Adoption of Solar Panels by Dutch Households

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With the gradual onset of more pronounced climate change effects, more countries are turning towards renewable energy sources. While the vast majority of effort is current spent on the diversification of energy production facilities at a national or super-national scale, one potential solution is energy generation by households.

Briguglio and Formosa (2017) identified Belgium, Australia and Malta as especially successful in involving household energy production in the national plan towards independence of fossil fuels. Fleiss, Hatzl, Seebauer, and Posch (2017) further notes the development of PV-CPI schemes in Austria. With the adoption of the (I)SDE+ subsidy and tax write-offs, the Dutch government is trying to promote similar efforts in the Netherlands. Already in 2014, the market for community energy initiatives in the Netherlands was considered burgeoning despite a market-oriented institutional arrangement (Oteman, Wiering, & Helderman, 2014).

While there has been exhaustive study towards the consumption of renewable energy by households, and the potential demand for household generated energy schemes, little quantitative research has been conducted investigating the determinants adoption of these technologies by individual households.

The majority of studies have been qualitative in nature. The thesis by Vasseur (2014) is particularly exhaustive in its segmentation of potential PV adopters in the Netherlands by survey responses. Especially financial variables were found to be drivers, although significant differences exist in within household dynamics between adopted and non-adopters. Further studies corroborate these findings, but add the sense of participation in green energy and social acceptance (i.e. installation of solar panels by neighbours) to be a major driver in adoption (Koch & Christ, 2018)(Strazzera & Statzu, 2017). Fleiss et al. (2017) finds that citizen's participation in CPIs is not ideologically driven, but almost purely an economic decision; a finding supported by recent evidence in Australia (Best, Burke, Nishitateno, et al., 2019). Qureshi, Ullah, and Arentsen (2017) paints a more nuanced picture, with financial and spatial considerations ranking high as barriers in the PV adoption decision, but environmental friendliness, energy

Figure 1. A map of the Netherlands divided by the areas of the net managers. Not included in the image is Endinet, responsible for major population areas in Noord-Brabant, which merged with Enexis as of January 1 2017. Taken from stroom en gas in Nederland (n.d.).

security and social acceptability ranking as the most important drivers.

Other papers focus on comparative national variables, using both macro-economic as well as policy indicators. Of particular interest is whether feed-in tariffs and other government pay-back schemes aid in boosting adoption rates. Van Hemmen (2011) find that feed-in tariffs were especially strong motivators in adoption rates, but monetary incentives were only as effective as socio-economic factors already present within a country. Smith and Urpelainen (2014) find a strong association between feed-in tariffs and production of renewable energy in industrial countries, but strongly doubt this being a causal relationship. While focusing on inter-municipality differences in Malta, Briguglio and Formosa (2017) finds that government support is indicative of uptake of PV technologies, along with house ownership and possession of roof space.

This paper aims to contribute the already existing literature by estimating the relationship between household renewable energy production and the described variables at a country-wide scale. The periods for which data is available proved to be important inflection point for the wide-scale adoption of PV technology in the Netherlands. While no policy variables were included, the inherent socio-economic differences between Dutch municipalities were enough to serve as good predictors.

Data

Electricity consumption data was provided through the open-access data infrastructure set up by the largest network managers in the Netherlands; Liander, Enexis (and Endinet), Stedin, Enuris and Westland Infra. Included are the anonymized (aggregated at 10 connections or more) consumption data for "kleinverbruikers" (individuals and small businesses), users with connections of less than 3 fuses at 80 amperes or capacity for 40 m^3 hr^{-1} of gas (Liander, 2019). The data are stored in comma delimited files, and are updated yearly to reflect usage over the past year. Beyond minor changes in notation, all companies use the same variables, units and delimiters for their records. As such, merging the files across companies can be done with confidence in consistent data.

To aggregate data from township to municipality level, an inner join was performed with the list of "Woonplaatsen" provided by the Dutch Statistics Bureau (CBS, n.d.). Absolute values were summed, whereas percentual values were combined using a weighted mean based on the number of connections present. This meant going from $\approx 300e+03$ rows to only 327 list-wise complete entries, where each row corresponds to a recognised municipality; from 's-Hertogenbosch to Zwolle.

Data for demographic control variables were taken from the regional reports of the CBS as well, with the smallest level of granularity corresponding to municipalities (**?**). Due to the current nature of the analysis, certain variables were not available yet for 2018 onwards, limiting the analysis to the year range 2013 (first year of records by netmanagers) to 2017 (last year recorded by CBS).

Cross-Sectional Analysis

The Dependent Variable

Household renewable energy (RE) production, is constructed as difference of the delivered and the consumed energy. It is expected that the production source is predominantly from PV technology. As expected, with greater adoption rates of solar panels by individuals, there is a strong time dependent trend, seeing a 5.12 factor increase over the 5 years analysed. Beyond just an increase in mean generated

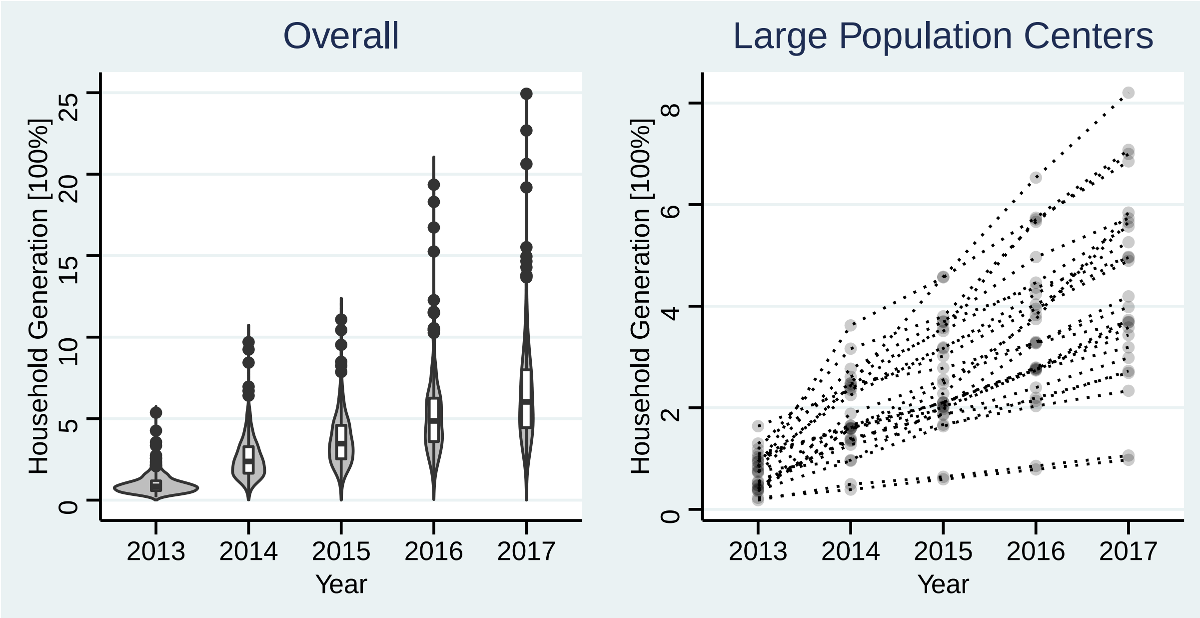

Figure 2. Time trends of energy generation by households. Sub-figure (a) shows both an increase in the mean of the dependent across time, and an increase in variance, indicating a non-stationarity, while sub-figure (b) shows trends for large population centres (n>100k). Across the dataset, no city recorded negative growth in self-generated electricity.

electricity, the variances have increased substantially also. The time trend of the dependent variable is depicted in fig. 2. With far greater numbers of positive outliers than negative ones, the dependent variable did not appear normally distributed (platykurtic and positive-skew), resulting in non-normal residuals in OLS. As such, the generated electricity variable was log-transformed. The model in terms of dependent variables is described below.

Model Specification

The quantity of household electricity generated within a municipality, in log form, is specified as a linear function of determinants. From the literature, four important groups of variables have been identified: i) the expected future profit derived from RET installation (Yield), ii) the investment necessary for installation (Cost), iii) the potential for installation due to non-financial constraints of households (Pot) and, iv) the potential due to demographic features of municipalities (Dem). This model may be specified as eq. 1, where bold-faced characters are the described sets of variables. Note that no time-indices are included, indicating the estimated model to be partitioned across period; the initial estimate treats the process as a series of successive cross-sections.

$$\begin{aligned}\log(\text{Generated}_i) = \beta_0 &+ \beta_i^{(\text{Yield})}\mathbf{x}_i^{(\text{Yield})} + \beta_i^{(\text{Cost})}\mathbf{x}_i^{(\text{Cost})} \\ &+ \beta_i^{(\text{Pot})}\mathbf{x}_i^{(\text{Pot})} + \beta_i^{(\text{Dem})}\mathbf{x}_i^{(\text{Dem})}\end{aligned} \tag{1}$$

Yield. While households have a direct incentive to use the energy produced from RETs as opposed to drawing from the net, it is reasonable to assume that energy production and consumption are not perfectly correlated. As an example, solar panel energy production is highly dependent on the time of day; no energy is produced at night. Furthermore, the seasonal pattern in production is expected to be inversely correlated to seasonal patterns in household energy consumption (**?**)(**?**); the colder months see lower production, but higher consumption and vice-versa.

While no direct profit can be derived from the extraneous production of RETs, as net-managers do not pay for energy delivered, the "saldeer" method does ensure reducing energy bills in the long-term (Rijksoverheid, 2019). As such, it is expected that the derived profit is directly proportional to the cost of the current energy consumption. Variables included in the aim to capture this effect are consumption density and household size. Consumption density directly measures the mean consumed energy per household, whereas household size captures the mean number of residents per address. Both variables are expected to carry positive signs, as increases in either would indicate an increase in energy consumption.

Cost. While the cost of solar panels and RETs have been dropping steadily in the Netherlands (MilieuCentraal (2019) reports a 16% between the periods included in the data), installation remains an extremely capital intensive investment. As such, it is expected that not all households will be able to afford installation.

Variables included that capture household ability to afford RETs are median wealth and mean property value. Both are expected to carry a postive sign; greater wealth should indicate greater ability to install RETs.

A third variable included are the share of households with smart meters. These

Table 1

Summary statistics for the variables included in the OLS regressions. Variables exhibiting non-normal distributions have been log-transformed, denoted by a lowercase l. Shares are percentages [%]; count units are depicted as [#].

Block	Variable	Unit	N	Mean	Median	SD	Min	Max
Dependent	lShare Generated	%	1,635	1.040	1.186	0.826	-1.731	3.216
Yield	Household Size	#	1,640	2.305	2.310	0.191	1.640	3.380
	lConsumption Density	kWh/house	1,640	4.791	5.329	1.864	-2.237	5.891
Cost	lProperty Value	€	1,635	5.396	5.330	0.222	4.779	6.382
	lMedian Wealth	€	1,640	2.529	2.407	0.836	-0.693	6.048
	Share Smartmeter	%	1,640	16.860	12.962	15.830	0.340	96.654
Potential	lConnection	#	1,640	9.402	9.344	0.930	3.434	13.01
	lHousing Density	km^{-2}	1,640	5.371	5.263	1.047	2.708	7.870
	Share Rented	%	1,640	35.712	34.205	8.534	18.411	71.154
Demographics	Share Males	%	1,640	49.73	49.725	0.798	46.76	53.48
	Approx. Age	#	1,640	42.36	42.452	2.198	31.06	48.14

devices are a necessary upgrade for solar panels and carry a cost. Hence, using the same argument as the other cost variables, the sign is expected to be positive. However, Dutch net managers have been installing smart-meters (with an opt-out option) with the goal of achieving 100% coverage by 2020 (**?**). The effect is thus expected to diminish with time.

Potential. While the cost and yield considerations might indicate strong incentive to adopt RETs, not all households have access the non-financial capacity to accommodate these technologies. As an example, apartment complexes will have plenty of households who might profit from RET installation, but lack the floor- and roof-space. Included variables that reflect these effects are the number of connections, share of rented households and the the number of households per km^2 (density). The number of connections serves as proxy for population, indicating urbanity of municipalities. Rented households are expected to reflect great difficulty in enacting structural change in the household, perhaps through increased apathy of the renter to the house which they do not own. The housing density instead captures the effect of diminished space per resident/household, increasing reluctance to adopt space-consuming technologies. Both variables are expected to carry negative signs.

Demographics. The final block of variables aims to capture the effect of population variations that influence adoption decisions. The variable age, in quadratic form, is expected to carry a positive first order but a negative second order term. With age comes the accumulation of wealth, making it easier to adopt RETs, however this also reduces the total yield of installation. The elderly will have the necessary funds, but the investment will not return nearly as much as for more youthful citizens. Interestingly, studies have found a significant gender effect Vasseur (2014).

Lastly, weather trends and other geographic dependent effects are expected to be relevant. No variable was available to directly capture these effects, and as such provincial indicators have been included in this first model. Municipality-level fixed-effects were considered once moving away from partitioned OLS estimation.

Estimation

The estimate of eq. 1 is done through a series of partitioned regressions; each cross-section of pooled municipalities includes only one time-period. Each cross-section contains 327 list-wise complete municipalities, except for 2017 which contains 5 fewer municipalities. The estimates of the coefficients are displayed in table 2.

Overall, the regressions achieved moderate predictive power with R^2 ranging between 0.50 and 0.64. Residuals appeared asymptotically normally distributed, although every consecutive year introduced a greater degree of left-ward skew. A Breusch-Pagan test provided strong evidence ($p < 0.01$) for heteroskedasticity for every period. Due to the severity of the evidence, a feasible generalised least squares was ran. The results are displayed in appendix table **??**. Note that besides a few changes in estimated coefficients, there exists stark similarity between estimation results. None of the inference results were altered, and as such the results in **??** may be considered heteroskedasticity-robust.

Already a number of interesting results are obvious. For interpretation of large coefficients, an exponential transformation must be applied for a percentual point change interpretation to be valid; as such the described coefficients differ from those displayed. Contrary to expectations, the coefficients on household size are strongly negative. Increasing the mean household size for a municipality by one person would reduce RE generation by between 42% and 62%. Neither consumption density or

Table 2

The partitioned OLS regressions. The Province Exclusion row provides the result of an F-test for exclusion of the 12 province dummy variables. The values of the provincial indicators are reported in appendix table 6.

Block	Variables	(2013) lGenerated	(2014) lGenerated	(2015) lGenerated	(2016) lGenerated	(2017) lGenerated
Yield	Household size	-0.979***	-0.902***	-0.659***	-0.543***	-0.686***
		(0.269)	(0.210)	(0.192)	(0.209)	(0.198)
	lConsumption Density	-0.062	-0.024	-0.175	-0.125	0.001
		(0.066)	(0.197)	(0.177)	(0.185)	(0.034)
Cost	lProperty Value	0.082	-0.031	-0.038	-0.152	-0.152
		(0.163)	(0.142)	(0.129)	(0.132)	(0.113)
	lMedian Wealth	0.269***	0.248***	0.206***	0.158***	0.140***
		(0.070)	(0.058)	(0.052)	(0.055)	(0.051)
	Share Smartmeter	0.011**	0.003	0.002*	0.002**	0.002**
		(0.004)	(0.002)	(0.001)	(0.001)	(0.001)
Potential	lConnection	-0.172***	-0.225***	-0.206***	-0.185***	-0.170***
		(0.060)	(0.050)	(0.045)	(0.048)	(0.043)
	lHousing Density	-0.133***	-0.106***	-0.118***	-0.106***	-0.108***
		(0.044)	(0.034)	(0.031)	(0.033)	(0.031)
	Share Rented	-0.037***	-0.038***	-0.033***	-0.031***	-0.032***
		(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
Population	Share Males	0.085**	0.060*	0.035	0.026	0.017
		(0.043)	(0.032)	(0.028)	(0.030)	(0.029)
	Age	0.235	0.665***	0.578***	0.633***	0.584***
		(0.268)	(0.201)	(0.179)	(0.187)	(0.181)
	Age^2	-0.003	-0.008***	-0.007***	-0.008***	-0.007***
		(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
	Province Exclusion	8.074***	18.975***	10.038***	9.174***	9.733***
	N	327	327	327	327	322
	R^2	0.50	0.63	0.61	0.61	0.64
	$\overline{R}^2$	0.47	0.60	0.58	0.59	0.61

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

property value are believed to be significant predictors.

On the contrary, median wealth is; with a 1% increase in median wealth increasing household electricity generation by between 0.15% and 0.31%. Furthermore, share of houses with smart-meters is significant, but steadily decreasing over panel years. While statistically significant, the coefficient is not economically significant, with a 1% increase in households with smart-meters having an effect between 0.2% and 0.3% after 2013.

The negative coefficients on installed connections and housing density suggest urban population centers have much more trouble with installation of RETs compared to more rural municipalities. A 1% increase in the first will result in roughly a 0.2%

decrease, while the second will see a 0.1% decrease. The share of rented households is also a strong negative predictor, with a 1% increase in renters indicating a 3% - 4% decrease in household generation.

Lastly, population factors indicates a quadratic age effect in most cross-sections while no strong evidence for a gender effect is found. In all years besides 2013, both the first- and second-order age terms are significant. As such, age on renewable energy production by households follows a inverted U-shape. Based on the coefficients, the optimum mean age for RETs is between 41 and 42. In every year, the provincial dummy variables are jointly strongly significant.

Dynamic Panel Analysis

Theoretical Framework

Assume municipalities -as an aggregate of households rather than an administrative unit- act as economic agents attempting to increase their adoption RET by households. Over the long run, municipalities are expected to reach a saturation point (or equilibrium) in their adoption of household renewable energy, determined by the control variables described in the previous section. These reflect the inherent differences between muncipalities' capacity for these household technologies. Symbollically, this relationship is described as,

$$y_t^* = \beta_0 + \beta \mathbf{x}_t + u_t \tag{2}$$

As is clear from fig. 2, the dependent variable is clearly not at an equilibrium point between 2013 and 2016. Instead, with the introduction and gradual social acceptance of RETs, there has been a strong positive time dependency. While these trends can be captured using simple trend and seasonal proxies, a method that specifically employs the panel-regression data structure is the *partial adjustment framework*. The key assumption of the partial adjustment framework is that annual change in the dependent is proportional to the difference between equilibrium and the current value. The inertia coefficient capturing the linear relationship between the two is generally referred to as the *speed of adjustment* parameter. Intuitively, this implies the step towards the desired level of energy production is dependent on the distance away from it.

$$y_t - y_{i,t-1} = \lambda(y_t^* - y_{t-1}) \tag{3}$$

Rewriting eq. 3 using eq. 2 provides one with an estimable equation of the following form, where the superscripts (*) and (t-1) denote the equilibrium and lagged coefficients respectively,

$$y_t = \lambda(\alpha_0 + \alpha\mathbf{x}_t) + (1 - \lambda)y_{t-1} + \lambda u_t \tag{4}$$

$$\hat{y_t} = \hat{\delta}_0 + \hat{\delta}^{(*)}\mathbf{x}_t + \hat{\delta}^{(\mathbf{t-1})}y_{t-1} \tag{5}$$

The initial estimates for λ and β follow as $1 - \hat{\delta}^{(\mathbf{t-1})}$ and $\hat{\delta}/\hat{\lambda}$ respectively. To further take into account the unobservable heterogeneous error across municipalities, a set of dummy variables, denoted by η, are introduced. The full model for estimation is thus,

$$\hat{y_t} = \hat{\delta}_0 + \hat{\delta}^{(*)}\mathbf{x}_t + \hat{\delta}^{(\mathbf{t-1})}y_{t-1} + \eta \tag{6}$$

Estimation

The results of estimation via the partial adjustment framework are displayed in table 3. Overall, the model achieves very strong predictive power, with R^2 values exceeding the 0.80 level. The significant results match those of table 2 for the first two estimation methods (both OLS). Note that the third estimands differ substantially from the prior two results, although this model shows the highest value of R^2. Due to the addition of fixed-effects (demeaning the independent variables via means of dummy variables of every municipality), a bias proportionate to the inverse of the considered time period Nickell (1981). For small time lengths, this can be substantial (in this case $\frac{1}{4}$). For this reason, OLS regression with added provincial level dummy variables is chosen as the 'best' available model.

Table 3

Regression estimates according to the Partial Adjustment Framework (see eqs. 4 and 6). Note that the displayed coefficients are the δ parameters. Conversion to speed of adjustment λ and equilibrium model β's is done for the second OLS regression in eqs. 7 and 8.

Block	Variables	(OLS) lGenerated	(OLS) lGenerated	(FE) lGenerated
Adjustment Speed	lGenerated$_{t-1}$	0.579***	0.537***	0.354***
		(0.010)	(0.009)	(0.015)
Yield	Household size	-0.294***	-0.264***	-0.722
		(0.070)	(0.071)	(0.704)
	lConsumption Density	-0.011***	-0.021***	-0.018***
		(0.003)	(0.003)	(0.003)
Cost	lProperty Value	-0.182***	-0.031	1.006***
		(0.033)	(0.041)	(0.278)
	lMedian Wealth	0.060***	0.069***	0.914
		(0.019)	(0.018)	(0.685)
	Share Smartmeter	0.000	0.001***	0.003***
		(0.000)	(0.000)	(0.001)
Potential	lConnections	-0.074***	-0.088***	0.863
		(0.017)	(0.016)	(0.654)
	lHousing Density	-0.088***	-0.044***	0.366**
		(0.009)	(0.011)	(0.143)
	Share Rented	-0.013***	-0.014***	-0.038***
		(0.002)	(0.002)	(0.012)
Demographics	Share Males	-4.167***	1.029	5.332
		(1.033)	(1.061)	(5.313)
	Approx. Age	0.145**	0.322***	-0.686**
		(0.063)	(0.066)	(0.333)
	Approx Age^2	-0.002***	-0.004***	0.010***
		(0.001)	(0.001)	(0.004)
	Dummy Exclusion	-	25.383***	4.300***
	Province Dummy	No	Yes	No
	Municipality Dummy	No	No	Yes
	N	1,303	1,303	1,303
	R^2	0.845	0.872	0.937
	$\overline{R}^2$	0.843	0.870	0.915

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Model residuals were visually approximately normally distributed, although this was expected given the large sample size. A Breusch-Pagan test provided strong evidence for heteroskedasticity (F(23, 1279) = 7.61, p< 0.001). Again, re-estimation via inverse variance weigthed least-squares provided a model with few significant changes to the OLS estimate. This GLS model is displayed in appendix table 8. Much like the cross-sectional OLS estimate, few differences exist between the re-estimated parameters and those displayed in table 3, and may be assumed to be robust under heteroskedasticity.

A serial correlation test without assuming strict exogeneity revealed strongly significant evidence for serial correlation ($\rho = 0.101, t(975) = 1.68, p > 0.05$). Prais-Winsten was used for re-estimation, also displayed in appendix table 8. While it did reveal a significant gender effect, few variables showed significant deviation from the OLS estimate. As such, the model estimates presented in table 3 are assumed to be robust under serial correlation.

The results in table 3 reflect the δ parameters according to eq. 6 and hold no practical significance on their own. The estimated results can be converted back to produce estimates directly comparable to those in table 2 for the equilibrium state once the rate of adjustment parameter λ if found. Note that conversion does not affect inference using the standard t-statistic as in table 3.

$$\Delta \log(\text{Generated}) = \underset{0.02}{0.46} \cdot (\log(\text{Generated})^* - \log(\text{Generated})_{t-1}) \tag{7}$$

$$\begin{aligned}
\log(\text{Generated})^* = & -\underset{0.15}{0.57} \log(\text{Housesize}) - \underset{0.01}{0.05} \log(\text{Consumption Density}) \\
& -\underset{0.03}{0.07} \log(\text{Propval}) + \underset{0.04}{0.15} \log(\text{Wealth}) \\
& + \underset{9e-04}{2.76e-03}\text{Smartmeter Share} - \underset{0.09}{0.19} \log(\text{Connections}) \\
& -\underset{0.02}{0.10} \log(\text{House Density}) - \underset{2e-03}{0.03} \text{ Rented Share} \\
& + \underset{-2.24}{2.22}\text{Males} + \underset{0.14}{0.70}\text{Age} - \underset{1e-03}{0.01} \text{ Age}^2 + \delta \cdot \eta_{province} \\
& N = 1303, R^2 = 0.87
\end{aligned} \tag{8}$$

The transformed coefficients are similar to those described in table 2, with the majority of the partial adjustment estimates falling within the ranges of coefficient values displayed. Differences might be explained by the addition of province level dummies. Intuitively these results make sense, as the regressions conducted in table 2 reflect the static equilibrium component of partial adjustment.

Beyond merely a robustness check of the originally estimated model, the main added value of these results is the specified speed of adjustment parameter. A value of 0.46 indicates a nearly 60% year-on-year reduction of the distance between the equilibrium and current situation. Naturally, not all of this is from new adopters; those who had RETs installed later in the year will bump the generated amount in year after. Furthermore, this parameter should not be interpreted as 60% of the potential adopters taking the plunge; however, it may certainly be expected that new adopters reflect a large proportion of the increase. A more thorough assessment of possible determinants of this parameter is provided in the next section.

Determinants of the Speed of Adjustment

In an attempt to predict the proportions of houses with solar panels in Malta, Briguglio and Formosa (2017) used education, both at the secondary and tertiary levels, along with pro-governmental support and favour for the green political party to extend their model beyond the variables included in table 2. While statistically insignificant in their model, Vasseur (2014) found a series of similar variables to be able to successfully discriminate voluntary and non-voluntary adopters. The preliminary findings of this study suggest that the level of urbanity is a currently neglected, but very important factor in adoption rates.

Where previous analyses stopped after considering the static situation, the model estimates that produced eqs. 7 and 8 can be extended to allow for interactions between the speed of adjustment and additional variables. From a methodology perspective, where the equilibrium model defined an upper bound for the growth, the interactions in the adjustment model allow for different slopes towards these upper bounds.

The introduced variables are the proportion of higher educated residents, defined

Table 4

Summary statistics for the variables interactions. Note that using the CBS definitions for urbanity, 1500 or more addresses per km^{-2} to be strongly urban, between 1000 and 1500 addresses to be urban and between 500 and 1000 to be rural.

Variable	Unit	N	Mean	Median	SD	Min	Max
lHigher Education	%	1,640	2.751	2.729	0.364	1.65	4.29
Left Vote Share	%	1,640	35.100	35.800	9.238	1.74	62.92
Share Rural	%	1,640	25.627	23.751	17.713	0.000	83.081
Share Urban	%	1,640	19.937	19.282	14.803	0.000	74.388
Share S. Urban	%	1,640	25.570	9.982	29.917	0.000	97.914

as those having attained a Bachelor degree or above, the proportion of urban or rural households, based on the address density within a radius about the household, and the proportion of votes for the left and progressive parties[1] in the 2017 Dutch general elections.

The estimates for the model with variable slopes is depicted in table **??**. Few of the slopes are significant, with greater tendency for the included intersect to be significant. Of note however, is the positive significant sign on the interaction with share of left votes, along with the negative sign on the intersect for the fully specified model (7). While these parties reflect the most environmentally progressive voters, their prevalence significantly slows the adoption of RETs; by 0.2 - 0.6% for an increased 1% received vote share. Furthermore, the explicit inclusion of variables controlling the urbanity of households manages to control a significant proportion of the remaining variance in the data. Not only is this reflected in the spike in R^2, but also a joint-significance test ($F(3, 1269) = 10.14, p < 0.001$). Lastly, tertiary education seems to have a strong effect on both raising the equilibrium and the speed of adjustment.

Conclusion

The aim of this study was to explore suggested determinants of PV and other RE technology adoption rates by households. Beyond corroboration of earlier existing research, with emphasis on Briguglio and Formosa (2017), the main contributions of this research include the partial adjustment framework, proving to be a flexible and

[1]The largest being GroenLinks, PvdA, SP, PvdD and D66

powerful tool for estimating product growth processes, and suggested determinants of the speed of adjustment parameter. While the idea that financial considerations are key in the adoption decision process was also found in this analysis, access to roof space and low-urban living space are at least equally as important. Furthermore, while growth seems fast nationwide, there do exist significant differences between education levels, along with an unexpected negative relationship with green political stances. More importantly, this research finds strong evidence that the adoption of RET is far more attractive for more rural habitats than urban ones, dampening the predictions for a sunny future in the Dutch PV market considerably (Vasseur, 2014)Oteman et al. (2014).

A potential area for future research might be the link between the partial adjustment model, household proximity and the concept of social acceptance. The research of Koch and Christ (2018), Strazzera and Statzu (2017) and Qureshi et al. (2017) seem to indicate these factors to play a crucial role. The speed of adjustment parameter might be seen as a social force, where the presence of more solar panels in the neighbourhood will induce surrounding households to also adopt these technologies, requiring more and more to appeal to more stubborn potential adopters.

Of further interest might be the addition of subsidy or loan data to take into account governmental support. While subsidies did exist at the municipality level during the considered time-span, these have been phased as the return on investment for PV technologies has become considerably more favourable. Regardless, findings with such measures taken into account could prove very beneficial for nations only starting to embrace RETs.

Naturally this study is not without its limitations. Of primary concern is the use of proxy dependent variable. Rather than looking at physical PV installations, this paper has take the proportional energy production. The finding that more rural habitats will tend towards more RET generation *proportionally* might be a trivial one considering the far lower total energy consumption of these municipalities. The findings of heteroskedasticity and serial correlation further suggest that OLS estimation may not be ideal, although corrections showed reasonable robustness. Given the short time span of the panel data a more efficient estimation method might exist. Otherwise, re-estimation of the findings in this paper is likely doable in the near future once more data has been released.

Table 5

Interaction effects with the adjustment speed parameter. Note that by the definition of λ as in eq. 3, the relationships are complementary; positive coefficients on the interactions are negative impacting the speed of adjustment, and vice versa. This is not the case for the added slope parameters.

Block	Variables	(1) lGenerated	(2) lGenerated	(3) lGenerated	(4) lGenerated	(5) lGenerated	(6) lGenerated	(7) lGenerated
Adjustment Speed	lGenerated$_{t-1}$	0.537***	0.460***	0.555***	0.582***	0.476***	0.557***	0.715***
		(0.056)	(0.029)	(0.021)	(0.024)	(0.032)	(0.060)	(0.116)
Higher Education	lGenerated$_{t-1}\times$ lHigherEduc	-0.001						-0.059**
		(0.020)						(0.024)
	lHigherEduc	0.112***						-0.153***
		(0.033)						(0.034)
Left Vote	lGenerated$_{t-1}\times$LeftShare		0.002**					0.002**
			(0.001)					(0.001)
	LeftShare		0.007***					-0.005**
			(0.001)					(0.002)
Urbanity	lGenerated$_{t-1}\times$ RuralShare			-0.001			0.008	1e-04
				(4e-04)			(0.012)	(5-04)
	RuralShare			0.002**			-2e-04	0.002*
				(5e-04)			(0.001)	(7e-04)
	lGenerated$_{t-1}\times$UrbanShare				-0.003***		-0.032**	-0.002**
					(5e-04)		(0.016)	(0.001)
	UrbanShare				0.003***		-0.003***	0.003**
					(0.001)		(4e-04)	(0.001)
	lGenerated$_{t-1}\times$SUrbanShare					0.001*	2e-04	-3e-04
						(2e-04)	(3e-04)	(4e-04)
	SUrbanShare					0.002**	8e-05	0.001
						(0.001)	(7e-05)	(0.001)
	Constant	2.912***	-5.171***	-2.699	-1.173	2.081	1.890	-2.306
		(0.906)	(1.667)	(1.687)	(1.835)	(2.863)	(2.854)	(1.277)
	N	1,303	1,303	1,303	1,303	1,303	1,303	1,303
	R^2	0.871	0.879	0.879	0.878	0.874	0.877	0.884
	$\overline{R}^2$	0.870	0.876	0.877	0.870	0.871	0.875	0.881

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

References

Best, R., Burke, P. J., Nishitateno, S., et al. (2019). *Understanding the determinants of rooftop solar installation: evidence from household surveys in australia* (Tech. Rep.). Centre for Climate Economics & Policy, Crawford School of Public Policy, The . . . .

Briguglio, M., & Formosa, G. (2017). When households go solar: Determinants of uptake of a photovoltaic scheme and policy insights. *Energy Policy*, *108*, 154–162.

CBS. (n.d.).

Fleiss, E., Hatzl, S., Seebauer, S., & Posch, A. (2017). Money, not morale: The impact of desires and beliefs on private investment in photovoltaic citizen participation initiatives. *Journal of cleaner production*, *141*, 920–927.

Koch, J., & Christ, O. (2018). Household participation in an urban photovoltaic project in switzerland: Exploration of triggers and barriers. *Sustainable cities and society*, *37*, 420–426.

Liander. (2019). *Klein- of grootverbruikaansluiting.* `https://www.liander.nl/algemene-voorwaarden/klein-of-grootverbruik`.

MilieuCentraal. (2019). *Zonnepanelen kopen.* `https://www.milieucentraal.nl/energie-besparen/zonnepanelen/zonnepanelen-kopen/pr`

Nickell, S. (1981). Biases in dynamic models with fixed effects. *Econometrica: Journal of the Econometric Society*, 1417–1426.

Oteman, M., Wiering, M., & Helderman, J.-K. (2014). The institutional space of community initiatives for renewable energy: a comparative case study of the netherlands, germany and denmark. *Energy, sustainability and society*, *4*(1), 11.

Qureshi, T. M., Ullah, K., & Arentsen, M. J. (2017). Factors responsible for solar pv adoption at household level: A case of lahore, pakistan. *Renewable and Sustainable Energy Reviews*, *78*, 754–763.

Rijksoverheid. (2019). *Duurzame energie.* `https://www.rijksoverheid.nl/onderwerpen/duurzame-energie/zonne-energie`.

Smith, M. G., & Urpelainen, J. (2014). The effect of feed-in tariffs on renewable electricity generation: An instrumental variables approach. *Environmental and resource economics*, *57*(3), 367–392.

Strazzera, E., & Statzu, V. (2017). Fostering photovoltaic technologies in mediterranean cities: Consumers' demand and social acceptance. *Renewable energy*, *102*, 361–371.

stroom en gas in Nederland, O. N. (n.d.). *Netbeheerders elektriciteit in nederland.* `https://www.energieleveranciers.nl/netbeheerders/overzicht-netbeheerders`. Energieleveranciers.nl.

Van Hemmen, H. (2011). Determinants of international solar panel adoption. *Environmental Science.*

Vasseur, V. (2014). *A sunny future for photovoltaic systems in the netherlands?: an analysis of the role of government and users in the diffusion of an emerging technology.* Maastricht University.

Table 6

The paritioned OLS regressions with province dummy variables included.

Block	Variables	(2013) lGenerated	(2014) lGenerated	(2015) lGenerated	(2016) lGenerated	(2017) lGenerated
Yield	Household size	-0.979***	-0.902***	-0.659***	-0.543***	-0.686***
		(0.269)	(0.210)	(0.192)	(0.209)	(0.198)
	lConsumption Density	-0.062	-0.024	-0.175	-0.125	0.001
		(0.066)	(0.197)	(0.177)	(0.185)	(0.034)
Cost	lProperty Value	0.082	-0.031	-0.038	-0.152	-0.152
		(0.163)	(0.142)	(0.129)	(0.132)	(0.113)
	lMedian Wealth	0.269***	0.248***	0.206***	0.158***	0.140***
		(0.070)	(0.058)	(0.052)	(0.055)	(0.051)
	Share Smartmeter	0.011**	0.003	0.002*	0.002**	0.002**
		(0.004)	(0.002)	(0.001)	(0.001)	(0.001)
Potential	lConnection	-0.172***	-0.225***	-0.206***	-0.185***	-0.170***
		(0.060)	(0.050)	(0.045)	(0.048)	(0.043)
	lHousing Density	-0.133***	-0.106***	-0.118***	-0.106***	-0.108***
		(0.044)	(0.034)	(0.031)	(0.033)	(0.031)
	Share Rented	-0.037***	-0.038***	-0.033***	-0.031***	-0.032***
		(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
Demographics	Share Males	0.085**	0.060*	0.035	0.026	0.017
		(0.043)	(0.032)	(0.028)	(0.030)	(0.029)
	Approx. Age	0.235	0.665***	0.578***	0.633***	0.584***
		(0.268)	(0.201)	(0.179)	(0.187)	(0.181)
	Approx. Age^2	-0.003	-0.008***	-0.007***	-0.008***	-0.007***
		(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Province	Drenthe (Base)	-3.029	-9.216*	-5.840	-6.565	-5.161
		(6.672)	(5.035)	(4.565)	(4.800)	(4.696)
	Flevoland	-0.317	0.191	0.140	0.071	-0.127
		(0.230)	(0.175)	(0.158)	(0.166)	(0.279)
	Friesland	-0.071	0.266**	0.084	-0.079	-0.280
		(0.166)	(0.127)	(0.116)	(0.123)	(0.251)
	Gelderland	-0.391***	0.245**	0.096	-0.011	-0.163
		(0.150)	(0.114)	(0.104)	(0.109)	(0.248)
	Groningen	-0.115	-0.130	-0.123	0.145	0.027
		(0.165)	(0.126)	(0.115)	(0.122)	(0.119)
	Limburg	0.146	0.052	-0.006	0.002	-0.074
		(0.162)	(0.123)	(0.110)	(0.116)	(0.115)
	Noord-Brabant	-0.516***	-0.438***	-0.407***	-0.474***	-0.598***
		(0.154)	(0.118)	(0.107)	(0.112)	(0.112)
	Noord-Holland	-0.505***	0.127	-0.012	-0.127	-0.289
		(0.162)	(0.126)	(0.115)	(0.121)	(0.249)
	Overijssel	-0.137	-0.089	0.003	0.055	-0.090
		(0.159)	(0.122)	(0.111)	(0.118)	(0.116)
	Utrecht	-0.292*	-0.264*	-0.247**	-0.269**	-0.388
		(0.175)	(0.134)	(0.121)	(0.128)	(0.255)
	Zeeland	-0.876***	-0.559***	-0.152	-0.099	-0.033
		(0.169)	(0.134)	(0.122)	(0.128)	(0.248)
	Zuid-Holland	-0.274*	-0.218*	-0.257**	-0.373***	-0.490**
		(0.163)	(0.130)	(0.118)	(0.123)	(0.249)
	N	327	327	327	327	322
	R^2	0.36	0.36	0.46	0.48	0.51
	$\overline{R}^2$	0.34	0.34	0.44	0.47	0.49

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7
FGLS results of the partitioned OLS model. Note the stark similarity to table **??**.

VARIABLES	(1) lGenerated	(2) lGenerated	(3) lGenerated	(4) lGenerated	(5) lGenerated
householdssize	-0.791***	-0.708***	-0.501**	-0.417**	-0.610***
	(0.255)	(0.216)	(0.198)	(0.211)	(0.203)
lconsdens	-0.101	-0.023	-0.136	-0.137	0.003
	(0.061)	(0.195)	(0.175)	(0.182)	(0.033)
lpropval	0.063	-0.030	-0.075	-0.123	-0.105
	(0.150)	(0.140)	(0.127)	(0.128)	(0.110)
lwealth	0.268***	0.261***	0.216***	0.178***	0.154***
	(0.064)	(0.058)	(0.051)	(0.054)	(0.050)
smartmeter_perc	0.009**	0.002	0.002*	0.002**	0.002**
	(0.004)	(0.003)	(0.001)	(0.001)	(0.001)
lconn	-0.175***	-0.228***	-0.205***	-0.192***	-0.175***
	(0.055)	(0.050)	(0.045)	(0.047)	(0.043)
lhousedens	-0.163***	-0.104***	-0.109***	-0.099***	-0.100***
	(0.042)	(0.034)	(0.031)	(0.033)	(0.031)
Rentedperc	-0.035***	-0.038***	-0.034***	-0.032***	-0.032***
	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
Maleperc	0.034	0.043	0.017	0.015	0.009
	(0.041)	(0.032)	(0.029)	(0.030)	(0.030)
approxAge	0.387	0.819***	0.756***	0.778***	0.687***
	(0.251)	(0.202)	(0.182)	(0.189)	(0.185)
approxAge2	-0.005*	-0.010***	-0.009***	-0.010***	-0.008***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Constant	-4.024	-12.326**	-9.428**	-9.734**	-7.747
	(6.285)	(5.120)	(4.662)	(4.853)	(4.790)
Observations	327	327	327	327	322
R-squared	0.554	0.638	0.622	0.627	0.648

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8

GLS estimation of the Partial Adjustment model with provincial dummy variables included.

VARIABLES	(WLS) lGenerated	(PW) lGenerated
L.lGenerated	0.555***	0.468***
	(0.009)	(0.009)
householdssize	-0.279***	-0.303***
	(0.070)	(0.093)
lconsdens	-0.019***	-0.019***
	(0.003)	(0.003)
lpropval	-0.022	0.007
	(0.041)	(0.054)
lwealth	0.060***	0.086***
	(0.018)	(0.024)
smartmeter_perc	0.001***	0.003***
	(0.000)	(0.000)
lconn	-0.080***	-0.101***
	(0.015)	(0.021)
lhousedens	-0.047***	-0.041***
	(0.011)	(0.015)
Rentedperc	-0.013***	-0.016***
	(0.001)	(0.002)
maleperc	1.253	2.637*
	(1.075)	(1.372)
approxAge	0.256***	0.337***
	(0.064)	(0.086)
approxAge2	-0.003***	-0.004***
	(0.001)	(0.001)
2.provinceFactor	0.036	0.080
	(0.056)	(0.078)
3.provinceFactor	-0.013	0.043
	(0.041)	(0.057)
4.provinceFactor	0.038	0.089*
	(0.037)	(0.052)
5.provinceFactor	0.023	0.003
	(0.040)	(0.057)
6.provinceFactor	-0.054	-0.071
	(0.039)	(0.054)
7.provinceFactor	-0.256***	-0.311***
	(0.038)	(0.053)
8.provinceFactor	-0.007	0.011
	(0.040)	(0.056)
9.provinceFactor	-0.026	-0.048
	(0.039)	(0.055)
10.provinceFactor	-0.135***	-0.172***
	(0.043)	(0.060)
11.provinceFactor	0.061	0.007
	(0.042)	(0.058)
12.provinceFactor	-0.169***	-0.203***
	(0.040)	(0.055)
Constant	2.563	4.842**