and public charging stations**
In the Netherlands all vehicles are registered by the Netherlands Vehicle Authority (RDW, in Dutch: Rijksdienst voor het Wegverkeer). The register contains information on the vehicle name, type and technical specification, the address of registration and the date of first admission. In the version of the dataset available to us the information on address is aggregated to PC4-level. It contains information on all alternative fuel vehicles, including passenger cars, business cars, busses, motor bikes and mopeds up to the 12th of May 2016. In total 310,073 alternative fuel vehicles are registered, of which 189,507 passenger cars. 114,505 of these are plug-in EVs.

Lease vehicles are often registered at a lease company. A lease vehicle will most often not be located in the same PC-4 area as it is registered. To deal with this issue we exclude PC-4 areas with major lease companies from our analysis, since the total number of EVs registered in that area will highly overestimate the total number of EVs actually located in that same
area. Based on a web search, we have identified 39 PC4 areas with large lease companies (see Table A.1 in Appendix A) with a total number of 42619 EVs registered (37% of the total EV fleet).

Also registered by the RDW are the public charging stations. The dataset includes information on the location, owner and technical specifications on all public charging and semi-public charging stations in the Netherlands. In the version of the dataset made available to us the information on the location is aggregated to PC4-level and contains charging stations registered before the 1st of January 2015. In total 7589 charging stations are included in the register.

Open data distribution grid operators
The four major grid operators of the Netherlands, Liander, Stedin, Enexis and Enduris, publish data on the energy use of households [72]–[75]. In this study we make use of the data on yearly electricity use of households, aggregated to PC4-level, and the profile of the yearly electricity use of an average household. Data on the latter one is published by Liander and available for a whole year with a one-hour resolution. The four major grid operators cover 92% of all postal codes of the Netherlands.

Solar irradiation
For our model of PV production, we use solar irradiation data as measured in 2014 in the Bilt, the Netherlands (latitude: 52.11°, longitude: 5.18°) by the Royal Netherlands Meteorological Institute (KNMI) [76]. The interval of the measurement for radiation data was 10 minutes and for the temperature and pressure values one hour.

Socio-demographic data
Most of the socio-demographic data we use in our analysis comes from the Central Bureau of Statistics (CBS) of the Netherlands. The CBS collects, edits and publishes national statistics related to societal needs[77]. Methods include collecting data from other registers, surveys and interviews. The variables we use in our analysis are from the years 2009 to 2014 and are aggregated to PC4-level.

Cadastral map
The Netherlands’ Cadastre, Land Registry and Mapping Agency publishes the cadastral map of the Netherlands. Municipalities are responsible for recording data on all buildings in the Netherlands, and the data is made available for the whole of the Netherlands. The map includes information on the location of addresses, the building footprint and the function of the buildings. We use the register to calculate the amount of rooftops and the building footprint of buildings with a residential function for every four-digit postal code of the Netherlands.

GroenLinks voters
The organisation Politieke Academie offers data-analyses of voters in the Netherlands. We use their data for the absolute number and percentage of GroenLinks voters for the national elections of 2010. GroenLinks got 624732 votes, 6.6% of total votes. In this election every voter was permitted to vote anywhere in the municipality of residence. At request it was also possible to vote in other municipalities. One should thus be careful with interpreting what the percentage of voters in a PC4-area says about the inhabitants of the area.

GroenLinks municipal council members
We acquired a dataset from the political party GroenLinks which contains the number of
municipal council members affiliated with GroenLinks. Since 1994, GroenLinks has had 309 council members, serving 481 terms in 161 different municipalities.

3.2 Characterization of PV and EV adopters

To characterize PV and EV adopters we performed two ordinary least squares (OLS) regressions, one with the number of PV installations per person and one with the number of EVs per person as the dependent variable. The level of our regression analysis is four-digit postal codes (PC4). The Netherlands is divided in 4052 four-digit postal codes with an average of 4173 inhabitants (with standard deviation of 4130). We log-transformed the dependent variables to produce normally distributed model residuals. Furthermore, before log-transforming we add the number 1 to the dependent variable, to deal with zeros in the dataset. This results in the following model:

\[
\log(Y_i + 1) = \alpha + \beta X_i + \epsilon
\]

where \(Y_i\) is the dependent variable for PC4 code \(i\), \(X_i\) the vector of explanatory variables for postal code \(i\), \(\alpha\) the intercept, \(\beta\) the vector of coefficients for the explanatory variables and \(\epsilon\) the random error coefficient. This analysis assumes spatially independent errors.

Our model enables us to characterize PV and EV adopters by yielding the best predictors for historical adoption at the neighbourhood level. We cannot be sure whether an explanatory variable drives the adoption process or rather serves as a proxy for an adoption driver. It is therefore important to interpret model results as predictors and not as drivers of adoption.

Based on the current EV and PV literature, various potentially related independent variables are included, presented in Table 2. To address the spatial structure of the neighbourhood, we include the address density. From what has been established in previous analyses, PV adoption tends to be lower in high density environments [38], [40], [41] whereas EV adoption has found to correlate positively with urbanity [52]. Also the classical adoption factors age, education are income are included [24]. Some studies on PV adoption have identified lower adoption rates among younger adults [25], [41]. For EV no strong indications could be found in previous research. To clarify age effects, in this study we include the proportions of younger (25-45) and older (45-65) middle age groups. Level of education is found as a factor predicting PV and, generally, EV adoption [30], [39], [41], [42], [46], [49], [51]. We include the percentage of lower educated in a neighbourhood, and consequently expect a negative effect of this factor on adoption. Interestingly, the effect of income differs among PV studies, with some studies finding a positive effect [30], [40], [41], [47] and others that see higher adoption among lower income groups [28], [39], [44], [46]. Uncertainty about the income effect is also present in the EV literature [49], though several studies do find a positive effect of income on EV adoption [49], [51]–[53]. We have additionally included a variable for household size, following indications in both the EV and PV literature that family households are more likely to adopt [45], [51]. Studies on both PV and EV adoption are cautious about the influence of environmental awareness [25], [44], [47], [78], [48]–[51]. To investigate the role of environmental awareness in PV and EV adoption, we included the percentage of voters for GroenLinks, the Dutch green party. To capture municipal policy favouring EV and PV, we have included a dummy variable indicating the presence of the GroenLinks in the municipal council. This party favours both technologies heavily, as part of a broader sustainability agenda\(^2\). We have additionally included variables exclusively for PV: the

\(^2\) See https://groenlinks.nl/standpunten for the political stance of GroenLinks (in Dutch)
number of rooftops per person, as control for total market size, and the total building footprint of households per person in the area, as an approximation for the size of rooftops. Finally, we have included two dependent variables exclusively for EV: the number of passenger vehicles per person, as control for total market size and expected to have a positive effect [52], and publicly available charging points per capita, as indicator for municipal policy (local government’s play a large role in the build-up public charging structure in the Netherlands).

Table 2 Description of independent variables used in regression models. The variables are explained and it is specified in which model they are used. Finally, we include the expected the effect of the variables will be on adoption levels, based on earlier literature. + indicates that positive effects have been found, - indicates that negative effects have been found, and +/- indicates that both positive and negative effects have been found.

| Variable name                          | Variable description                                           | Data source                                                                 | Used in model for: | Expected effects on PV adoption | Expected effects on EV adoption |
|----------------------------------------|----------------------------------------------------------------|----------------------------------------------------------------------------|-------------------|---------------------------------|---------------------------------|
| Address density (per km²)              | Number of addresses per km²                                    | The Netherlands’ Cadastre, Land Registry and Mapping Agency                 | PV and EV         | -                               | +                               |
| Age 25-45 (%)                          | Percentage of population between age 25 and 45                  | CBS                                                                        | PV and EV         | -                               |                                 |
| Age 45-65 (%)                          | Percentage of population between age 45 and 65                  | CBS                                                                        | PV and EV         | +                               |                                 |
| Household income (Euros)               | Average income of households                                   | CBS                                                                        | PV and EV         | +/-                             | +/-                             |
| Household size (persons)               | Average number of persons per household                        | CBS                                                                        | PV and EV         | +                               | +                               |
| Lowly educated (%)                    | Percentage of population with education level not higher than primary school or vmbo (lower vocational education) | CBS                                                                        | PV and EV         | -                               | -                               |
| GreenLeft municipal council members since 2006 (Y/N) | Whether or not GreenLeft (GroenLinks) had alderman in 2006-2014 | GroenLinks                                                                 | PV and EV         |                                 |                                 |
| GreenLeft voters 2010 (%)              | Percentage of GreenLeft (GroenLinks) voters for the national elections of 2010 | Politieke Academie                                                        | PV and EV         |                                 |                                 |
| Household rooftops (pp)                | Number of household rooftops per person                        | The Netherlands’ Cadastre, Land Registry and Mapping Agency                 | PV                |                                 |                                 |
| Total building footprint (m² pp)       | Total building footprint of households in m²                    | The Netherlands’ Cadastre, Land Registry and Mapping Agency                 | PV                |                                 |                                 |
| Passenger vehicles (pp)                | Number of passenger vehicles                                   | CBS                                                                        | EV                |                                 | +                               |
3.3 Estimating future diffusion of PV and EV

To estimate future diffusion of PV and EV, we use the Bass model of diffusion. The model describes the typical S-curve of innovation adoption and assumes that purchase decisions are influenced by external sources and internal sources, which creates two distinct groups of adopters: the innovators and the imitators. The mathematical formulation of the model is:

\[
\frac{f(t)}{1-F(t)} = p + qF(t)
\]

(2)

where \(f(t)\) is the change of the installed base fraction, \(F(t)\) is the installed base fraction, \(p\) is the coefficient of innovators and \(q\) is the coefficient of imitators.

The cumulative number of adopters can be described by:

\[
A(t) = m \frac{1-e^{-(p+q)(t-t_0)}}{1+q \frac{p}{p+q} e^{-(p+q)(t-t_0)}}
\]

(3)

where \(A(t)\) is the cumulative number of adopters, \(m\) is the total market size and \(t_0\) is the time at which diffusion starts. We then predict the amount of PV adopters and EV adopters by fitting Equation (3) to the available data, using a non-linear least squares method based on the numerical global optimization algorithm \textit{NMinimize} in Wolfram Mathematica 11.1.

We made an estimate of the total market size (parameter \(m\)). For PV, we assume the market size to be equal to the number of rooftops in an area, while for EV we assume the market size to be equal to the number of vehicles in an area. We consider both estimates to be optimistic, since not every rooftop is suitable for PV and not every vehicle could be replaced by EV. The results from our study can therefore be considered optimistic; both on how much PV can contribute to electricity production and on how much EVs can contribute to load balancing. We have performed a sensitivity analysis on total PV and EV market size to investigate the effect of our estimates on the final results.

The Bass model describes aggregated diffusion patterns, and is not bound to a specific spatial scale. The model could hold for cities, countries, continents or the world, dependent on the specific patterns of the technology diffusion. However, the model is not useful for small scales, for our case the neighbourhood level, since there is not enough aggregation of adopters.

In our study, we modelled the diffusion of so-called NUTS-3-regions in the Netherlands [79]. The Netherlands is divided into 40 NUTS-3-regions, which are used for analytical purposes and are constructed based on a nodal classification principle. The uptake of EV and PV in these areas shows the typical pattern of aggregated innovation diffusion. One of the major

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3 The variable passenger vehicles (pp) contains some outliers, due to vehicles registered at company addresses. The Dutch statistics agency has also published a cleaned dataset with solely private cars on the “neighbourhood” (N=3096) level [99]. This is an aggregation level comparable to the (N=4048) postcode areas of this study. In this dataset no neighbourhoods have > 1 car per inhabitant. Based on this dataset, we have decided to remove all neighbourhoods with more than 1 car per capita from our analysis.
advantages of using the NUTS-3-level is that a large share of commuting takes place within these regions, so that it is reasonable to assume that EVs stay within the same area during the day.

3.4 Consequences for the transition to sustainable energy

We use the results from the Bass model of diffusion to investigate the impact of PV and EV diffusion and the energy system. In order to do so, we link several datasets and run simulations on the potential contribution of V2G systems to increasing the PV self-consumption of NUTS-3-regions in the Netherlands. Figure 1 presents an overview of our method, while the rest of this section details the data sources and calculation methods for the different model elements.

![Figure 1](image)

**Figure 1** Overview of our method to calculate the impact of PV and EV diffusion on the energy system for each NUTS-3 region in the Netherlands. We use the number of PV installations and EVs as predicted by the Bass model and combine this with data and estimates of average PV yield, household electricity demand, EV charging demand, available storage for V2G and hourly profiles to construct hourly profiles for electricity production, demand and available storage. The first two of these are used to calculate the annual electricity demand and supply, while all three profiles are used to calculate the self-consumption of a region.

3.4.1 PV-power production

We compare the estimated annual energy yield of PV installations to total annual electricity demand for each NUTS-3 area. We estimate the annual energy yield by multiplying the amount of PV systems, following from the Bass model, with the average nominal power of the PV systems and the specific PV yield.

We use the following assumptions. First, we assume that the average nominal power of PV systems is constant over time. Since 2011 the average nominal power of new PV systems has remained roughly constant, varying between 3.8 and 4.2 kWp. The current average nominal power of PV systems does vary between different NUTS 3-areas, from 2.4 to 5.5 kWp. However, it is not clear what this current variation will mean for future PV-installations. Therefore, for the sake of simplicity, we choose a constant average nominal power across the NUTS-3-areas. Secondly, we assume the specific annual PV yield to be 875 kWh/kWp, which...
is the current adopted average PV yield for the Netherlands [80]. As the efficiency of PV systems is expected to increase due to technological developments, this yield can be expected to increase as well. However, PV systems will increasingly be installed in residential areas where some rooftops are better suitable for PV than others, for instance due to orientation and shading, decreasing the average PV yield. To investigate this effect, we perform a sensitivity analysis with varying PV yields and PV orientations.

In order to explore how a possible transition towards a system in which PV solar panels produce enough energy to cover all demand for residential electricity and EV charging, we ran additional simulations. We calculated the average nominal power needed for this scenario to be 12.9 kWp, more than three times the current average of 4 kWp. Though the efficiency of PV solar panels still increases, it seems unlikely that increases in efficiency will be enough to reach this average nominal power of rooftop PV systems. However, factors other than increased efficiency could also contribute to an increased PV yield per household. Current experiments with local energy cooperatives [81], [82] or crowdfunding [83] show promising signs of allowing consumers to invest in PV systems not placed on their own rooftop. As a transition to a system based on 100% PV seems unlikely, we include these results from our simulations in as an ‘extreme’ benchmark scenario, and relate the results to the discussion of off-grid PV solar based systems.

We model hourly PV yield with the open source package PVLIB [84], based on KNMI solar irradiation data. Specifications of the Sanyo HIP-225HDE1 module and the Enphase Energy M250 inverter were used as input for the model. The modelled PV modules have an azimuth of 180 degrees and a tilt of 37 degrees, which are the optimal conditions for PV production in the Netherlands [85]. Figure 2 presents the resulting PV-power production. As the diffusion of PV solar panels progresses more panels will be installed on rooftops with sub-optimal orientation. This will alter the shape of the hourly PV yield profile. Solar panels directed to the east will produce more energy in the morning as compared to solar panels directed to the south, and solar panels directed to the west will produce more energy in the evening compared to other directions. To investigate the effect of PV panel orientation we include different PV orientations in our sensitivity analysis.

![Figure 2](image-url)  
**Figure 2** PV yield and household load profiles, a) hourly PV yield (3.5 kWp system size) and household load, both averaged over a whole year; b) daily PV yield (3.5 kWp, 2014) and household load. The total annual PV yield covers total annual household electricity demand. PV yield is modelled with PV LIB [84] using data provided by KNMI [76], household load is based on data provided by grid-operator Liander [72]

### 3.4.2 Electricity demand households

We calculate the annual electricity demand from aggregating the data on total household electricity demand of 2015 as provided by the Dutch grid operators to the NUTS-3 level [72]–[75]. Finally, we assume that the total household electricity demand stays constant over time.
The growth in household electricity demand in the EU-15 has been very limited, only 1%/a in the period 2000-2010 and household electricity demand is projected to decline with 0.6%/a in the period 2010-2020 and 0.3%/a in the period 2020-2030 [86]. Given these small effects we deem our assumption to be reasonable. The hourly profile of household demand is based on data published by Liander [72] and presented in Figure 2.

3.4.3 Electricity demand EVs

To calculate the annual electricity demand of EVs, we assume that EVs drive on average the same distance as passenger vehicles do now, around 13,000 km per year for the Netherlands [77]. Assuming an average driving efficiency of 0.2 kWh/km and an average battery conversion efficiency of 90%, i.e., similar to a previous study [10], the annual electricity demand of an EV is ~2900 kWh. We then construct an hourly demand profile for EVs based on data from June and December 2012 published by the foundation E-Laad [87]. We thus assume that the charging patterns of EVs stay the same over the years. It is uncertain how realistic this assumption is, because of the developments in the field of smart charging. Smart charging (i.e., shifting in time of EV charging patterns) could, in addition to vehicle-to-grid, further increase self-consumption of PV-power, but is outside of the scope of this study.

3.4.4 Self-consumption

We define self-consumption as the percentage of locally produced (within the region) PV power used within an area, either by the households or EVs connected to charging stations. Note that we use the concept of self-consumption on a regional scale, and not on the household level for which it is typically used. A high level of self-consumption is beneficial for the integration of distributed energy sources in the electricity grid, since power transport over the grid decreases when the energy produced is consumed locally. PV self-consumption can be increased by storing energy in batteries or shifting demand to times of energy production (DSM) [9]. For the present study we only look at the potential contribution of EVs to increase self-consumption as it is currently not attractive for Dutch consumers to invest in PV storage systems, because of the national net-metering policy and the adoption level of PV storage systems is negligible. The Dutch government has announced to change the net-metering policy [22], which will most likely result in a more positive business case for PV storage in the future.

In order to calculate the total self-consumption for the NUTS-3 areas we use the hourly profiles for PV yield, household demand and EV demand. By comparing the PV yield with the electricity demand we can determine the surplus or shortage of PV power to cover demand for each hour of the year. We then assume that all the EVs in a NUTS-3 area can be used for storage when stationary. Using a simplified storage model, we calculate the annual self-consumption for each region. The model allows for the EVs as mobile storage units to be charged during times of surplus PV power, and discharged during times of shortage of PV power, to cover household electricity demand. In case not enough storage capacity is available to deal with the surplus of PV power, the produced electricity is fed back to the grid. To determine what percentage of the EV fleet is stationary, we use data based on a 2005 Swiss mobility survey [88]. We run this model for a whole year, starting at January 1st to December 31st, with a time resolution of one hour.

Next, we need to use the following assumptions. Both the charging and discharging efficiency of the EVs is 90% [10]. We assume that EVs remain within the same NUTS 3-area. The NUTS 3-area are defined so that a large share of commuting takes place within the NUTS 3-region [79]. In the results presented in this paper we assume the average battery capacity
available for V2G services to be 5 kWh. This is one third of the average battery capacity of 15 kWh in the current EV-fleet\(^4\). There is of yet no clear idea on how much battery capacity of EVs could be used for V2G services. Given this uncertainty, we chose to perform a sensitivity analysis for available battery capacity.

A factor that can affect the potential contribution of V2G to increasing PV self-consumption is the maximum charging rate of individual EVs. The maximum charging rate sets a cap to how much energy can be stored in EVs for each time-step. In our model, we aggregate all EVs in a region to determine the self-consumption. The data on EV charging and the percentage of car fleets that are stationary as a function of time of day is on an aggregate level. One advantage of this aggregation is that it takes less computational time to run our model, but a disadvantage is that we cannot keep track of the individual charging rates and SOC levels of the EVs. To determine the charging rate needed to increase PV self-consumption, we calculate the average charging rate per EV in a region for each time-step. In doing so we can determine whether the needed charging rate per EV is feasible.

The charging rate of an EV is affected by its SOC level. When the SOC level approaches 100% the charging rate will significantly decrease. This effect is not included in our model, instead present a sensitivity analysis for available battery capacity.

4. Results
This section presents and discusses our results. Section 4.2 presents the results of our regression analysis, section 4.3 presents our estimations for the future diffusion of PV and EV, and section 4.4 links our future diffusion estimates to the energy system. Finally, section 4.5 presents our sensitivity analysis.

4.1 EV and PV diffusion
The current distribution of EV and PV in the Netherlands in the 40 NUTS-3 regions (Figures 3a and 3b) shows that the two technologies have different spatial adoption patterns. Figures 3c and 3d show the density of our measures of market size, household rooftops and passenger vehicles. The density for both market sizes is highest in the urbanized areas of the Netherlands, and lower in the rural areas. The density of passenger vehicles is particularly high (1144 vehicles per square kilometre) in the NUTS-3 region agglomeration The Hague, the region with the highest population density.

PV is relatively popular in rural areas, especially in the North-eastern part of the Netherlands, while EV is popular in urbanized areas, especially in the Western part of the Netherlands where the major cities are located. The percentage of household rooftops with PV installations varies between regions from 2.5% to 15%, which means that the diffusion of PV has reached the stage of early adopters, according to Rogers’ classification. The percentage of EVs in the total vehicle fleet varies between regions from 0.29% to 1.7%, which means that the diffusion of EV is still in the innovator phase.

\(^4\) Based on the 28 most popular EV models in the Netherlands, which cover 93% of the total EV fleet
Figure 3 Current market share and market size of PV and EV per NUTS-3 area, a) percentage of household rooftops with PV-installations, b) percentage of EVs in total vehicle fleet, c) number of household rooftops per square kilometre, d) number of passenger vehicles per square kilometre. For the whole of the Netherlands, 5.5% of household rooftops have PV solar panels. In total EVs cover 1.5% of the car fleet. We exclude EVs registered in a postal code containing a large lease company in our analysis. The number of EVs not registered in such a postal code cover 0.95% of the total car fleet.

4.2 Characterization of PV and EV adopters
This section presents the results from our regression analyses. Table 3 presents the coefficient estimates and the diagnostics of our analyses for total PV adoption and total EV adoption in the Netherlands. Based on these results we can establish a general profile of PV adopters and EV adopters, and in turn compare these characteristics. The explanatory variables used in the models are described in section 3.2. Appendix B contains Tables B.1, B.2, and B.3, which present the summary statistics. Additionally, we have included Table B.4, containing the correlations of the variables and Table B.5, containing all variables publicly available. We have checked the models with the variance inflation factor, and found that there is no issue with multicollinearity in our models.

PV adopters generally live in areas with low address density, large houses and a middle-aged population with a lower than average income and an overrepresentation of GroenLinks voters. Additionally, a larger household size has a positive effect on PV adoption, whereas a larger share of people with low education levels has a negative effect. The adjusted R-squared is 0.437, comparable to R-squared values found in similar PV diffusion studies [38], [39]. This profile of PV adopters stands in contrast to EV adopters, who generally live in areas with a
large vehicle fleet, a higher than average income, and lower levels of middle-aged residents. Municipal policy plays a part in EV diffusion, as indicated by the positive effects on EV adoption of the build-up of public charging and GroenLinks party council members. The adjusted R-squared for this model is lower than for PV (adj. R-squared=0.053). This indicates that EV adopters are a more diverse group than PV adopters, with a higher variation in socio-demographic characteristics\(^5\).

Table 3 General profile of PV adopters and EV adopters. The table presents the coefficient estimates for the log transform of the total number of PV installations per person and the log transform of the total number of EVs per persons (PC4 areas) for the Netherlands. Standard errors in parentheses, *** p < 0.001, ** p < 0.01, * p < 0.05. The results allow the comparison of the characteristics of the PV and EV adopter groups. The data sources of the variables are described in section 3.1, the variables are described in section 3.2.

| Variable                                      | Estimates of coefficients for the log transform of PV installations (pp) | Estimates of coefficients for the log transform of EVs (pp) |
|-----------------------------------------------|------------------------------------------------------------------------|---------------------------------------------------------|
| (Intercept)                                   | -0.0131 *** (0.0039)                                                   | 0.00472 (0.00390)                                       |
| Address density (1000 * km\(^2\))             | -0.00106 *** (0.00016)                                                 | 0.00000114 (0.000149)                                  |
| Age 25-45 (%)                                 | -0.0000699 (0.0000570)                                                 | -0.0000168 (0.0000544)                                 |
| Age 45-65 (%)                                 | 0.000231 *** (0.000062)                                                | -0.000180 ** (0.000061)                                |
| GroenLinks city council members since 2006 (Y/N) | 0.000231 *** (0.000062)                                                | 0.00106 ** (0.00039)                                   |
| GroenLinks voters 2010 (%)                    | 0.000801 *** (0.000094)                                                | -0.000144 (0.000093)                                   |
| Household income (k Euros)                    | -0.000514 *** (0.000047)                                               | 0.000116 ** (0.000045)                                 |
| Household rooftops (pp)                       | -0.00165 (0.00351)                                                     | -                                                      |
| Household size (persons)                      | 0.0165 *** (0.0010)                                                   | -0.000816 (0.000945)                                  |
| Lowly educated (%)                            | -0.000298 *** (0.000036)                                               | -0.00000259 (0.0000339)                               |
| Passenger vehicles (pp)                      | -                                                      | 0.0212 *** (0.0036)                                    |
| Public charging stations (pp)                 | -                                                      | 1.75 *** (0.24)                                        |
| Total building footprint (m\(^2\) pp)         | 0.000503 *** (0.000026)                                                | -                                                      |

Diagnostics

| Observations | 3020 | 2986 |
|--------------|------|------|
| R\(^2\)      | 0.453 | 0.057 |
| Adjusted R\(^2\) | 0.450 | 0.053 |
| F Statistic  | 248.7 (p-value: 0.000) | 17.83 (p-value: 0.000) |

4.3 Estimating future diffusion of PV and EV

Figures 4a and b give the estimated Bass model diffusion curves for EV and PV for each region. The model results indicate that, based on current diffusion, total market saturation (all household rooftops) of PV could already be reached by 2035, while for EV total market saturation (all passenger vehicles) is not reached until 2045. Furthermore, the figures illustrate the large differences in adoption speed for the different regions.

In figure 4a, one line stands out: the orange line with the fastest diffusion rate. This line corresponds to the region of North-eastern Groningen. A possible explanation for the high market share is a specific subsidy scheme for this region. A large gas field is located in North-

\(^5\) In our robustness analysis, we found one outlier to have an influence on the results for EVs. When taking out this outlier, the significant variables as presented remain significant with the same sign, but low education becomes a positive predictor and household size become a negative predictor. Furthermore, the adjusted r-squared value becomes 0.185, indicating a better fit with the data. Our results for PV are not sensitive to outliers, indicating that as adoption levels increase outliers will have a lesser impact on results.
eastern Groningen, and the region has suffered from earthquakes due to gas drilling. To compensate its inhabitants for damages due to earthquakes, several subsidy schemes are available, including subsidies to have solar panels installed.

Figure 4 Results from the Bass model, a) projections of PV diffusion, b) projections of EV diffusion. The thick black line gives the diffusion curve for the whole of the Netherlands, while the other lines represent the different NUTS 3-areas. The colour coding is consistent across both figures.

4.4 Consequences for the transition to sustainable energy
For each region we modelled and calculated the potential to move to an integrated energy and mobility system where consumers consume locally produced renewable energy. We compare the annual amount of locally produced PV-power to the annual electricity demand of households.

Figures 5a and 5b provide model results assuming an average nominal power of PV systems of 4 kWp, which is equal to the current average in the Netherlands. Figure 5a shows that, when PV market saturation is reached, annual PV power production is 31% of electricity demand of households and EVs. Figure 5b indicates that storage in EVs to match supply and demand is pivotal to reach 100% self-consumption. Furthermore, the figures show large differences between regions, especially in the period 2020-2030, since PV adoption speed is then on the steep part of the S-curve. When total market saturation is reached, large differences remain in the potential to meet electricity demand with PV power, due to the number of household rooftops available to install PV solar panels.

Figures 5c and 5d present the results from the simulations with an average nominal power of PV systems of 12.9 kWp. In this scenario, the annual PV yield is equal to the annual energy demand. The patterns are similar to the patterns shown in figures 5a and 5b, and clearly demonstrate the potential of V2G technology to increase self-consumption levels.

Figure 5e shows the total electricity demand for EV charging as percentage of the total electricity demand. These results hold for both PV diffusion scenarios. The results illustrate the potentially large impact of EV diffusion on electricity demand. When EV diffusion reaches market saturation, EV charging demand could make up almost 40% of total electricity demand nationally, varying between 30% and 53% for the different NUTS-3 regions.
**Figure 5** Model results for development in PV-power production and development in self-consumption, a) projections of PV-power production/electricity demand with average nominal power of 4 kWp; b) projections of self-consumption with average nominal power of 4 kWp and on average 5 kWh per EV available for V2G services, c) projections of PV-power production/electricity demand with average nominal power of 12.9 kWp. d) projections of self-consumption with average nominal power of 12.9 kWp and on average 5 kWh per EV available for V2G services. e) projections of EV charging demand/electricity demand. The thick black line gives the average for the whole of the Netherlands, while the other lines represent the different NUTS 3-areas. The colour coding is consistent across all figures. In the graphs for self-consumption, the red dashed line represents the level of self-consumption of the Netherlands without EV charging and the blue dashed line represents the level of self-consumption of the Netherlands when no V2G is used.

Figures 6a and 6b show frequency distributions of the average charging power per EV for each time-step of our simulations. For most charging sessions, which include the charging power needed for load balancing via V2G technology, charging power is below 1 kW. The average charging power never exceeds 7 kW. The charging power available in current EV charging stations often exceeds 3 kW indicating that the charging power needed for the EVs in our scenarios should be feasible in practice.
Figure 6 Model results for the frequency distribution of average charging power of the EV over the period 2005-2050. For this time period we calculated for each hour the charging power needed for the EVs and for V2G services and divided this by the number of EVs available at a charging station. a) Results for the scenario with average nominal power of 4 kWp and on average 5 kWh per EV available for V2G services, b) Results for the scenario with average nominal power of 12.9 kWp and on average 5 kWh per EV available for V2G services.

In Figure 7 we map our model results on the map of the Netherlands, using the average nominal power of 4 kWp. In some rural regions PV-power production is high, covering up to 70% of household and EV electricity demand. In urban areas in the western part of the Netherlands PV power production remains limited, especially in the area of Greater Amsterdam, where production levels exceed 30% of demand only after 2025. Because PV-power production is relatively low, the demand for load balancing is low, and small EV-fleets can suffice to reach high amounts of regional self-consumption. However, in regions in the where EV-fleets, such as North-East and the South, are small self-consumption levels are low.

In Figure 8 we map our model results, using the average nominal power of 12.9 kWp. The issue arising from PV and EV diffusion is clear from these maps. In the Western and Eastern regions PV and EV diffusion is such that high self-consumption can be achieved. However, even with an average nominal power of 12.9 kWp the total PV-power in these regions is too low to cover household and EV demand. In contrast, in the South and North there is excess PV-power. Combined with a lack of EVs for load balancing, self-consumption is low in these regions. Furthermore, the lag of EV diffusion compared to PV diffusion is clear in the maps; regional self-consumption is lowest in 2025, while in 2050 it is higher again.
Figure 7 Map of model results for 2020, 2025 and 2050, a) PV-power production/household electricity demand. b) self-consumption of households. We assume an average nominal power of PV systems of 4 kWp and an average battery capacity of 5 kWh per EV available for V2G
Figure 8 Map of model results for 2020, 2025 and 2050, a) PV-power production/ household electricity demand, b) self-consumption of households. We assume an average nominal power of PV systems of 12.9 kWp and an average battery capacity of 5 kWh per EV available for V2G.

4.5 Sensitivity analysis
This section presents a sensitivity analysis for the national average PV self-consumption, our main indicator. The relation of variables such as market size, average nominal PV power and EV storage size with annual PV yield and EV charging demand is linear. However, in the calculation for PV self-consumption all these factors interact non-linearly.
Figure 9 presents our results for variation of PV market size and EV market size for both our scenarios. Figure 10 shows our results for variation of the average nominal power of PV systems and available EV battery capacity for V2G services assuming 100% market share. The key message arising from these results is that with current average nominal power of PV systems, issues with regional PV self-consumption arise with high market penetration, while low market penetration of EVs is sufficient to solve these issues. However, with high nominal power of PV systems PV self-consumption might become a problem early in the diffusion process, and large EV fleets can be key to address this issue.

![Figure 9](image9.png)  
**Figure 9** Contour plots of the results from the sensitivity analysis on the effect of PV market size and EV market size on self-consumption. PV market size is measured as percentage of total household rooftops, and EV market size is measured as percentage of total passenger vehicles. a) Results for the scenario with average nominal power of 4 kWp and on average 5 kWh per EV available for V2G services, b) Results for the scenario with average nominal power of 12.9 kWp and on average 5 kWh per EV available for V2G services.

![Figure 10](image10.png)  
**Figure 10** Contour plot of the results from the sensitivity analysis on the effect of average nominal power of PV systems market size and average EV battery capacity available for V2G services. For this analysis we assume that 100% of household rooftops have PV installed and 100% of passenger vehicles are EVs.

Finally, Tables 4 and 5 show our results for varying PV orientation. We ran simulations with all PV panels directed south, east and west. Additionally, we ran one “mixed” scenario with one third of the PV panels directed south, one third directed east and one third directed west.
In our scenario with average nominal PV power of 4 kWp, the levels of self-consumption do not differ much amongst these scenarios. However, the PV yield does, and varies between 80-87% of the optimal scenario of all panels directed south. In this case, having all panels directed south is the most attractive scenario. However, when average nominal power increases, a trade-off of annual PV yield and PV self-consumption will arise, as shown by the results in Table 5. The hourly PV production profile of panels directed east or west is better aligned with household demand and EV charging and availability profiles than the hourly PV production profiles of PV panels directed south. In these scenarios, annual self-consumed PV power is higher than the scenario with all panels directed south. These results indicate that as average nominal power of PV panels increases, having PV panels of mixed orientation can have large benefits for a grid manager.

| Orientation | Self-consumption (%) | Annual PV yield (TWh) | Annual self-consumed PV yield (TWh) |
|-------------|----------------------|-----------------------|-------------------------------------|
| South       | 98.1                 | 17.6                  | 17.2                                |
| East        | 99.6                 | 14.1                  | 14.1                                |
| West        | 99.8                 | 14.3                  | 14.3                                |
| Mixed       | 99.7                 | 15.3                  | 15.3                                |

Table 5 Results from the sensitivity analysis on the effect of PV orientation on national PV self-consumption and annual PV yield, and the product of these factors the annual self-consumed PV yield. In the mixed orientation one third of the PV panels is directed south, one third is directed east and one third is directed west.

5. Discussion

We have analysed the diffusion of PV and EV in The Netherlands. Stark differences are observed between the spatial patterns of EV and PV diffusion. The main contribution of this paper is the establishment of the geographical misfit between EV and PV diffusion and the implications this has for the transition to smart energy systems. We provide further evidence for the claim that space matters in energy transitions [89] and investigate the viability of V2G systems for different regions in the Netherlands.

Differences in diffusion patterns can be partially explained by differences in socio-demographic characteristics of the adopter groups. Several of the key predictor variables for PV adoption, such as household size, education level, age and address density have been identified before as important predictors [38], [41], [42], [47]. We found the average income in a neighbourhood to be a negative predictor of PV adoption levels, which is consistent with
some studies [28], [39], [44], [46], but opposite to others [30], [40], [41], [47]. Furthermore, we found that neighbourhoods with a high amount of GroenLinks voters to have high PV adoption levels, further indicating that environmental awareness plays a role in PV adoption [25], [44], [47], [78]. We have identified the passenger vehicles per person, municipal policy, household income, and age as significant predictors for EV adoption. Passenger vehicles is a positive predictor, which could be due to EVs being popular or more acceptable as second car, as found in previous studies [90]–[93]. However, there are some notable differences with earlier literature. Age has not been identified before as a strong predictor, while our model did not show significant results for address density, household size and education level, which were found to be important in earlier studies [49], [51], [52]. Furthermore, our model explains less of the variation in EV adoption levels than in PV adoption levels, indicating that EV adopters are a more diverse group than PV adopters. These results stand in contrast with the results of Rai et al. [6], who found PV adopters to be likely to consider purchasing a plug-in vehicle. Though there is some consistency among the literature on socio-demographic variables predicting PV and EV adoption, the discrepancies between studies seem to suggest differences among countries, indicating the importance of local circumstances in adoption of clean energy technologies.

We show to what extent users may contribute to a transition towards a smart grid based on decentralized renewables by extrapolating initial diffusion data via the Bass model of diffusion. A main issue we have identified is the large variation of PV diffusion for different regions of the Netherlands. The regional variation not only lies in the rate of diffusion but also in potential for the households to install PV-systems on their rooftops. EVs have a large potential to increase regional self-consumption of PV power via V2G technology. However, the number of EVs might not be sufficient to achieve high levels of self-consumption, especially for some regions with both high PV adoption and low EV adoption. Furthermore, EV diffusion clearly lags behind PV diffusion. Our scenarios demonstrate that, while V2G systems have clear benefits, PV and EV are not “in sync”. Not only do the supply and demand patterns differ, also different regional diffusion pattern affect the viability of such systems. Our results indicate that different grid architectures are suitable for different types of regions: while in urban regions micro-grids may be efficient, it might be necessary to strengthen grid connections between rural areas to areas where electricity demand is high. Therefore, it is pivotal to take regional adoption into account when constructing energy scenarios.

We have run scenarios with the current average nominal power of PV systems and with the average nominal power needed to cover 100% of electricity demand on an annual basis. For both scenarios it seems likely that non-distributed generation facilities will continue to play a role in the energy production. In the first scenario, annual PV yield only covers around 30% of total electricity demand. In our second scenario, PV self-consumption levels become so low that it seems unlikely to be easily solved, either by V2G services or other types of solutions.

We use several simplifying assumptions to calculate coverage of electricity demand by PV yield and self-consumption, e.g. household energy demand stays constant, the nominal power of PV-systems remains the same, and EVs have 5 kWh of storage available. These parameters can easily be adapted when more data becomes available. We have performed a sensitivity analysis for several of the most uncertain factors in our model. The results from this analysis showed that with current average nominal power of PV systems PV-self consumption will become an issue only with high PV adoption levels, and could potentially be solved easily with relatively small EV-fleets. However, when PV yield per PV installation increases issues
with PV self-consumption will arise much earlier in the diffusion process, and large EV-fleets will be needed for load balancing. Such issues could be partially solved by having PV solar panels with more eastward or more westward orientations, since the hourly production profile of panels with such orientations is better aligned with hourly residential demand, EV charging, and EV availability profiles.

Our work explores the dynamics of the energy transition in the Netherlands, but we do not claim to make accurate predictions of the diffusion processes. The assumptions we base our model on, such as total market sizes for PV and EV and availability of EVs for V2G-services, are optimistic with respect to the potential of PV power production and self-consumption. Our scenarios should therefore be interpreted as optimistic as well. Since the diffusion of both PV and EV is still in an early phase, we claim that our model results are rather useful explorations of future diffusion, but are unsuitable for accurate market size prediction, since energy technologies may have different lengths of take-off phases [94]. Furthermore, we do not take into account possible issues that may arise like grid access costs, uncertainty about battery durability and high amounts of waste or second-life batteries. Our study assumes that households can only use PV technology for energy production and only do load balancing with V2G technology. We thus ignore competition with other technologies in electricity or mobility, which may hinder PV and EV diffusion.

The Bass model as employed in this study has been criticised for not taking into account the systemic nature of the diffusion of clean energy technologies [57], [63]. These authors argue to use more complex diffusion models such as agent-based models for scenario building. Though we recognize these criticisms, we chose to use the Bass model, because a) its validity is widely tested, and the diffusion theory it rests on has also proven useful for clean energy technology diffusion [58], [95]–[97], and b) we focus on adoption and scenarios on a regional level for an entire country. The Bass model is suitable for application on micro-level diffusion data of all PV and EV in the entire country. Micro-level data on parameters included in more complex models, such as attitudes towards a technology, would entail a different survey-based research design. Gathering such data for all regions of a country would require a very large survey, making such models difficult to apply to an entire country. For future research on sub-country level, it would be worthwhile to explore the application of complex diffusion models, when more data becomes available.

A second limitation of our approach of taking into account all PV and EV adoption in a whole country is that we use data from neighbourhoods for identifying adopter characteristics. This means that we should carefully interpret the results because of the “ecological fallacy” [98]: relationships found on the group level not necessarily transfer to the level of individuals in these groups.

Based on our findings we can articulate some policy recommendations. Grid operators could prepare for these regional differences by exploring solutions other than V2G for grid balancing. To stimulate PV and EV diffusion in regions where diffusion has been slow, policies could be aimed at consumer groups currently underrepresented in one of the adopter groups, to ensure that the diffusion does continue beyond innovators and early adopters. Results from our regression analysis show that EV diffusion is partly driven by municipal policy, and the build-up of public charging infrastructure has a large influence on EV adoption. Municipalities that want to stimulate EV adoption can take advantage of this insight. Such policies could for instance be targeted at middle-aged people, who are underrepresented in the group of EV-adopters.
When diffusion increases and more adoption data becomes available, the accuracy of our model results will increase. The model can be applied to other regions and other distributed generation or storage technologies as long as sufficient data is available. An interesting future technology to include could be PV system batteries, since these could further increase PV self-consumption in areas or time-frames in which V2G systems are insufficient to achieve high levels of PV self-consumption.

6. Conclusion
We have performed a study in which we focus on how consumer adoption of PV solar panels and electric vehicles (EV) may influence the transition towards smart sustainable grids. Based on historical diffusion data of PV and EV in the Netherlands, we have characterized the adopter groups of these technologies and build scenarios for future diffusion. Furthermore, we investigate how the joint deployment of these technologies may impact the local energy system and assess the viability of the integration of PV and EV in vehicle-to-grid systems. We find large differences in the spatial diffusion patterns of PV and EV using 40 regions in the Netherlands, which will have impact on the viability of vehicle-to-grid systems. Despite limitations inevitable in scenario studies, we demonstrate that taking spatial diffusion patterns into account is important in energy planning and give an example of how integrating socio-economic models and diffusion data contribute to energy systems modelling.

Statement of data availability
We use a variety of datasets as inputs for our study. Some of the data is publicly available and referred to in-text. This includes data we took from the Central Bureau of Statics of the Netherlands [77] (also included in Table B.5), the four major Dutch DSOs [72]–[75] and the Royal Netherlands Meteorological Institute [76]. Other datasets were purchased or shared under restriction. This includes data from the Production Installation Register, The Netherlands Vehicle Authority, The Netherlands’ Cadastre, Land Registry and Mapping Agency, Stichting Politieke Academie and GroenLinks. These data are available from the corresponding author on reasonable request and with the permission of the relevant third party.

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**Appendix A: Lease companies**

Table A.1 contains the major lease companies and the 4-digit postal codes where they are located, based on an extensive web search. We exclude these postal codes from our analysis.

| Lease Maatschappij                                         | Postcode |
|-----------------------------------------------------------|----------|
| Mistergreen Electric Lease B.V.                           | 1011     |
| RCI Financial Services                                    | 1119     |
| BEMA Finance                                              | 1175     |
| Koops Furness Lease                                       | 1311     |
| Leaseplan                                                 | 1314     |
| Autoplanning Algemene Lease Maatschappij BV               | 1322     |
| Stern Lease B.V.                                          | 1446     |
| Europcar/Multirent/National Car Rental Haarlem            | 2031     |
| Schiphol/ALD Automotive                                    | 2132     |
| BMW Nederland B.V./BMW Group Financial Services           | 2289     |
| Kamsteeg Auto Lease                                       | 2321     |
| Achilles Autolease                                        | 2516     |
| Stichting Nederlandse Mobiliteit 2.0/PSA Finance Nederland | 3011     |
| AA Lease B.V./Sixt/Ames Autolease                         | 3316     |
| Business Lease Nederland B.V.                             | 3439     |
| Europcar/NS/Greenwheels                                   | 3521     |
| Santander Lease/Justlease/Sternrent/Terberg Leasing       | 3526     |
| car2go/Mercedes-Benz Financial Services Nederland         | 3528     |
| MultiLease B.V./Go Lease B.V.                             | 3543     |
| Business Lease Nederland B.V.                             | 3708     |
| MKB Lease B.V.                                            | 3812     |
| Volkswagen Leasing B.V./DutchLease Nederland              | 3824     |
| Broekhuis Lease                                           | 3845     |
| Arval Lease                                               | 3991     |
| Alcredis Finance/A.R.M. Autoleasing                      | 4131     |
| Kyoto Lease                                               | 4451     |
| ING Car Lease/Alphabet Lease/GE Capita                    | 4817     |
| Opel Nederland                                            | 4822     |
| Autopon Lease                                             | 5232     |
| Athlon Car Lease B.V.                                     | 5611     |
| Tesla Motors/Driessen AutoLease B.V.                      | 5628     |
| J&T AutoLease                                             | 5688     |
| H4 Car Lease B.V.                                         | 7418     |
| Lease Unlimited                                           | 7421     |
| Total Car Lease                                           | 7468     |
| Huiskes-Kokkeler Autolease                                 | 7554     |
| Company                        | Code |
|-------------------------------|------|
| Friesland Lease B.V.          | 9201 |
| Century Auto Lease            | 9480 |
| Noordlease B.V./AutoLease Groningen | 9723 |
Appendix B: Summary statistics of variables used in regression models

Table B.1 Summary statistics of variables used in regression models

| Statistic                                           | N   | Mean       | St. Dev. | Min | Q1  | Median | Q3   | Max  |
|-----------------------------------------------------|-----|------------|----------|-----|-----|--------|------|------|
| Inhabitants                                         | 4,020 | 4,173.34 | 4,134.44 | 0   | 685 | 2,675  | 6,826 | 28,600 |
| PV systems                                          | 4,025 | 68.57     | 68.57    | 0   | 16  | 43     | 97   | 1,359 |
| EVs                                                 | 4,025 | 28.02     | 204.22   | 0   | 2   | 8      | 22   | 7464  |
| Address density (per km²)                           | 4,025 | 923.21    | 1,704.87 | 0   | 46.1| 159.5  | 1036 | 15670 |
| Age 25-45 (%)                                       | 3,994 | 23.74     | 6.59     | 1.56| 20.21| 22.81  | 25.91| 100   |
| Age 45-65 (%)                                       | 4,006 | 30.43     | 6.35     | 3.33| 27.13| 30.39  | 33.33| 100   |
| GreenLeft voters (2010) (%)                         | 3,321 | 6.11      | 3.16     | 0.20| 4.12 | 5.49   | 7.22 | 25.91 |
| GreenLeft city council members since 2006 (Y/N)     | 4,025 | 0.373     | 0.484    | 0   | 0   | 0      | 0    | 1     |
| Household income (Euros)                            | 3,575 | 35,899.19 | 6,661.87 | 11,800| 31,700| 35,600 | 39,350| 106,800 |
| Household rooftops                                  | 4,025 | 1,249.701 | 1,216.22 | 1   | 234 | 843    | 1,980 | 7,804 |
| Household size (persons)                            | 4,020 | 2.348     | 0.342    | 1.13| 2.17 | 2.37   | 2.55 | 5     |
| Lowly educated (%)                                  | 3,215 | 47.49     | 8.17     | 10  | 43  | 48     | 52   | 75    |
| Passenger vehicles                                  | 4,021 | 1,879.70  | 1,791.45 | 6   | 399 | 1,322  | 2,970 | 22,549 |
| Public charging stations                            | 4,025 | 1.86      | 3.62     | 0   | 0   | 1      | 2    | 43    |
| Total building footprint (m²)                       | 4,025 | 116,577.8 | 104,015.0| 2.12| 295.80| 871.81 | 1,803.34| 5,654.40 |

Table B.2 Summary statistics of variables used in the regression model for PV adopters. The N for these variables is lower than in the original data-sets, because we have removed rows with incomplete data

| Statistic                                           | N   | Mean       | St. Dev. | Min | Q1  | Median | Q3   | Max  |
|-----------------------------------------------------|-----|------------|----------|-----|-----|--------|------|------|
| Log (PV systems (pp + 1))                            | 3,020 | 0.022     | 0.13     | 0   | 0.011| 0.018  | 0.026 | 0.097 |
| Address density (per km²)                           | 3,020 | 1178.77    | 1882.07  | 0.03| 83.36| 317.34 | 1573.94 | 15666.97 |
| Age 25-45 (%)                                       | 3,020 | 24.31     | 5.44     | 8.99| 20.95| 23.23  | 26.32 | 52.46 |
| Age 45-65 (%)                                       | 3,020 | 29.40     | 4.57     | 9.78| 26.64| 29.24  | 32.26 | 48.55 |
| GreenLeft voters (2010) (%)                         | 3,020 | 6.07      | 4.86     | 0.2 | 4.10 | 5.49   | 7.20 | 25.91 |
| GreenLeft city council members since 2006 (Y/N)     | 3,020 | 0.383     | 0.49     | 0   | 0   | 0      | 1    | 1     |
| Household income (Euros)                            | 3,020 | 35441.46  | 6222.89  | 19,000| 31,400| 35,300 | 38,800 | 106,800 |
| Household rooftops                                  | 3,020 | 0.32      | 0.07     | 0.01| 0.30 | 0.34   | 0.37 | 0.66  |
| Household size (persons)                            | 3,020 | 2.31      | 0.31     | 1.23| 2.14 | 2.34   | 2.50 | 3.57  |
| Lowly educated (%)                                  | 3,020 | 47.56     | 8.13     | 10  | 43  | 48     | 52   | 75    |
| Total building footprint (m² pp)                    | 3,020 | 32.63     | 10.97    | 6.13| 24.65| 32.16  | 39.97 | 87.40 |

Table B.3 Summary statistics of variables used in the regression model for EV adopters. The N for these variables is lower than in the original data-sets, because we have removed rows with incomplete data, removed postal codes with a lease company located in it, and have removed postal codes with a value of passenger vehicles per person higher than 1.

| Statistic                                           | N   | Mean       | St. Dev. | Min | Q1  | Median | Q3   | Max  |
|-----------------------------------------------------|-----|------------|----------|-----|-----|--------|------|------|
| Log (EVs (pp + 1))                                  | 2,986 | 0.004     | 0.009    | 0   | 0.002| 0.003  | 0.004 | 0.421 |
| Address density (per km²)                           | 2,986 | 1170.84   | 1877.29  | 3.22| 82.60| 313.82 | 1563.28 | 15666.97 |
| Age 25-45 (%)                                       | 2,986 | 24.25     | 5.38     | 8.50| 20.93| 23.21  | 26.24 | 52.46 |
| Age 45-65 (%)                                       | 2,986 | 29.27     | 4.48     | 9.78| 26.68| 29.66  | 32.26 | 48.55 |
| GreenLeft voters (2010) (%)                         | 2,986 | 6.06      | 3.12     | 0.2 | 4.08 | 5.47   | 7.18 | 25.91 |
| GreenLeft city council members since 2006 (Y/N)     | 2,986 | 0.382     | 0.49     | 0   | 0   | 0      | 0    | 1     |
| Household income (Euros)                            | 2,986 | 35436.70  | 6218.07  | 19,000| 31,400| 35,300 | 38,800 | 106,800 |
| Household size (persons) | 2,986 | 2.31 | 0.31 | 1.23 | 2.14 | 2.34 | 2.51 | 3.57 |
|--------------------------|-------|------|------|------|------|------|------|------|
| Lowly educated (%)       | 2,986 | 47.60 | 8.10 | 10   | 43   | 48   | 52   | 75   |
| Passenger vehicles (pp)  | 2,986 | 0.475 | 0.086 | 0.181 | 0.429 | 0.487 | 0.533 | 1    |
| Public charging stations (pp) | 2,986 | 0.0004 | 0.0008 | 0 | 0 | 0.0002 | 0.0005 | 0.011 |

**Appendix C: Supplementary data**

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.erss.2018.06.003

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