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Heterogeneity in the Adoption of Photovoltaic Systems in Flanders

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Abstract

We study the determinants of PV adoption in the region of Flanders (Belgium), where PV adoption reached high levels during 2006-2012, because of active government intervention. Based on a unique dataset at a very detailed spatial level, we estimate a Poisson model to explain the heterogeneity in adoption rates. We obtain the following findings. First, local policies have a robust and significant impact on PV adoption, providing indirect evidence that the larger regional incentives formed the basis for the strong development of PV adoption in the region. Second, there is a strong unconditional income effect, implying a Matthew effect in the subsidization of PVs. Our third finding is however that this income effect is largely driven by the fact that wealthier households are more likely to adopt because they tend to be larger (and hence higher users), are more frequent house owners (who capture more of the benefits), or own houses that are better suited for PV. We can thus identify the channels through which wealthier households are more likely to benefit from the PV support. Finally, we identify the importance of several housing characteristics: PV adoption tends to be more likely in larger and in more recently built houses. In several extensions, we consider the determinants of the average size of installed PVs, and the differential impact of certain variables over time.

Keywords*:* Adoption of photovoltaic systems; renewable energy sources; Poisson regression

JEL-classification:

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1. INTRODUCTION

Worldwide, many countries have rolled out policies to stimulate the use of renewables for the production of electricity, the overarching motivations for these policy initiatives being security of supply and climate change. Within the group of renewable technologies, solar technologies have been among the most stimulated ones, despite their relatively unfavorable cost structure compared to other renewable technologies.

A distinguishing factor of the solar technology is its scalability, i.e. it is a technology that can easily be adopted by small (residential) customers. From a political perspective, this is a favorable characteristic as renewables policies targeting residential photovoltaic systems (PVs) have an immediate visibility impact. Over the past decade, many countries worldwide have thus taken policy initiatives to foster the adoption of PVs, for example through tax credits or production subsidies. However, few years later, many of these countries also decided to roll back these initiatives, as they turned out to be much more expensive than initially anticipated, due to the generous subsidy schemes that were put in place.

Policymakers became increasingly aware of the socioeconomic impacts that are linked to the large scale adoption of PV through the net metering principle, which implies that customers are only charged for the net amount of electricity they use on an periodical basis (Cai et al. (2013), Darghouth et al. (2011)). As infrastructure costs are recovered through a surcharge on the kWh price, an unanticipated side effect of the net metering principle is that PV customers end up contributing less for these costs than non PV owners do, despite the fact that they also use the grid infrastructure intensively. Moreover, it has been widely shown that higher income customers typically also consume more electricity, implying that they are faced with larger incentives to adopt PV as they then can avoid paying these infrastructure charges. This evolution, the so-called 'death spiral' (Borenstein and Bushnell (2015)), which has been observed in many countries, has made that policy makers are considering to roll back policy initiatives in support of PV.

Generous support policies also made the adoption of residential PV very popular in Flanders, the largest region of Belgium. Our main purpose is to explain the spatial adoption pattern of PV that emerged, by including a rich set of socioeconomic and housing variables in our empirical model. In short, we ask the question why adoption is higher in some areas and lower in others.

The decision to adopt a PV system has recently been studied from different perspectives. While some of these studies use interviews and survey data as their source of information (Jager (2006), Schelly (2014), Vasseur and Kemp (2015), Willis et al. (2011), Faiers and Neame (2006)), most studies use data on all PV installations as the basis for their analysis, possibly limited to a geographical subset of the full database (Bollinger and Gillingham (2012), Crago and Chernyakhovskiy (2014), Davidson et al. (2014), Drury et al. (2012), Kwan (2012), Letchford et al. (2014), Macal et al. (2014), Richter (2013), Robinson et al. (2013), Rode and Weber (2011)). Within this last group of studies, Macal et al. (2014) and Robinson et al. (2013) use agent-based modelling to analyze the PV adoption decision, while all other studies follow an empirical approach in assessing the factors that determine the decision to adopt PV.

A first strand in this empirical literature focuses on whether peer effects are observed in the diffusion process of PV (Bollinger and Gillingham (2012), Letchford et al. (2014), Macal et al. (2014), Richter (2013), Robinson et al. (2013), Rode and Weber (2011)). A second strand of literature focuses on understanding other determinants, in particular the role of state policy incentives (Crago and Chernyakhovskiy (2014)), third-party PV products (Drury et al. (2012) and environmental, economic, social and political factors on PV adoption behavior (Kwan (2012), Davidson et al. (2014)). The latter two papers are the most relevant for our study in terms of type of data and empirical approach. They study the role of geospatial information (such as environmental, social, economic and political factors) on the adoption of residential PV across the US and California.

This paper contributes to this second strand of literature in various ways. First, we incorporate a much richer set of socioeconomic characteristics than in previous work, which gives interesting new insights. To illustrate this, we will use the set of covariates used by Kwan (2012) as a benchmark for comparison. Furthermore, we include a set of housing characteristics, which has not been considered in previous work. As such, we explain the underlying reasons for the previously documented fact that PV adoption is more likely when the house value is high. In addition, our data set is at a much finer level of aggregation than previous work. Our unit of observation is the statistical sector, which on average contains only 280 households, much less than the number of households within US zip codes. In contrast with other work, we do not only look at the number of PVs, but also at the size of the installed PVs, and we compare differences between early and late adopters.

Finally, this paper is, to our knowledge, the first study focusing on explaining heterogeneity in the adoption of PV, using the complete installed base of PV in a region outside the US.[1] The case of Flanders is rather unique in the sense that the average PV adoption in the region was close to 9%, which is high compared to the countries or regions studied before.

To study the determinants of PV adoption, we use a Poisson model with some adjustments to deal with spatial patterns in the data.[2] We obtain the following main findings. First, local policies have a robust and significant impact on PV adoption, providing indirect evidence that the larger regional incentives formed the basis for the strong development of PV adoption in the region. Second, there is a strong unconditional income effect, implying a Matthew effect in the subsidization of PVs. Our third main finding is, however, that the direct income effect almost vanishes if we also control for socioeconomic variables: PV adoption is especially large among the larger households (who are high users of electricity), among house owners (who capture more of the benefits of their investment) and in houses that are better suited for PV. Hence, wealthier households are more likely to adopt and benefit from the PV subsidies, not because of their higher income per se, but rather because they are more likely to adopt PV as higher users, as more frequent house owners and because they have houses that are better suited for PV. Finally, we identify the importance of several housing characteristics: PV adoption tends to be more likely in larger and in more recently built houses. In several extensions, we consider the determinants of the average size of installed PVs, and the differential impact of certain variables over time.

These findings shed light on the factors that have influenced past adoption decisions. This can help policymakers and other stakeholders in the sector to reassess past policies and, when necessary, to revise future policies promoting the adoption of PV.

Section 2 briefly describes the policy measures in place in Flanders, as they are considered to be a major driver in the adoption of PV. Section 3 describes the data. Section 4 introduces and motivates our empirical approach. Section 5 discusses the empirical results for the determinants of PV adoption, and two extensions (size of installed PVs and the differences between early and late adopters). Finally, section 6 concludes.

2. POLICY MEASURES TO SUPPORT RESIDENTIAL PV IN FLANDERS

Most used traditional sources of electricity production are linked to high emissions of carbon dioxide and the depletion of natural resources. Governments therefore encourage the diffusion of new technologies to switch towards a more environmentally friendly way of producing electricity.

In Belgium, the policy towards renewable energy sources (RES) is largely a regional matter, i.e. the three regions, Flanders, Wallonia and the Brussels Capital Region, each have developed their

[1] Richter (2013) and Rode and Weber (2011) also study a non-US region (England and Wales, and Germany) on the basis of the complete installation base, but their focus is on the presence of peer effects.

[2] Our Poisson model differs from Kwan (2012), who estimates a zero-inflated negative binomial model on US data and from Davidson et al. (2014), who uses a log-linear specification. We motivate our model in section 4, and report robustness analysis with respected to a zero-inflated negative binomial in the Appendix.

own RES support policies. Nevertheless, there are also additional support measures by the Federal Authority and by many of the 308 local municipalities. We first discuss general support measures, applicable to all households and then describe the local support measures, which show variation across municipalities, enabling us to quantify their impact in our cross-sectional analysis.

2.1. General support, applicable to all households[3]

Households benefit from two types of general support measures: up-front investment support and support associated with future green electricity production.

Investment support: subsidy, tax cut and green loans

In 2002, the regional government of Flanders introduced its first support scheme for PV. The program consisted of subsidies to private investors, amounting to 65% of the total investment cost. The program started with a limited budget and was renewed annually. The program was phased out in 2006 and 2007 with subsidies of 10% of the investment costs.[4]

As of 2004, the Belgian federal government offered a tax credit to individuals undertaking energy efficiency and certain renewable energy investments in their homes. A tax credit of 40% is granted for investments in a variety of technologies, including PV. The percentage has varied over time. Also the maximum allowed tax credit has changed, ranging from €500 in 2004 over €2600 in 2008 to €3600 in 2011, the last year in which the tax credit applied to PV investments.[5] The federal government also allows a reduced VAT rate of 6% instead of 21% on investments, including PV, if it is used to renovate a house that is older than 5 years (10 years from 2016 on).[6]

Finally, an interest-rate subsidy of 1.5% and a tax reduction of 40% on the residual interest on loans taken out was granted for such investments (green loans) from 2009-2011. Among other conditions, the capital borrowed in the framework of the green loan must amount to at least €1250, subject to a ceiling of €15 000.[7]

Support associated with future green electricity production: net metering and green certificates

All PV installations with a maximum capacity of 10 kW are eligible for net-metering, while larger installations need to apply for a separate access point or meter. Electricity produced by residential installations is automatically deducted from electricity consumed and excess production is injected into the grid (the so-called backward running kWh-meter). However, in case an installation injects more electricity than it has taken from the grid during a billing period, this amount is not financially reimbursed. The distribution system operators (DSOs) initially provided this service for free but, after numerous recommendations of government agencies and legislative procedures, the DSOs introduced a annual fee of around 100 EUR/kW of the inverter of the PV in July 2015.[8]

Next to the benefits of net metering, households received public support in the form of Tradable Green Certificates (TGC) for their electricity production. These certificates could be sold to the DSOs at a guaranteed price for a fixed number of years. The TGC program started under very

[3] The website of the International Energy Agency was used to write this overview (http://www.iea.org/policiesandmeasures/renewableenergy/?country=Belgium), supplemented with sources that will be cited when used.

[4] Furthermore, the subsidizable investment cost was capped to 7000 €/kWp and a maximum subsidizable capacity of 3kW. See KB 10 February 1983, changed by Flemish government in 15 July 2005; Government brochure: Subsidieregeling voor elektriciteit uit zonlicht (2005).

[5] Moreover, since 2009 it was possible to spread the tax credit over four years, such that the maximum allowed credit became less binding.

[6] http://www.vlaanderen.be/nl/bouwen-wonen-en-energie/bouwen-en-verbouwen/btw-tarief-van-6-bij-renovatie-van-woningen

[7] http://minfin.fgov.be/portail2/nl/themes/dwelling/energysaving/green.htm

[8] http://www.vlaanderen.be/nl/bouwen-wonen-en-energie/elektriciteit-aardgas-en-verwarming/prosumententarief-voor-eigenaars-van-zonnepanelen-windmolens-en-wkk-installaties-10-kw-en-met

generous conditions in 2006, with a guaranteed price of €450 per MWh for 20 years. Since 2010, the conditions gradually became less favorable, and since 2014 there is no more public support. This was motivated by the fact that the budgetary costs were very high and the prices for PV systems had in any case decreased considerably. During the period 2006-2013, the TGC system was a major source of support. At the government's used interest rate of 15%, the present value of the subsidy amounted to approximately €10000 for a PV with an average capacity.[9] The appendix provides a more detailed overview of the TGC policy.

2.2. Local support by municipalities

Municipalities have the authority to provide support to the deployment of renewables on their territory. Many municipalities have used that power through a variety of mechanisms, such as investment subsidies, which also apply to PV installations. These subsidies range from 10% to 25% of the investment cost, typically capped at a maximum amount of €500 to €1000. Since these policies show sufficient variation across municipalities, we will incorporate a measure of these subsidies in our empirical analysis. The policies will be discussed in more detail in section 3.

At the same time, it will be useful to keep in mind that the benefits from local support are considerably less important than those from the public support from green certificates. Even the maximum support of €1000 in some municipalities is about ten times lower than the subsidies in the form of green certificates. We will come back to this when interpreting our empirical results.

3. THE DATA

Our empirical analysis is based on three main data sources. The cornerstone of the analysis is a database provided by the Flemish energy regulator, VREG. This database contains all PVs installed in Flanders between the beginning of 2006 and the end of 2012[10], and is matched with a dataset on the statistical sector where the PV system has been installed. We link the resulting database to two other data sets we constructed: a dataset containing information on municipal policy measures, and a dataset with socioeconomic and housing information available at the statistical sector level.

3.1. Data on residential PV installations in Flanders

The database from the Flemish energy regulator contains information on the location, size and installation date of all RES systems in Flanders. Since we are interested in PV adoption since 2006, we remove all non-PV installations and PV installations installed before 2006 (722), leaving us with 226115 units. Furthermore, since we are interested in residential PV installations, we remove all installations with a capacity larger than 10kW, resulting in a further decrease to 220464 installations (so 2.50% of PV installations drop out).[11] Table 1 shows descriptive statistics on the installed PV units in Flanders at the end of 2012. With 220464 installed PVs on a total of 2.58 million households, the adoption rate amounted to 8.55%.

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[9] Consider an interest rate of 15% and a 5kW system that produces 4.25MWh/year. For the period 2006-2009 the present discounted value of a guaranteed certificate price of €450/MWh during 20 years is equal to €13767. For the period 2010-2012, the guaranteed price decreased, and similar calculations show the present discounted value of the support decreased to on average €8867. Overall, the average support benefit was €10261.

[10] The first registered PV is already in 1997 and we are able to collect real-time data but we use the 2006-2012 adoptions only because we can be more confident they are all registered in the database. This is because the VREG also distributed the green certificates through this system which were beneficial during this period.

[11] This approach was suggested by the VREG and was also followed by Kwan (2012). Moreover, for some support policies the $10kW$ criterion is also used to qualify for support.

VARIABLES	*sum*	*N*	*mean*	*st. dev.*	*min*	*max*
Capacity of PV in kW*	2 077 070	226 115	9.19	54.1	0.003	6221
Capacity of PV in kW if <10kW*	1 057 458	220 464	4.80	2.13	0.003	10
Flemish households in 2007		2 577 058				

*: On 31 December 2012.

Table 1: Summary statistics on PV in Flanders.

We match the PV installations to statistical sectors, which are very disaggregate local areas – typically a set of streets – grouped by socioeconomic, urban and morphological structural features, governed by the Belgian Statistics Office ADSEI. Flanders consists of 9182 statistical sectors, so with a total number of households in Flanders of about 2.58 million, the average statistical sector contains on average about 280 households.[12] Based on the installation addresses of the PVs and a precise description of which streets belong to which statistical sector, we can link each PV to a unique statistical sector. This will subsequently enable us to link the data to socioeconomic information at the level of the statistical sector, and to data on public support measures at the more aggregate municipality level.

Out of the 220464 residential PV installations, only 3634 (or 1.65%) could not be matched to the correct sector due to unidentifiable errors in the address. As the information in the PV database was imputed by the owners of the PV, the matching of the two databases was prone to spelling mistakes, typos and other kinds of errors. We corrected these as much as possible and consider it is reasonable to assume that the remaining errors do not correlate with relevant variables for our analysis. These unmatched installations are therefore excluded from the econometric analysis. In a limited number of cases, an observation could not be uniquely linked to one statistical sector. In those cases, the observation was randomly assigned to one of the remaining candidate sectors. Figure 1 provides a first impression on the spatial distribution of PV installations in Flanders, showing the adoption rates per statistical sector at the end of 2012.

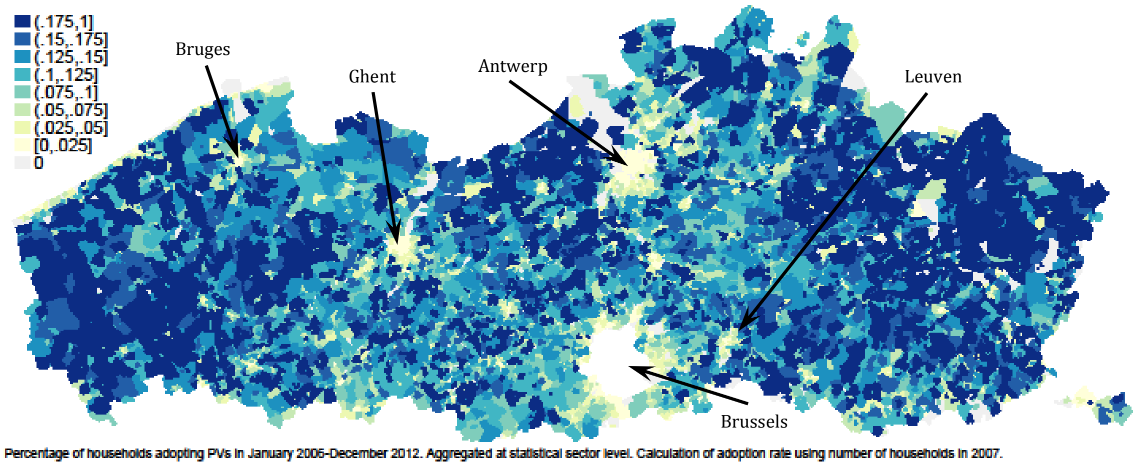

Figure 1: The spatial distribution of PV installations in Flanders

Based on this figure, some first observations can be made. More urban areas (Brussels, Bruges, Ghent, Antwerp and Leuven) seem to have a lower density of PV installations, as can be seen from the white or light-shaded spots. More rural areas such as the northern part of the province of Limburg (east part) and the province of West Flanders (west part) seem to have much higher adoption rates. One possible explanation could be that PV installations can potentially capture more sunlight in rural areas than in urban areas because in rural areas people are more likely to

[12] To put this in perspective, the whole country of Belgium consists of 19,781 sectors. For more information, see: http://statbel.fgov.be/nl/statistieken/gegevensinzameling/nomenclaturen/admin-geo/statistische_sector/

live in (semi-)detached houses, which makes it easier to install a PV. We will consider these and other possible explanations in our econometric analysis below.

3.2. Socioeconomic and housing data

We match the PV database with socioeconomic census data at the level of the statistical sector, available through the SEE2001 census by the Belgian Statistics Office, ADSEI, of which some variables were updated with 2007 data.[13] Since participation is obligatory and 95% of the households filled out the questionnaire, we expect that the survey is representative.[14] In addition, we make use of income statement data of the same source (ADSEI). Finally, we obtain additional housing characteristics from the Belgian cadaster and use publically available outcomes of municipality elections.

The selection of the variables used in the empirical analysis below was based on the relevant literature. Table 2**Error! Reference source not found.** summarizes these variables, and we briefly describe them in the following paragraphs.

SEE2001 census[15]

A first variable is the **number of households**. This is important to calculate adoption rates and to have a variable of which we expect to have a proportional impact on the number of PVs. A second variable is **household age**, defined by the age of the reference person of the household, i.e. the person who is mostly in charge of important decisions. Studies on PV adoption have shown that older people are less likely to adopt (Bollinger and Gillingham (2012), Kwan (2012), Willis et al. (2011)) and some also show a negative effect for younger people. Some studies also show effects related to **ethnicity**, with whites being more likely to adopt (Bollinger and Gillingham (2012), Kwan (2012)). We expect similar results when using nationality as an explanatory variable. Furthermore, we use **gender** as a variable as some studies found that males are more likely to adopt new technologies (e.g. Bollinger and Gillingham (2012)). Information costs are also considered important in the decision to adopt, especially in case of a new technology. We therefore include the level of **education**. Kwan (2012) found a positive effect for the level of education. Note that next to the information benefits, the level of education is also positively correlated with environmental preferences (Mills and Schleich (2009), Hersch and Viscusi (2006)) or it could be seen as a proxy for lifetime wealth (Hersch and Viscusi (2006)). Another variable with similar intuition is the **occupational status** or sector of employment. Kontogianni et al. (2013) found that people working in the public sector are more likely to adopt PV rather than other RES technologies. **Household size** can also play a role, as larger households have a higher electricity consumption and can share the fixed investment cost among a larger group of beneficiaries (Mills and Schleich (2009)). **Population density** is included as an explanatory factor, as we can expect that the amount of open space raises the possibility to capture sunlight, which should have a positive impact on the number of PV installations. Kwan (2012) uses a similar measure by taking housing density into account.

The presence of a principal-agent problem in the renting market prevents a correct allocation of the investment cost of a PV installation among tenant and landlord. To investigate this, we include **house ownership status**, defined as the proportion of owner-occupied houses. Crago and Chernyakhovskiy (2014) and Mills and Schleich (2009) found evidence for the presence of a principal-agent problem.

What makes our study different from Kwan (2012) is that we also include variables that capture housing characteristics. The SEE2001 survey contains some interesting variables to investigate

[13] Algemene Sociaal-Economische Enquête 2001 (http://statbel.fgov.be/nl/statistieken/gegevensinzameling/volkstelling/2001/).

[14] For a minority of sectors, information on some variables is not available for privacy reasons, as the number of households living in that sector was too small. This is typically the case for sectors with less than 20 registered inhabitants.

[15] For some of the variables we have more recent data than from the 2001 census. We use 2007 data for number of households, population density, household age, household size, gender and ethnicity.

these effects, like **double glazing** and **roof insulation** and **quality of the roof**. Note that, in the latter case, it is not clear what to expect: a bad roof could be negatively or positively correlated with investment of PV. It would be negatively correlated if a bad roof condition would result in postponing PV adoption because extra investment costs are required to repair the roof. Alternatively, a bad roof quality could also be seen as a proxy for procrastination behavior, i.e. for delaying major works. On the other hand, economies of scope can be realized by jointly repairing the roof and installing PV panels.

We also try to capture a household's **environmental awareness**. For this, we use a proxy based on the answer given on the question 'Does your house have roof insulation?'. The proportion of people that were able to answer this question is assumed to reflect how people care about energy efficiency. This is similar to the approach taken by Mills and Schleich (2009) in their study on the adoption of solar thermal installations, where they include data on people's awareness of the energy class of their washing machine. Mills and Schleich (2009) did not find any significant impact.

Cadaster data

We obtained additional housing characteristics from the Belgian cadaster in 2011. The added variables are the **house type**, **house size** (measured by built area), **house age** and the **house value** (measured by its cadastral income). House age and value are studied by Davidson et al. (2014), They find that both variables are important in explaining adoption, as well as number of rooms in the houses (which probably correlates a lot with our house size variable).

Income data

For income we have annual data at the statistical sector level. However, for privacy reasons these data are published only if the number of tax declarations in a statistical sector reaches a threshold level. This threshold level has changed over time: before 2007, the threshold was 20 households for information on the average and median income per tax declaration, from then onwards, the threshold increased to 200 households for the average income, while staying at 20 households for information on the median income level. Using 'average income per tax declaration' data of 2007 or later would result in a loss of about 3500 observations. We therefore decided to use the 2006 data to construct a proxy for the geographical income distribution in Flanders.

We use the **average income** per household rather than the average income per tax declaration. We do this because tax declarations need to be filled out by all adults, thus also including for example students. On the other hand, some couples fill out one common tax declaration, others do not.

Next to a measure of central tendency, we also have information on the **dispersion of income** per tax declaration in a statistical sector. Unfortunately, the information we have does not allow to calculate a measure of dispersion at the household level. We therefore use the dispersion measures of the income declarations in our empirical analysis. More specifically, we include the interquartile coefficient of income per tax declaration within a statistical sector, calculated as the difference between the third and first quartile, divided by the median income per tax declaration. This measure of income inequality in a sector allows one to draw conclusions on the effect of high incomes that cannot be seen by using average household income.

VARIABLES	*N*	*mean*	*St. dev.*
Total count of PV	9,182	23.66	24.87
Total capacity of PV in kW	9,182	113.6	119.3
Average capacity of PV	8,542	4.972	1.268
Households (log)	8,991	5.035	1.318
Income: average (log)	8,504	10.51	0.226
Income: dispersion (log)	8,504	4.657	0.207
Subsidy (1000EUR)	9,182	0.138	0.209
House value: <EUR500	8,998	0.222	0.185
House value: EUR500-EUR744	8,998	0.237	0.141
House value: EUR745-EUR999	8,998	0.185	0.111
House value: EUR1000-EUR1499	8,998	0.226	0.151
House value: EUR1500-EUR2499	8,998	0.100	0.134
House value: >EUR2500	8,998	0.0293	0.0975
Population density (log)	8,978	6.300	1.765
Age: <25	8,647	0.0153	0.0215
Age: 25-34	8,647	0.117	0.0563
Age: 34-44	8,647	0.201	0.0561
Age: 45-65	8,647	0.394	0.0829
Age: >65	8,647	0.272	0.0793
Educ: other	8,979	0.0610	0.0665
Educ: no high school	8,979	0.378	0.113
Educ: high school	8,979	0.300	0.0752
Educ: college	8,979	0.261	0.109
Foreigners	8,991	0.0479	0.0787
Left votes	9,182	0.155	0.100
Environmental awareness	8,989	0.871	0.115
House owner	8,986	0.780	0.171
Household size: 1	8,647	0.250	0.107
Household size: 2	8,647	0.347	0.0643
Household size: 3 or 4	8,647	0.328	0.0878
Household size: >4	8,647	0.0743	0.0401
Male	8,991	0.500	0.0462
Occup: other	8,964	0.0217	0.0277
Occup: blue coll priv sector	8,964	0.258	0.113
Occup: white coll priv sector	8,964	0.329	0.108
Occup: self-employed	8,964	0.164	0.105
Occup: public sector	8,964	0.227	0.0906
House age: before 1971	9,021	0.567	0.232
House age: 1971-1980	9,021	0.145	0.132
House age: 1981-1990	9,021	0.102	0.100
House age: 1991-2000	9,021	0.108	0.0941
House age: after 2000	9,021	0.0779	0.0768
House size <45m2	8,998	0.0121	0.0420
House size 45-64m2	8,998	0.0506	0.0906
House size 65-104m2	8,998	0.227	0.181
House size 105-184m2	8,998	0.455	0.172
House size >184m2	8,998	0.256	0.193
House type: detached	9,014	0.531	0.317
House type: semi-detached	9,014	0.206	0.149
House type: terraced	9,014	0.183	0.223
House type: apartment	9,014	0.0795	0.165
Double glazing	8,982	0.737	0.118
Roof insulation	8,977	0.581	0.135
Roof: good condition	8,986	0.826	0.0793

Table 2: Summary statistics

We expect income to influence the adoption process for at least two reasons. First, investing in a lucrative investment can be difficult or impossible due to liquidity constraints (Mills and Schleich (2009)). Second, investing in PV can be considered as a revelation of environmental preferences and such kinds of goods usually are considered luxury goods (Fransson and Gärling (1999)). Thus, demand may increase more than proportionally with income. For PV, Kwan (2012) finds a positive income effect for annual incomes between 25,000 and 100,000 dollars. On the other hand, based on stated preference data, Willis et al. (2011) find a negative income effect for most RES technologies, including PV.

Election results

Finally, we also use data on voting behavior, more precisely the average percentage of votes for leftwing parties (green and socialist parties) in the municipal elections of 2000 and 2006.[16] It should be noted, however, that the green party only participated in 110 out of the 308 municipalities in these elections. When the party did not participate, the number of votes was set equal to zero. Similar data are also available for the Federal elections of 2010, but we opted to use the 2000 and 2006 results as they concern municipal elections and are therefore available at a smaller level of aggregation.

Controlling for environmental preferences is common in the literature. Typically, authors use proxies like the possession of hybrid vehicles (Bollinger and Gillingham (2012), Crago and Chernyakhovskiy (2014)), votes for green ballot initiatives (Kahn and Vaughn (2009)), votes for left parties or membership of certain green organizations (Kwan (2012), Kahn and Vaughn (2009)). Positive effects are found for most of these proxies. A similar conclusion is found by Jager (2006), based on survey data.

3.3. Data on local support policies for residential PV

Since we essentially provide a cross-sectional analysis, we focus on policy measures with a local scope by the 308 municipalities, as these show the required cross-sectional variation. Other studies have shown that local support policy can influence adoption behavior (Jager (2006), Kwan (2012)). While these local measures were quantitatively less important than the policies imposed by the Flemish government, they can still indirectly be informative about the impact of these other policies.

Data on local support schemes were obtained from a website maintained by the VEA.[17] We recovered information on the availability of support mechanisms at a municipality level at three dates: 21 April 2011, 22 June 2011 and 3 July 2012.[18]

As shown in Figure 2, 185 or about 60% of the local authorities did not provide any local (financial) support for PV adoption in April 2011. About one year later, this number has increased to 235 (or about 75% of the municipalities). In this period, it became clear for many stakeholders that current (successful) policies to support investment in PV could not be maintained because of their budgetary impact. Since our empirical analysis is cross-sectional, we will use the information of the support mechanisms in use in April 2011. We consider this to be the most

[16] The data was downloaded from http://www.npdata.be/BuG/159-Verkiezingen-2012/Verkiezingen-2012.htm and the source mentioned was: vlaanderenkiest.be.

[17] Vlaams Energie Agentschap (= Flemish Energy Agency).

[18] A potential problem with this data is that the municipalities provide the information on a voluntary basis, so that the support measures in some municipalities may not have been registered. As a check, we took a sample of ten municipalities that – according to the VEA information – do not provide local support to PV installations. Information from these municipalities' websites confirmed that none of these municipalities provide financial support for PV, suggesting that the information in the VEA database provides an accurate picture of the actual situation.

representative for our analysis (as it falls in the middle of the period over which PV adoption occurred in our sample).

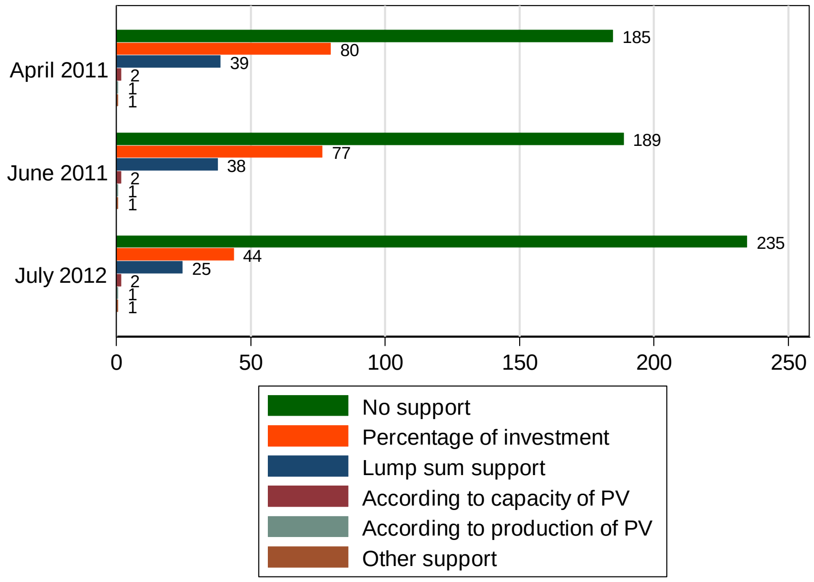

Figure 2: Local PV support initiatives in Flanders.

Among the municipalities that provide financial support in April 2011, most used some kind of investment support mechanism rather than subsidizing production. A majority of municipalities used a capped variable subsidy, expressed as a percentage of the investment cost. About 40 municipalities gave a lump sum investment subsidy. Two municipalities subsidized PV based on the capacity installed and one municipality subsidized electricity generation based on PV. Figure 3 shows the distribution of the size of the main support mechanisms. In practice, the caps for the variable subsidies are quite low in most municipalities. It is therefore a reasonable simplification to assume the caps are binding, which allows us to create one local support variable, which is either the lump sum subsidy or the cap in case of a variable subsidy.[19]

[19] The two municipalities offering a different kind of support are omitted from the second stage regression where we explain municipality fixed effects.

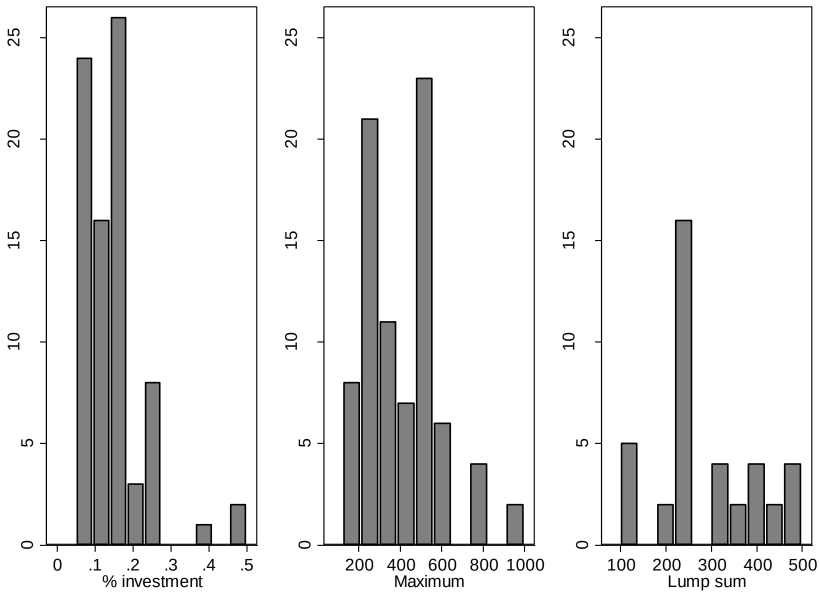

Figure 3: Distribution of support policies of municipalities in April 2011.

4. THE MODEL

As discussed in the previous section, we combine the VREG database on PV installations with demographic data at the quite disaggregate level of the statistical sector. We model the total count of PV installations in a statistical sector at a particular date as a function of different groups of variables.[20]

To motivate our model, Figure 4 shows the distribution of the main dependent variable: the number of PV installations per statistical sector.

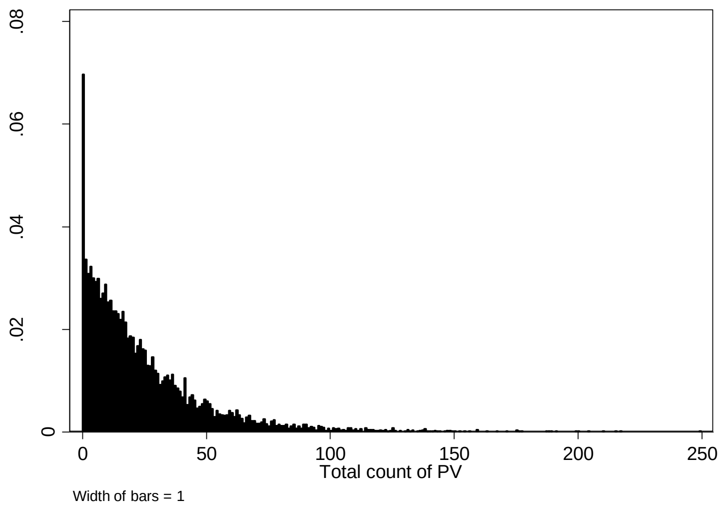

Figure 4: Distribution of the number of PVs per statistical sector (situation December 2012).

[20] This total count at any particular date in our database can reasonably be assumed to be equal to the sum of all registered installations up to that point. This is because after the first PV installation in 1997 only 722 PVs were installed until 2006, and the average life expectancy of a PV system lies between 15 and 30 years.

To analyze these count data, we focus on a Poisson regression model with robust standard errors. This model assumes that the outcome variable, the number of PV installations, follows a Poisson distribution. More specifically, the conditional mean function in the Poisson model has the exponential form:

$$E[PV_i|\mathbf{x}_i] = \exp(\mathbf{x}'_i\beta + \gamma \ln(\#\text{households}_i) + \eta_m)$$

where PV_i is the total number of PVs in statistical sector i, β measures the effect of the covariates in vector $\mathbf{x}_i$, γ is the elasticity with respect to the number of households and η_m is a municipality fixed effect for statistical sector i belonging to municipality m. Because of the exponential form, the parameters can be interpreted as semi-elasticities for linear regressors and as elasticities for regressors in log-form. Note that the number of households controls for the fact that statistical sectors are not of equal population size. We expect the number of PVs to rise proportionally to the number of households, $\gamma = 1$.

A potential issue with the Poisson distribution is the violation of the equidispersion property, according to which the conditional variance of the outcome is equal to the conditional mean. However, to obtain consistent parameter estimates, only a correct specification of the conditional mean is required. Misspecification of the variance function may still affect the standard errors, which we correct using the standard sandwich covariance matrix, as suggested by Santos Silva and Tenreyro (2006).[21]

Another potential issue is that the model does not separately deal with the occurrence of zeros, as is done in zero-inflated count models. Kwan (2012) used a Zero-Inflated Negative Binomial (ZINB) model to study PV adoption in the US. A ZINB model consists of a Negative Binomial (NB) count regression model for most of the data, and a separate binary choice model to estimate the zero values outside the NB model (excess zeros). We prefer the Poisson model in our application for several reasons. First, the magnitude and significance of the parameter estimates from this model are easier to interpret. Second, the number of statistical sectors with zero values for the number of PV installations is relatively low in our sample (6.9%).[22] Furthermore, simulation evidence suggests that the estimates obtained with a Poisson model remain reliable even with a large number of zeros (Santos Silva and Tenreyro (2011)). Finally, the estimates from commonly used zero-inflated models such as the Zero-Inflated Poisson or ZINB are not robust to distributional misspecification, so that inference on the estimated parameters may be biased.[23] In the appendix we nevertheless show that our results are robust for the alternatives considered here.

We made several adjustments to the model to deal with the spatial patterns in our data. Since the 9182 statistical sectors are clustered in the 308 municipalities of Flanders, we include fixed effects η_m for every municipality.[24] We thus control for unobserved heterogeneity at the municipality level. A further adjustment is made on the covariance matrix of the estimates. Since we can assume correlation is present between the residuals of sectors within the same municipality, we use cluster robust standard errors.

[21] Because the Poisson model does not require a correct specification of the variance function, we do not extend the model to a negative binomial specification, which relaxes the equidispersion property by allowing for a more flexible variance function. For a more elaborate discussion on count data models, see Cameron and Trivedi (2013). They also explain that a negative binomial regression can be consistent if only the conditional mean is correctly specified, provided that the NB2 type is chosen.

[22] It is even lower in the final specification, which excludes the very small statistical sectors because, due to privacy concerns, these sectors do not have information on tax records.

[23] A solution would be to use a Zero-inflated Poisson Quasi-likelihood model. But with a low number of zeros, as in our sample, this would be more sensitive to finite sample bias (Staub and Winkelmann (2013)).

[24] Although it is estimated using maximum likelihood, a Poisson regression model doesn't suffer from the incidental parameter bias (Cameron and Trivedi (2013)).

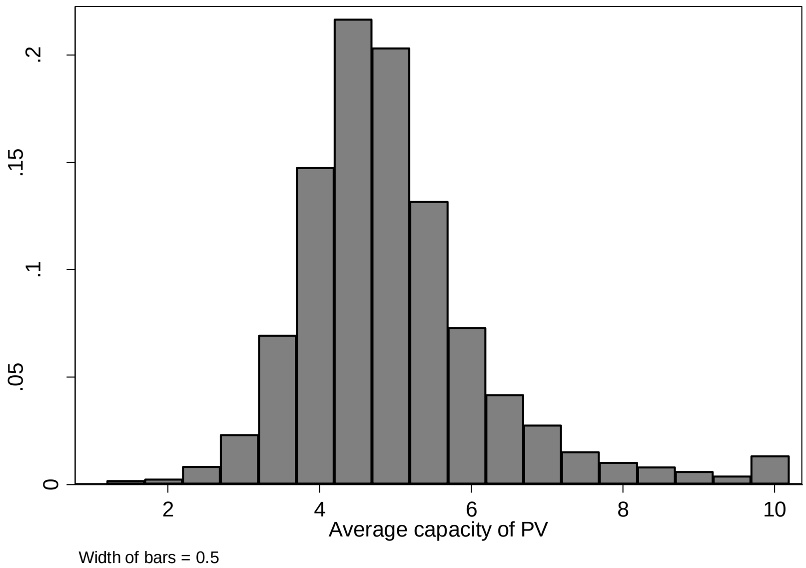

Figure 5: Distribution of the average capacity of PVs per statistical sector (situation December 2012)

Because the Poisson model already includes a full set of municipality fixed effects η_m, we cannot separately identify the effect of variables observed at the municipality level (subsidy and left votes). A standard solution is to estimate the Poisson model with municipality fixed effects η_m in a first stage, and perform an OLS regression of the estimated fixed effects on the municipality-level variables and a constant in a second stage. To obtain consistent standard errors, we estimate both stages simultaneously in a Generalized Method of Moments framework, by converting both the Poisson maximum likelihood estimator and the OLS regression to moment conditions (Newey (1984)).[25]

In addition to explaining the number of PV installations per statistical sector, we will also look at decision about the size of a PV, by looking at the average installed capacity. Figure 5 shows the distribution of the average size of PV installations per statistical sector. It is worth nothing that the Poisson model can still be used to estimate the effects of the various determinants. In fact, Santos Silva and Tenreyro (2006) show that because consistent estimation only requires the correct specification of the conditional mean, it is also preferred to analyze continuous dependent variables if researchers are interested in estimating (semi-)elasticities. We therefore continue to use the Poisson model to explain the average installed capacity (as well as total installed capacity), but our results are robust for alternative estimators such as OLS.

5. RESULTS

This section discusses the empirical results. In section 5.1 we discuss the main model, which aims to explain the *total number of PV installations* per statistical sector. Section 5.2 discusses the results for a model that focuses on two alternative dependent variables: the *average size of the PV installations* and the *total installed capacity*. Both models focus on the situation as registered at the end of 2012. In section 5.3 we distinguish between two periods, identified on the basis of structural changes in the Flemish and local support mechanisms that were put in place.

Note that the categorical covariates are relative proportions of a particular characteristic in the statistical sector, expressed as a fraction of the total number of inhabitants, households or houses. Since the various sets of categorical covariates add up to one, we exclude one covariate per set,

[25] Two municipalities supported PV adoption using a policy instrument that did not fit our analyses. These two municipalities are ignored in the second stage.

and interpret these as the reference groups. The tables below explicitly show these reference groups with a coefficient set to zero. As discussed above, the parameters of these categorical variables (and the other linear variables) have the interpretation of semi-elasticities, indicating the percentage change in the dependent variable resulting from a unit change in the covariate. The parameters of covariates that were transformed in logarithms can be interpreted as elasticities.

5.1. Main model: explaining the adoption of PV

Table 3**Error! Reference source not found.** summarizes the results for various Poisson regressions to explain the number of PV installations. Model 1 includes a set of economic and social variables similar to Kwan (2012). Model 2 includes additional social variables for which we have information. Finally, Model 3 is the richest specification as it also includes a new set of housing characteristics.

For all models, the municipality fixed effects were jointly significant. Furthermore, for all models $\boldsymbol{\gamma}$ is very close to 1, and for the second and third model the null hypothesis of $\boldsymbol{\gamma = 1}$ cannot be rejected. This shows that the total number of PV installations increases proportionally with the number of households.[26]

Model 1: basic socioeconomic variables

Model 1 includes a set of variables as close as possible to the ones considered by Kwan (2012), with two exceptions. First, in the set of economic variables we do not consider the cost of electricity, since this information is not available at the level of the statistical sector or municipality in Flanders, and electricity prices likely do not show sufficient regional variation to identify the effects. Second, as an environmental variable we do not include solar radiation because this variable also shows only limited variation within the region of Flanders. Generally speaking, unless we indicate otherwise below, the results of Model 1 confirm the findings obtained earlier by Kwan (2012).

First consider the economic variables. We find a statistically significant and economically important effect of **average income** on the number of PV installations, with an estimated income elasticity of 1.032. Note that this elasticity is conditional on the other variables included in the model. The unconditional income elasticity (without controlling for other variables) is even higher and is equal to 1.635. This reflects the fact that high income households tend to have other characteristics that make them more likely to adopt or that they live in houses or neighborhoods that are more suitable for PVs.[27] The large unconditional effect of income indicates that a Matthew effect exists, i.e. wealthier households benefit proportionally more from the government support policies for PV as they have higher adoption rates.

The **dispersion of income** within a statistical sector plays a significant role. An increase in income dispersion, as measured by the interquartile coefficient, raises PV adoption. Hence, income distribution matters, presumably because adoption mainly takes place by the upper tail of the distribution. Note that this is different from Kwan's finding where the highest income category adopts less than middle income households.

The **value of a house**, measured by cadastral income, has a significant effect on the number of PV installations, in line with the findings of Kwan (2012).[28] Generally speaking, the number of PV

[26] In simpler specifications where we only include income or a limited set of variables, we found that $\gamma < 1$, suggesting that the number of households then captures the effect of other variables omitted from the specification.

[27] This unconditional elasticity of 1.635, with a standard error of 0.247, was obtained from a model without any other control variables and restricting $\gamma = 1$. Since this model has no other parameters, we do not show it separately.

[28] Cadastral income is a hypothetical rent based on the property description and valuation listed in the property register, also called the land registry income.

installations first increases in the house value, but at a certain point it becomes decreasing until the impact becomes insignificant (relative to the reference group for the lowest house value).

Local subsidies for PV installations (which vary across municipalities) have a positive and statistically significant effect, with an estimated semi-elasticity of 0.221. The elasticity decreases only marginally to 0.176 when adding additional control variables, suggesting it is not largely driven by the effect of correlated unobservables. This estimate implies that a doubling of the local subsidy rate (say from the €138 to €276 in an average municipality) would increase adoption by 2.46%.[29] As we discussed in section 2, the local subsidies were only a small part of the subsidies given in Flanders. This suggest that subsidization can be very effective in promoting PV. In fact, the main subsidy benefits came from the green certificates, which were granted at the regional level and were about €10,000 for an average system (5kW) during the considered period. Our estimate of the local subsidy effect then suggests that without the Green Certificates the total number of adoptions in the average municipality would have been 82.8% lower.[30].

[29] To compute the exact effect of a policy change, write the expected number of adopters in municipality i as $E(PV_i) = \exp(\beta s_i + A_i)$, where s_i is the subsidy (in €1000) with the estimated parameter $\beta = 0.176$ and A_i captures all other local determinants of adoption. Then the percentage change in the number of PVs after a change in subsidies Δs_i is $\exp(0.176\, \Delta s_i) - 1$. Hence, with $\Delta s_i = 0.138$ the percentage change is $\exp(0.176 \times 0.138) - 1$ =0.0246.

[30] Similar to the previous footnote, with $\Delta s_i = -10$ the percentage change is $\exp(-0.176 \times 10) - 1 = -0.8280$.

VARIABLES	Model 1		Model 2 1+extra hh char		Model 3 2+extra house	
Households (log)	0.960*	(0.009)	0.997*	(0.007	1.011*	(0.007)
Income: average (log)	1.032*	(0.096)	0.000	(0.065	0.094	(0.061)
Income: dispersion (log)	0.547*	(0.044)	0.301*	(0.035	0.152*	(0.034)
Subsidy (1000EUR)	0.221*	(0.101)	0.190*	(0.075	0.176*	(0.058)
House value: <EUR500	0		0		0	
House value: EUR500-EUR744	0.407*	(0.067)	0.485*	(0.065	0.027	(0.070)
House value: EUR745-EUR999	0.682*	(0.077)	0.602*	(0.066	0.001	(0.063)
House value: EUR1000-EUR1499	0.771*	(0.103)	0.791*	(0.076	0.127	(0.076)
House value: EUR1500-EUR2499	0.369*	(0.138)	0.582*	(0.098	-0.269*	(0.091)
House value: >EUR2500	0.044	(0.206)	0.275*	(0.130	-0.732*	(0.136)
Population density (log)	-	(0.006)	-0.063*	(0.005	-0.048*	(0.007)
Age: <25	0		0		0	
Age: 25-34	7.945*	(0.927)	1.457*	(0.576	0.226	(0.435)
Age: 34-44	9.099*	(0.824)	1.475*	(0.526	0.318	(0.404)
Age: 45-65	7.049*	(0.833)	0.568	(0.529	-0.454	(0.402)
Age: >65	6.112*	(0.850)	0.310	(0.544	-0.735	(0.403)
Educ: no high school or other	0		0		0	
Educ: High school	-0.149	(0.150)	-0.132	(0.125	0.133	(0.118)
Educ: College	-	(0.135)	-0.330*	(0.116	0.011	(0.106)
Foreigners	-	(0.364)	-2.766*	(0.269	-2.118*	(0.230)
Left votes	0.097	(0.232)	0.128	(0.184	0.203	(0.140)
Environmental awareness			2.330*	(0.176	1.172*	(0.161)
House owner			0.323*	(0.084	0.383*	(0.068)
Household size: 1			0		0	
Household size: 2			0.948*	(0.130	0.345*	(0.117)
Household size: 3 or 4			2.158*	(0.138	1.056*	(0.122)
Household size: >4			1.563*	(0.237	0.860*	(0.219)
Male			0.274	(0.198	0.285	(0.186)
Occup: blue coll priv sector and			0		0	
Occup: white coll priv sector			0.078	(0.119	0.284*	(0.117)
Occup: self-employed			-0.204	(0.111	0.116	(0.123)
Occup: public sector			0.114	(0.131	0.365*	(0.124)
House age: before 1971					0	
House age: 1971-1980					0.320*	(0.057)
House age: 1981-1990					0.484*	(0.061)
House age: 1991-2000					0.566*	(0.068)
House age: after 2000					1.055*	(0.077)
House size <45m2					0	
House size 45-64m2					1.340*	(0.377)
House size 65-104m2					1.675*	(0.362)
House size 105-184m2					2.281*	(0.357)
House size >184m2					2.456*	(0.364)
House type: detached					0	
House type: semi-detached					0.283*	(0.058)
House type: terraced					0.078	(0.057)
House type: apartment					-0.542*	(0.066)
Double glazing					0.344*	(0.075)
Roof insulation					-0.441*	(0.070)
Roof: good condition					0.443*	(0.115)
Constant	-	(1.161)	-5.660*	(0.834	-7.308*	(0.788)
Observations	8472		8471		8471	
Loglikelihood 1st stage	-		-28660		-27419	
R^2 2nd stage	0.0153		0.0199		0.0360	

Notes: Results from GMM estimation of Poisson model as discussed in the text. Robust standard errors in parentheses, clustered by municipality. * indicates p<0.05. Dependent variable is total number of PV installations at the end of 2012. Unless otherwise indicated, the explanatory variables are expressed as percentages. 0-values indicate the variable is reference category.

Table 3: Estimation results for main model: total number of PV installations at the end of 2012

Now consider the social variables. **Population density** has a significant negative impact on PV adoption, with an elasticity of about -0.1. This can be expected since in urbanized areas there is less space to install PVs on top of roofs. The **household age** also plays a significant role in the adoption of PV. Compared with the reference group with age below 25, all other age groups have a much higher propensity to adopt. This propensity is highest for the age group 34-44, followed by the age group 25-34. These are typically the age groups that build or renovate new houses in Flanders. Note however that the household age becomes unimportant once we control for more variables in Model 2 and 3, discussed below. Perhaps surprisingly, and also in contrast with Kwan (2012), **education** does not have a positive impact on PV adoption: a high school degree has an insignificant effect and college degree even seems to reduce the adoption rate. This may reflect a higher opportunity cost of time, or it may be due to omitted variables that are correlated with college education that make people less likely to adopt. The latter explanation appears to be more likely because in our richer specifications below education has no significant effect or only a significant effect in the early years.

As predicted by the literature, **ethnicity** plays a significant and important role in PV adoption: an increase in the number of foreigners by 1% point reduces the number of PV installations by 0.38%. Even after adding control variables, the effect remains large at 0.21%. This may reflect disparities in the support for environmentalism and environmentally responsible practices across different ethnical groups (e.g. Johnson et al. (2004) as discussed in Kwan (2012)).

Finally, the percentage of **left votes** has an insignificant effect on PV adoption. This differs from Kwan (2012), who found a significant positive effect.

Model 2: additional household characteristics

Model 2 extends the basic specification to include additional social variables, that were not included in previous studies.

In the 2001 census, households were asked about the presence of roof insulation in their house. We consider the fraction of households that was able to answer this question as a measure of **environmental awareness** and expect this fraction to have a positive impact on the number of PV systems adopted in a sector, which is confirmed by the results of Model 2.

House ownership status turns out to have a strong positive and statistically significant impact on PV adoption. Hence, PV adoption is more likely on the roofs of owned than on the roofs of rented houses. This is consistent with previous work, which has established that house renting forms a barrier to the adoption of new technologies within the house, as it is often difficult to allocate the benefits and the cost between tenants and landlords (Jaffe and Stavins (1994), Sutherland (1996)).

We also consider **household size** as a driver of PV adoption. We expect larger households to invest more in PV, because they are larger consumers of electricity and because they can spread the fixed costs of adoption over more household members; see also Mills and Schleich (2009) for a discussion on the relation between household size and technology. This is confirmed by the estimates presented. Compared with the reference group of singles, households with 2 and especially with 3-4 members are much more likely to adopt a PV. Households with more than 4 members also invest significantly more in PV, but less so than households of 3 or 4 persons.

Previous studies have suggested that **gender** influences technology adoption, e.g. Venkatesh et al. (2000). The share of male residents was included to test the hypothesis that male residents would have higher adoption rates. We only find weak support for this, as the effect is positive but estimated fairly imprecisely.[31]

Model 2 also includes **occupational status** as a social covariate, where occupation is defined as having a job in the public or private sector, being self-employed or being in another category. For

[31] As a further test, we included a variable to distinguish between the share of single male and single female households. According to this specification, single male households are significantly more likely to adopt than single female households.

private sector occupations we also distinguish between white collar and blue collar workers. Our results suggest that public sector employees are more likely to adopt, especially when compared with self-employed. This may be due to better information on subsidies within this group or greater environmental awareness. Note that this is only estimated sufficiently precisely after including the housing characteristics of model 3.

Including the above variables has a considerable impact on several of the variables included in the previous model, which was close the set-up of Kwan (2012). Most interestingly, the impact of average income becomes small and statistically insignificant. Hence, while income dispersion has a significant effect, average income has no direct effect on PV adoption. It only plays an indirect role as it is correlated with several of the new variables included in Model 2, most notably with house ownership status and household size.[32] The impact of house value essentially remains unchanged and significant. Finally, the age variables have a much smaller impact, conditional on the new included variables. This can be explained by the significant role of house ownership, which typically starts at a higher age than 25.

Model 3: adding housing characteristics

Model 3 considers the role of a detailed set of housing characteristics on PV adoption: house age, house size and various measures of house conditions. We find that the parameters of most of these variables are statistically significant with the expected sign. Furthermore, the inclusion of these housing characteristics makes some of the social variables less important.

Everything else constant, one may expect to see more PVs on the roofs of recently built houses. We indeed find that **house age** has a negative effect on PV adoption. With houses built before 1971 as the benchmark, we find that the rate of adoption decreases with the age of the houses. A hypothesis test on the equality of the estimated effects was rejected for all consecutive periods, except for houses built between 1981 and 2000. By far the biggest adoption rate occurs in houses built after 2000. Note that after including house age there is no longer a significant impact of the owner's age on PV adoption. Hence, we may conclude that it is not the owner's age per se but rather the age of the house where the owner lives that influences PV adoption. The negative effect for the retired age group, marginally insignificant, could reflect the fact that older generations have less concern for global warming and environmental issues than younger generations or have a lower knowledge of the technology (Kwan (2012), Torgler et al. (2008), Carlsson-Kanyama et al. (2005)).

One may also expect the **size of the house**, measured as the size of the built-up area, to have a positive impact on PV adoption (Walsh (1989), Mills and Schleich (2010)). We find that this is indeed the case. A larger size raises the probability of adoption relative to the reference case of a built-up area of less than $45m^2$. Houses in the reference category are probably too small to have sufficient roof surface to easily install a PV, let alone with the desired capacity. Larger sizes typically imply a larger roof surface, resulting in more flexibility to avoid disturbances on the roof (shadow from trees or chimneys, window vents…) and thus an increased probability of adoption. With an average electricity consumption of about $4000kWh$, most households would require an installation of about $5kWp$ which, under ideal conditions, requires a roof surface of about $40m^2$. Ceteris paribus, we therefore expect to see decreasing returns on increased size.

Note that including house size reduces the previously estimated effect of household size, but it is interesting to note that the effect of household size remains highly significant. Hence, size matters for both a technological reason (larger roofs) and a demand reason (more return on investment when electricity consumption is higher).

Regarding the **house type**, we distinguish between apartments, (semi-)detached and terraced houses, with detached houses as the reference category. As expected, areas with a relatively larger share of apartments have lower adoption rates. Also terraced houses have difficulties in

[32] This conclusion is based on the results of several regressions where we extend Model 1 with different combinations of the variables we added in Model 2. The regression tables are not shown in this paper but are available upon request.

installing PVs. Perhaps somewhat surprisingly, we find a stronger effect for semi-detached houses.

We include two proxies for the energy efficiency status of the house: double glazing and roof insulation. Both measures point in different directions however. In line with our intuition, a one percentage point increase in the share of houses with **double glazing** will result in a statistically significant increase in the number of PVs adopted of 0.34%. However, a one percentage point increase in the share of houses with **roof insulation** decreases the number of PVs adopted with a significant 0.44%. One explanation for the latter result is that the data on roof insulation date from 2001, whereas the data on PV adoption date from 2006 or later. Over the last decade, the Flemish government has also made efforts to stimulate households to invest in energy efficiency in general and roof insulation in particular (both through financial incentives and through information provision). The Flemish Energy Agency reports that, over the period 2006-2012, more than 285,000 dwellings applied for and received a subsidy for roof insulation (Vlaams Energieagenschap (2013)). We conjecture that this additional financial incentive for roof insulation also triggered landlords or tenants to also invest in PVs while improving the roof insulation.

From the discussion in section 3 it was not clear what to expect from the **quality of the roof**. This variable could have a positive effect if it served as a proxy for procrastination behavior or because a damaged roof requires an extra investment that makes investing in PV more difficult. A negative effect is also possible because of economies of scope in repairing the roof and installing a PV. From our results we can conclude that the latter explanation is less likely as we find a positive effect.[33]

As a final observation, we note that once we include the housing characteristics, the previously estimated positive effects for the value of a house drop considerably: they either become insignificant and, for the highest house values, even show a negative impact. This suggests that the included housing characteristics are important to explain adoption behavior, and the value of the house served as a proxy for these in Model 1 and 2. The fact that the impact of the highest house values, conditional on other housing characteristics, is negative, may indicate that these houses, or their inhabitants, have certain unobserved characteristics that make PV adoption less likely. One of these unobserved characteristics is the esthetics of a house. This usually becomes more important for expensive houses, and PVs generally tend to degrade the looks of the house.

5.2. Explaining the size of the adopted PV installations

The previous analysis considered the determinants of the total number of PV installations. We now consider the determinants of the total installed capacity and the average size of these installations. Table 4 shows the results of the Poisson models, where we include the same set of explanatory variables as in Model 3. For ease of comparison, the left column again shows the results for the total number of PV installations (Model 3). The middle two column shows the results for the total capacity of PV (Model 4) and the right two column show the results for the average size (Model 5).

In general, the determinants of adoption (Model 3) and of total capacity (Model 4) are very similar. This can be explained by looking at the effects on the average size of an installation (Model 5), as most variables turn out to be insignificant.

There are, however, some interesting cases where a variable affects both the number of installations and the average size of an installation in the same direction. First, foreigners not only tend to adopt less, but they also invest in smaller PV systems. Second, in areas with a high population density both the number of installations and the average size tend to be lower. Finally, in houses with double glazing both the adoption rate and the average size of adoption are larger.

[33] Note that roof quality is correlated with, but not the same as, having roof insulation. To assess whether roof quality (partly) picks up the impact of roof insulation, we estimated a model without the variable roof quality. This gave almost the same estimate for the impact of roof insulation.

As a result, for these variables the count effect and the size effect reinforce each other, so these variables have an even stronger impact on total installed capacity.

There are also some cases where a variable affects the number of installations and the average size of an installation in the opposite direction. Most interestingly, house owners (as opposed to renters) and white collar employees have a higher adoption rate, but they invest in smaller average sizes. The same is true for houses built after 2000: these have a higher adoption rate but a smaller average size. This may be because more recently built houses tend to be smaller than older houses. For these variables the count effect is counteracted by the size effect, but in all cases it appears that the count effect dominates, so that the variables have qualitatively the same impact on the number of installations as on the total installed capacity.

Finally, there are some variables that affect the average size but not the number of PV installations. Most notably, males and self-employed people are not more likely to adopt, but when they adopt they tend to invest in larger PVs. As a result, these variables have a positive impact on total capacity, despite having an insignificant impact on the number of PV installations. The same holds for left votes and for young households (25-34).

In sum, the effects on average capacity of foreigners (-), males (+), the 25-34 years age group (+) and left votes (+) suggests environmental and technological preferences should not be neglected when discussing PV size choices. In contrast, more natural determinants like house size or household size seem to be less important. Note however from the small differences between Model 3 and Model 4 that all variables, including the preference-related ones, seem to play a much more important role in deciding to adopt, rather than in deciding on the size.

VARIABLES	Model 3 (total number)		Model 4 (total capacity)		Model 5 (average size)	
Households (log)	1.011*	(0.007)	1.000*	(0.007)	-0.013*	(0.003)
Income: average (log)	0.094	(0.061)	0.061	(0.067)	0.014	(0.025)
Income: dispersion (log)	0.152*	(0.034)	0.114*	(0.035)	-0.027	(0.016)
Subsidy (1000EUR)	0.176*	(0.058)	0.186*	(0.063)	0.007	(0.023)
House value: <EUR500	0		0		0	
House value: EUR500-	0.027	(0.070)	-0.025	(0.073)	-0.052	(0.035)
House value: EUR745-	0.001	(0.063)	-0.048	(0.072)	-0.027	(0.037)
House value: EUR1000-	0.127	(0.076)	0.102	(0.078)	-0.011	(0.032)
House value: EUR1500-	-0.269*	(0.091)	-0.252*	(0.100)	0.076*	(0.038)
House value: >EUR2500	-0.732*	(0.136)	-0.823*	(0.140)	0.051	(0.065)
Population density (log)	-0.048*	(0.007)	-0.065*	(0.007)	-0.024*	(0.003)
Age: <25	0		0		0	
Age: 25-34	0.226	(0.435)	0.308	(0.473)	0.428*	(0.209)
Age: 34-44	0.318	(0.404)	0.367	(0.430)	0.245	(0.195)
Age: 45-65	-0.454	(0.402)	-0.450	(0.431)	0.233	(0.191)
Age: >65	-0.735	(0.403)	-0.747	(0.435)	0.163	(0.185)
Educ: no high school or other	0		0		0	
Educ: High school	0.133	(0.118)	0.232	(0.128)	0.085	(0.064)
Educ: College	0.011	(0.106)	-0.192	(0.109)	-0.209*	(0.057)
Foreigners	-2.118*	(0.230)	-2.154*	(0.229)	-0.170*	(0.060)
Left votes	0.203	(0.140)	0.367*	(0.143)	0.127*	(0.046)
Environmental awareness	1.172*	(0.161)	1.207*	(0.173)	0.116	(0.064)
House owner	0.383*	(0.068)	0.214*	(0.072)	-0.206*	(0.036)
Household size: 1	0		0		0	
Household size: 2	0.345*	(0.117)	0.373*	(0.124)	0.002	(0.058)
Household size: 3 or 4	1.056*	(0.122)	1.212*	(0.130)	0.107	(0.066)
Household size: >4	0.860*	(0.219)	1.115*	(0.243)	0.100	(0.080)
Male	0.285	(0.186)	0.399*	(0.192)	0.250*	(0.109)
Occup: blue coll priv sector	0		0		0	
Occup: white coll priv sector	0.284*	(0.117)	0.141	(0.119)	-0.189*	(0.063)
Occup: self-employed	0.116	(0.123)	0.937*	(0.131)	0.652*	(0.056)
Occup: public sector	0.365*	(0.124)	0.224	(0.135)	-0.205*	(0.066)
House age: before 1971	0		0		0	
House age: 1971-1980	0.320*	(0.057)	0.359*	(0.060)	0.011	(0.026)
House age: 1981-1990	0.484*	(0.061)	0.516*	(0.062)	-0.031	(0.033)
House age: 1991-2000	0.566*	(0.068)	0.565*	(0.075)	-0.014	(0.040)
House age: after 2000	1.055*	(0.077)	0.945*	(0.083)	-0.138*	(0.038)
House size <45m2	0		0		0	
House size 45-64m2	1.340*	(0.377)	1.326*	(0.400)	-0.052	(0.141)
House size 65-104m2	1.675*	(0.362)	1.690*	(0.375)	-0.043	(0.111)
House size 105-184m2	2.281*	(0.357)	2.379*	(0.371)	0.049	(0.111)
House size >184m2	2.456*	(0.364)	2.738*	(0.379)	0.187	(0.115)
House type: detached	0		0		0	
House type: semi-detached	0.283*	(0.058)	0.262*	(0.058)	-0.002	(0.025)
House type: terraced	0.078	(0.057)	-0.031	(0.059)	-0.080*	(0.029)
House type: apartment	-0.542*	(0.066)	-0.563*	(0.070)	0.034	(0.035)
Double glazing	0.344*	(0.075)	0.424*	(0.079)	0.090*	(0.039)
Roof insulation	-0.441*	(0.070)	-0.424*	(0.080)	0.011	(0.035)
Roof: good condition	0.443*	(0.115)	0.339*	(0.123)	-0.063	(0.058)
Constant	-7.308*	(0.788)	-5.140*	(0.873)	1.540*	(0.376)
Observations	8471		8471		8311	
Loglikelihood 1st stage	-27419		-70883		-14881	
R^2 2nd stage	0.0360		0.0531		0.0346	

Notes: Results from GMM estimation of Poisson model as discussed in the text. Robust standard errors in parentheses, clustered by municipality. * indicates p<0.05. Dependent variable is resp. total number of PV installations, total installed capacity and average size at the end of 2012. Unless otherwise indicated, the explanatory variables are expressed as percentages. 0-values indicate the variable is reference category.

Table 4: Estimation results for effect on capacity

5.3. Understanding variation over time

As discussed in section 2, the mass adoption of PV installations started in 2006 after the introduction of the green certificates subsidy program of the Flemish government. In this section we divide the sample in two periods to ask whether the influence of certain covariates changed over time as the subsidy program became less generous. The first period runs from January 1st, 2006 to December 31st, 2009. This corresponds to the period in which the initially announced path of minimum prices per green certificate was not questioned, and was at its highest value (€ 450). The second period covers January 1st 2010 up to December 31st, 2012. In 2010, the value of a green certificate decreased for the first time and at that point the public debate on the appropriateness of the level of the minimum prices started. This regularly led to new announcements of reduced subsidy amounts for the green certificates. It is therefore interesting to compare both periods, to assess whether different determinants mattered after the policy change. Although the first period was longer, we find that only 62,905 residential PVs were installed during this period while 157,559 were installed in the second period. Table 5 shows the results, comparing the results for both periods with the model we had for total adoptions. The last column shows the p-values of a Wald test that tests if the estimated parameters differ between both periods.

Many of the parameters do not change significantly over the two periods. We concentrate our discussion on those parameters that significantly changed over time. The first group consists of parameters that mainly played a role in the first period. We indicate this by shading the relevant parameters in grey shading during the first (middle columns). The second group consists of parameters that mainly played a role in the second period. We indicate this by shading these parameters in grey during the second period (right columns).

First consider the group of variables that mainly played a role in the first period. Average income per household, which had a small and insignificant effect during the whole period, in fact had a positive impact during the first period (with an elasticity of 0.204), while it had essentially no impact during the second period. Recall that these elasticities are conditional on the other variables included in the model. The unconditional income elasticity also drops significantly from 1.9 to 1.5 (not reported in the tables).[34] Hence, a Matthew effect is present throughout the full period, but it has declined during the second half. Note that this declined effect is precisely when the subsidy program became less generous. Similarly, we find that the impact of income dispersion became smaller during the second period.

Among the household characteristics, a college or university degree had no significant effect over the entire period, but it does have a significant positive effect at the 10% level during the first period. This suggests that educated people become more quickly aware of subsidy programs, though less educated people eventually catch up. We also did not find a significantly higher adoption rate for males over the whole period, but they do show a higher adoption rate during the first period. Large households (over 4 members) especially adopted during the first period, though even in the second period these households had a higher adoption rate. Next, the role of occupational status seems to have diminished over time: white collar and public sectors workers only show a larger adoption rate during the first period. Finally, terraced houses showed higher adoptions during the first period but not over the entire period.

[34] The income elasticity during the first period was 1.941 with a standard error of 0.214, and the income elasticity during the second period was 1.509 with a standard error of 0.261. The chi^2-statistic of the Wald test of equality was 49.37 which corresponds to a p-value of 0.000.

VARIABLES	Model 3		Model 6 3 in 2006-2009		Model 7 3 in 2010-2012		6 = 7 p-value
Households (log)	1.011*	(0.007)	1.018*	(0.010)	1.009*	(0.007)	0.383
Income: average (log)	0.094	(0.061)	0.204*	(0.072)	0.048	(0.069)	0.041*
Income: dispersion (log)	0.152*	(0.034)	0.260*	(0.051)	0.107*	(0.040)	0.010*
Subsidy (1000EUR)	0.176*	(0.058)	0.187*	(0.080)	0.158*	(0.066)	0.743
House value: <EUR500	0		0				
EUR500-EUR744	0.027	(0.070)	0.067	(0.099)	0.010	(0.077)	0.589
EUR745-EUR999	0.001	(0.063)	0.052	(0.083)	-0.014	(0.078)	0.532
EUR1000-EUR1499	0.127	(0.076)	0.266*	(0.097)	0.071	(0.081)	0.037*
EUR1500-EUR2499	-0.269*	(0.091)	-0.284*	(0.118)	-0.273*	(0.104)	0.931
>EUR2500	-0.732*	(0.136)	-0.883*	(0.172)	-0.652*	(0.149)	0.162
Population dens (log)	-0.048*	(0.007)	-0.051*	(0.009)	-0.047*	(0.007)	0.583
Age: <25	0		0		0		
Age: 25-34	0.226	(0.435)	0.201	(0.735)	0.229	(0.466)	0.971
Age: 34-44	0.318	(0.404)	0.641	(0.716)	0.199	(0.417)	0.535
Age: 45-65	-0.454	(0.402)	-0.099	(0.672)	-0.613	(0.420)	0.436
Age: >65	-0.735	(0.403)	-0.405	(0.669)	-0.870*	(0.425)	0.482
Educ: no /other	0		0		0		
Educ: High school	0.133	(0.118)	-0.101	(0.199)	0.237	(0.129)	0.110
Educ: College	0.011	(0.106)	0.311	(0.168)	-0.137	(0.117)	0.013*
Foreigners	-2.118*	(0.230)	-2.520*	(0.304)	-1.989*	(0.231)	0.031*
Left votes	0.203	(0.140)	-0.023	(0.196)	0.284	(0.148)	0.096
Environmental aware.	1.172*	(0.161)	0.795*	(0.230)	1.336*	(0.160)	0.004*
House owner	0.383*	(0.068)	0.413*	(0.102)	0.367*	(0.073)	0.655
Household size: 1	0		0		0		
Household size: 2	0.345*	(0.117)	0.269	(0.174)	0.373*	(0.131)	0.582
Household size: 3 or 4	1.056*	(0.122)	1.007*	(0.187)	1.075*	(0.138)	0.741
Household size: >4	0.860*	(0.219)	1.565*	(0.329)	0.548*	(0.219)	0.000*
Male	0.285	(0.186)	0.756*	(0.324)	0.098	(0.209)	0.071
Occup: blue coll/other	0		0		0		
Occup: white coll	0.284*	(0.117)	0.781*	(0.175)	0.090	(0.129)	0.000*
Occup: self-employed	0.116	(0.123)	-0.003	(0.163)	0.170	(0.142)	0.355
Occup: public sector	0.365*	(0.124)	0.676*	(0.172)	0.262	(0.142)	0.031*
House age: before 1971	0		0		0		
House age: 1971-1980	0.320*	(0.057)	0.155*	(0.076)	0.390*	(0.063)	0.002*
House age: 1981-1990	0.484*	(0.061)	0.474*	(0.099)	0.483*	(0.069)	0.928
House age: 1991-2000	0.566*	(0.068)	0.576*	(0.106)	0.545*	(0.075)	0.793
House age: after 2000	1.055*	(0.077)	0.668*	(0.103)	1.210*	(0.092)	0.000*
House size <45m2	0		0		0		
House size 45-64m2	1.340*	(0.377)	1.128*	(0.393)	1.389*	(0.419)	0.478
House size 65-104m2	1.675*	(0.362)	1.415*	(0.358)	1.753*	(0.401)	0.287
House size 105-184m2	2.281*	(0.357)	2.182*	(0.364)	2.292*	(0.394)	0.730
House size >184m2	2.456*	(0.364)	2.306*	(0.369)	2.501*	(0.398)	0.532
House type: detached	0		0		0		
House type: semi-det.	0.283*	(0.058)	0.292*	(0.074)	0.277*	(0.065)	0.854
House type: terraced	0.078	(0.057)	0.240*	(0.075)	0.018	(0.060)	0.002*
House type: apartment	-0.542*	(0.066)	-0.502*	(0.087)	-0.552*	(0.073)	0.580
Double glazing	0.344*	(0.075)	0.445*	(0.123)	0.309*	(0.086)	0.333
Roof insulation	-0.441*	(0.070)	-0.422*	(0.107)	-0.452*	(0.082)	0.808
Roof: good condition	0.443*	(0.115)	0.503*	(0.159)	0.434*	(0.129)	0.683
Constant	-7.308*	(0.788)	-	(0.959)	-6.612*	(0.891)	
Observations	8471		8471		8471		
Loglikelihood 1st stage	-27419		-19675		-25286		
R^2 2nd stage	0.0360		0.0172		0.0341		

Notes: Results from GMM estimation of Poisson model as discussed in the text. Robust standard errors in parentheses, clustered by municipality. * indicates p<0.05. Dependent variable is total number of PV installations in each period. Unless otherwise indicated, the explanatory variables are expressed as percentages. 0-values indicate the variable is reference category. Equality of estimates tested using Wald test (last column). Shaded cells denote where a variable mainly had an effect in only one of the two periods.

Table 5: Estimation results over time

Now consider the group of variables that mainly played a role in the second period, and less so in the first period. This is true for environmental awareness as it became more pronounced in the second period. We also see an interesting result for house age, where houses of the 70s catch up with houses of the 80s and 90s, and the youngest group shows a significantly higher adoption rate in the second period. This might result from the fact that households are credit constrained and therefore unable to buy a PV right after a large investment in building a house. An alternative explanation is that it follows from the VAT rate policy in Flanders that allows a 6% VAT-rate instead of 21% to renovate houses, which includes installing a PV, that are at least 5 years old. Therefore households living in new houses have an incentive to postpone their investment.

We conclude that our results are relatively robust for adopters that are differentiated by the timing of their investment. There are however some differences as college degrees and high incomes were only important in the beginning, perhaps because of higher information costs. We also find a stronger unconditional income elasticity during the first period, implying an even more important Matthew effect when subsidies were higher. Finally, new adopters often live in newer houses and are more aware of environmental issues.

6. SUMMARY AND CONCLUSION

This paper has extended previous work on explaining the heterogeneity in the adoption of PV, by considering a much richer set of household characteristics and including a new set of housing characteristics in a single framework. Furthermore, this is one of the first studies that analyzes the complete installed base of PV in a region outside the US. More specifically, we combined various data sources to generate a comprehensive dataset for the entire region of Flanders, where PV adoption has reached high levels because of active government policies during 2006-2012. We used a Poisson model to quantify the relative importance of socioeconomic variables at a very small level of aggregation (on average 280 households).

We can summarize our findings of the main model as follows. First, the local subsidies have a robust and significant impact on PV adoption in all specifications. While the local subsidies were quantitatively relatively modest, this finding is indirect evidence that the larger incentives at the regional level (mainly through green certificates and net metering) have formed the basis for the strong development of PV adoption in Flanders (and presumably in many other regions or countries).

Second, the unconditional income elasticity (without controlling for other covariates) is as high as 1.6, and even 1.9 in the first period when subsidies were at its highest level. This suggests a strong Matthew effect in the sense that richer households disproportionately benefited from the subsidies. The income elasticity is still a sizeable 1.032 if we control for a similar set of covariates as in Kwan.

Our third main finding is, however, that the direct income effect almost vanishes if we also control for household size and house ownership. Larger households are more likely to adopt because they tend to consume more electricity and can spread the fixed investment costs over larger absolute savings in energy costs. House owners can reap a larger part of the benefits from their investments. We can thus explain the channel through which wealthier households are more likely to benefit from the PV subsidies: this is not because of their higher income per se, but rather because they are more likely to adopt PV as high users and as more frequent house owners and because they live in houses that are better suited for PVs.

Our final main finding concerns the role of the housing characteristics, which has not been considered in previous work. We find that both house size and house age play an important role: PV adoption is more likely in larger and in more recently built houses. Interestingly, accounting for this information reduces the significance of house value, suggesting our included set of housing characteristics captures the most relevant aspects of housing in the adoption of PVs. Furthermore, accounting for house age also makes the impact of household age insignificant, indicating that younger households do not have stronger incentives per se to adopt PVs, but rather do this because they live in more recently built houses.

In a first extension we show that most of the considered covariates have a smaller impact on the size, measured by its capacity, of the installed PVs. This implies that most covariates have a similar impact on the total number of installations as on the total installed capacity. A surprising result is that we do not find very strong results for natural explanations for larger PVs like household size or house size. Instead, we find that variables we link more to environmental and technological preferences are important for the chosen size.

In a second extension we show that the impact of most covariates is stable over time, with some interesting exceptions. For example, education did not seem to play a significant role over the entire period 2006-2012. But college degrees have been faster adopters during 2006-2009. We also see that new adopters often live in newer houses, and environmental awareness became more important once subsidies started to decline.

More generally speaking, our analysis shows that the inclusion of covariates that – probably due to a lack of availability – are not typically included in other studies, has an impact on the effects found for the covariates that were included in these studies. As a result, some of the conclusions in earlier work may need qualification. In particular, it turns out that the direct impact of income, house value and household age is less important than previously found, while there is an important role for housing characteristics and household size. Finally, we show that heterogeneity not only plays a role in the decision to adopt, but also for the desired size and that there are some differences between early and late adopters.

This paper provides an elaborate overview of how heterogeneity plays a role in the diffusion of PV. Furthermore, it provides a first step towards a more elaborate analysis of the adoption of PV. Various other questions may be considered in future research. A first extension would be to further explore the role of peer effects, along the lines of Bollinger and Gillingham (2012), Letchford et al. (2014), Richter (2013) and Rode and Weber (2011), but after controlling for a richer set of covariates that may explain the heterogeneity in PV adoption across areas. A second line of future research will be to also look into the dynamics of PV adoption, where questions such as ‘What determines the rate of diffusion?’, and ‘What factors determine the timing of adoption?’ are addressed.

7. APPENDIX

7.1. *Tradable Green Certificates*

This appendix provides further details on the tradable green certificates which were the main type of public support during the rapid adoption in the period 2006-2012.

Tradable Green Certificates: the starting years (2002-2009)

The backbone of renewables support in Flanders originates from the Electricity Decree in 2000. This decree provides the legal framework for the Tradable Green Certificates (TGC) mechanism that started off on January 1, 2002.[35] As in many other countries, under the TGC mechanism electricity suppliers and large end-users connected to the transmission grid receive a quota obligation to cover a minimum target percentage of their electricity sales by green electricity. As shown in Table 6 the minimum target was below 1% at the start in 2002, but it was scheduled to gradually increase to 13% in 2021.

Delivery date	***Initial target*** *(RES as a % of electricity sales)*	***Revised target (2010)***	***Fine*** *(per missing certificate)*
March 31, 2003	0,80%		€75,00
March 31, 2004	1,20%		€100,00
March 31, 2005	2,00%		€125,00
March 31, 2006	2,50%		“
March 31, 2007	3,00%		“
March 31, 2008	3,75%		“
March 31, 2009	4,50%		“
March 31, 2010	5,25%		“
March 31, 2011	6,00%		“
March 31, 2012	7,00%		“
March 31, 2013	8,00%	14,00%	€118,00
March 31, 2014	9,00%	15,50%	€100,00
March 31, 2015	10,00%	16,80%	“
March 31, 2016	10,50%	18,00%	“
March 31, 2017	11,00%	19,00%	“
March 31, 2018	11,50%	19,50%	“
March 31, 2019	12,00%	20,00%	“
March 31, 2020	12,50%	20,50%	“
March 31, 2021	13,00%	20,50%	“

Notes: Before 2013 TGCs were given for each produced MWh. From 2013 the amount of MWh that was necessary for one certificate was variable over time and revised each six months. New PV systems with a capacity <10kW are excluded from TGCs since 14 June 2015.

Table 6: Targets and fines in the Flemish TGC system.

[35] For a more extensive description of the (evolution of the) Flemish TGC, we refer to Verbruggen (2004), Verbruggen (2009) and Verhaegen et al. (2009).

In 2004, the TGC mechanism was adapted to include a system of minimum TGC prices per technology for a guaranteed number of years. For most technologies, the minimum prices have ranged between €60 and €90 per MWh for a period of 10 years, and these minimum prices have so far not been binding yet. The only exception is PV, where the minimum price was much higher and the guaranteed period much longer. As shown in Table 7 the minimum TGC prices for PV were as large as €450 per MWh in the early years (2006-2009), and the guaranteed period for this minimum price was 20 years. Installations put into operation in 2010 or later have gradually received lower support, for a shorter period of time.

Tradable green certificates: recent revisions (2009-2014)

In 2009 the Flemish TGC support mechanism was revised on a number of elements, to be implemented between 2009 and 2014. The revisions related to three features. First, the renewables targets for the period 2010-2020 were adapted (see column 2 in Table 6) and would be evaluated on a triennial basis (under the constraint that the targets can never be reduced). Second, starting from 2010 onwards, certificates issued for PV installations on dwellings with badly insulated roofs were not to be accepted any more to satisfy quota obligations.[36] A third major element in the 2009 revision was the reduction in the fine per missing certificate from €125 to €100, starting from March 31, 2015. This change was motivated by the expectation that, in the years to come, there would be a shortage of certificates, with the risk that TGC prices would soar.

In the fall of 2010, a second round of major revisions was announced by the Flemish Minister of Energy. These revisions were triggered by two observations. First, it was observed that the very generous financial support for PV, as implemented with the first wave of major revisions, resulted in an enormous increase of the installed capacity of PV and thus also in a major increase of the financial burden put on distribution companies. Second, the incumbent electricity generator in Belgium (Electrabel) announced the reconversion of a large coal plant to a biomass installation. This single project would increase the installed renewables generation capacity in Flanders with about 180 MW. To put this into perspective: in 2010, the available capacity of onshore wind generation in Flanders was equal to 240 MW. It was estimated that this new power plant would generate more than 1 million certificates per year, which is about 30% of the total number of certificates issued in 2010. The proposed revisions contained one element with relevance for this paper. The minimum prices for PV certificates were changed once again and were now also differentiated according to the size of the installation (with lower minimum prices for larger installations).

In 2012, a third round of downward revisions of the guaranteed minimum support levels for residential PV systems was decided upon, together with a reduction of the duration of the support to 10 years for installations built between August 1st 2012 and December 31st 2012.[37] As of 2013, the minimum support is set equal to €93 per certificate for a period of 15 years. Also, banding is used to determine the number of certificates per 1000kWh of electricity generation. The banding factors are revised every 6 months and depend on the date of installation of the PV system. Since June 14th 2015, new PV systems with a capacity smaller than 10kW are excluded from TGC support.[38]

Figure 6 shows how the TGC mechanism and its various revisions resulted in a large increase in the number of certificates for the various technologies since 2007. In 2007 most of the certificates were for biomass and there were almost no certificates for PV. In 2009 and 2010 the number of PV

[36] Note that this limitation only accounts for dwellings. Currently, PV installations on commercial buildings, garages and garden houses can still be used to satisfy the quota obligation.

[37] http://www.vlaanderen.be/nl/bouwen-wonen-en-energie/elektriciteit-aardgas-en-verwarming/groenestroomcertificaten-voor-zonnepanelen.

[38] http://www.vreg.be/nl/bedrag-minimumsteun-vanaf-2013

certificates started to increased drastically, and by 2013 they made up about one third of all certificates.

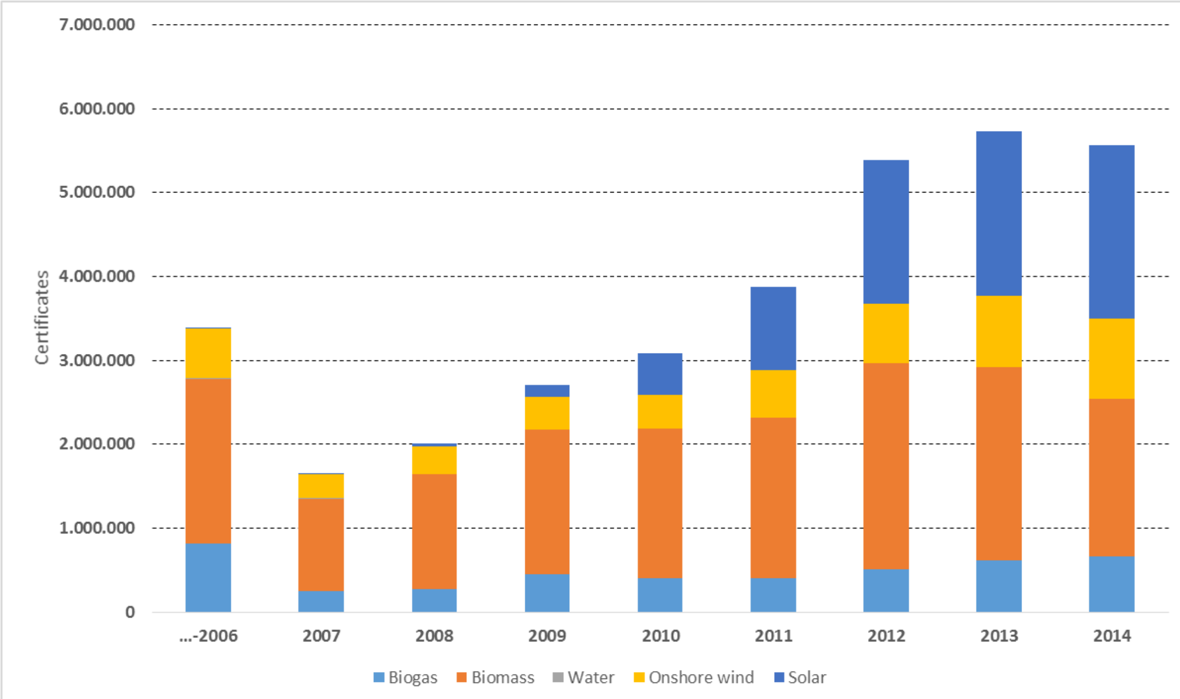

Figure 6: Number certificates issued per type of technology per year (VREG (2015)).

Put into operation in		Date of change of the Energy decree 08-05-2009		07-08-2010		10-06-2011		30-07-2012		28-06-2013	
		Support	***Duration***	***Support***	***Duration***	***Support***	***Duration***	***Support***	***Duration***	***Support***	***Duration***
2006 - 2009		€450	20								
2010		€350	20	€350	20						
2011	*Jan. – June*	€330	20	€330	20						
	July – Sept.	€330	20	€330	20	€300	20				
	Oct. – Dec.	€330	20	€330	20	€270	20				
2012	*Jan. – Mar.*	€310	20	€310	20	€250	20				
	Apr. – June	€310	20	€310	20	€230	20				
	July – July	€310	20	€310	20	€210	20				
	Aug.– Dec.	€310	20	€310	20	€210	20	€90	10		
2013		€290	20	€290	15	€190	15	€93	10	€93	15
2014		€250	20	€250	15	€150	15	€93	10	€93	15
2015		€210	20	€210	15	€110	15	€93	10	€93	15
2016		€170	20	€170	15	€90	15	€93	10	€93	15
2017		€130	20	€130	15	€90	15	€93	10	€93	15
2018		€90	20	€90	15	€90	15	€93	10	€93	15
2019		€50	20	€50	15	€90	15	€93	10	€93	15
2020		€10	20	€10	15	€90	15	€93	10	€93	15

Notes: Before 2013 TGCs were given for each produced MWh. From 2013 the amount of MWh that was necessary for one certificate was variable over time and revised each six months. New PV systems with a capacity <10kW were excluded from TGCs since 14 June 2015.

Table 7: Minimum price support in € per TGC for PV installations ($< \mathbf{250\ kWp}$).

7.2. *Alternative models*

In this section we compare popular alternative models for our preferred specification (Model 3). We compare the Poisson model with a Negative Binomial (NB2) and their zero-inflated counterparts ZIP and ZINB. While the Poisson and NB2 model only require the conditional mean to be correctly specified, the ZIP and ZINB are not robust to misspecification of higher moments. We therefore also compare with the Staub and Winkelmann (2013) zero-inflated Poisson quasi-likelihood approach (ZIPQL). Although this model provides consistent estimates without correct specification of higher moments, the low number of zero observations in our dataset can result in important small sample bias.

We use the same variables in both the count-part of the model and the binary part that explains the zeros, except for the municipality dummy variables. We exclude these dummy variables from the binary part of the model to avoid convergence problems, as this adds a lot of variables and we only have a limited number of zeros. For simplicity, we do not calculate the GMM covariance matrix but simply focus on the first stage of the model (so we do not perform a second stage regression of the municipality fixed effects on the municipality-level variables, left votes and local subsidy). We do not show the results of the binary part of the model but focus on the count part of the models as this is our main interest.

Table 8 shows that our estimates are robust. Not only is the qualitative interpretation the same but also the estimated coefficients are almost identical. This was expected for the Poisson and NB2 model, as consistent estimation only requires the correct specification of the conditional mean function, which is identical for both models. But also the zero-inflated models confirm the robustness of our results. Furthermore, note that the standard errors are similar because all estimators use the cluster-robust covariance matrix.

VARIABLES	Poisson (first stage of model 3)		NB2		ZIP		ZINB		ZIPQL	
Households (log)	1.011*	(0.007)	1.009*	(0.007)	1.008*	(0.007)	1.005*	(0.007)	0.979*	(0.011)
Income: average (log)	0.094	(0.061)	0.088	(0.064)	0.076	(0.060)	0.062	(0.061)	-0.044	(0.067)
Income: dispersion (log)	0.152*	(0.034)	0.148*	(0.037)	0.154*	(0.034)	0.151*	(0.037)	0.061	(0.048)
House value: <EUR500	0		0							
House value: EUR500-EUR744	0.027	(0.070)	-0.008	(0.072)	0.026	(0.071)	-0.012	(0.073)	0.080	(0.097)
House value: EUR745-EUR999	0.001	(0.063)	0.012	(0.065)	0.006	(0.062)	0.018	(0.062)	0.017	(0.105)
House value: EUR1000-EUR1499	0.127	(0.076)	0.109	(0.075)	0.134	(0.075)	0.121	(0.072)	0.133	(0.111)
House value: EUR1500-EUR2499	-0.269*	(0.092)	-0.267*	(0.089)	-0.253*	(0.090)	-0.245*	(0.088)	-0.045	(0.140)
House value: >EUR2500	-0.732*	(0.136)	-0.782*	(0.138)	-0.730*	(0.136)	-0.779*	(0.135)	-0.644*	(0.252)
Population density (log)	-0.048*	(0.007)	-0.049*	(0.007)	-0.047*	(0.006)	-0.048*	(0.007)	-0.014	(0.010)
Age: <25	0									
Age: 25-34	0.226	(0.436)	0.022	(0.451)	0.284	(0.438)	0.091	(0.448)	1.018*	(0.510)
Age: 34-44	0.318	(0.404)	0.125	(0.421)	0.412	(0.412)	0.224	(0.427)	1.065*	(0.497)
Age: 45-65	-0.454	(0.403)	-0.684	(0.425)	-0.337	(0.409)	-0.548	(0.430)	0.669	(0.475)
Age: >65	-0.735	(0.404)	-0.977*	(0.419)	-0.628	(0.413)	-0.855*	(0.427)	0.208	(0.475)
Educ: no high school or other	0									
Educ: High school	0.133	(0.118)	0.165	(0.125)	0.112	(0.117)	0.132	(0.122)	0.044	(0.146)
Educ: College	0.011	(0.106)	0.040	(0.104)	0.014	(0.105)	0.044	(0.103)	-0.227	(0.182)
Foreigners	-2.118*	(0.230)	-2.058*	(0.227)	-2.100*	(0.227)	-2.031*	(0.223)	-1.619*	(0.167)
Environmental awareness	1.172*	(0.161)	1.243*	(0.162)	1.096*	(0.156)	1.151*	(0.164)	-0.022	(0.262)
House owner	0.383*	(0.068)	0.390*	(0.071)	0.392*	(0.068)	0.395*	(0.072)	0.435*	(0.105)
Household size: 1	0									
Household size: 2	0.345*	(0.117)	0.338*	(0.117)	0.338*	(0.118)	0.334*	(0.118)	0.435*	(0.159)
Household size: 3 or 4	1.056*	(0.122)	1.063*	(0.132)	1.068*	(0.123)	1.087*	(0.129)	1.196*	(0.170)
Household size: >4	0.860*	(0.219)	0.930*	(0.217)	0.864*	(0.224)	0.952*	(0.222)	2.072*	(0.311)
Male	0.285	(0.186)	0.248	(0.198)	0.271	(0.182)	0.221	(0.192)	0.141	(0.308)
Occup: blue coll priv sector and other	0									
Occup: white coll priv sector	0.284*	(0.117)	0.330*	(0.125)	0.255*	(0.114)	0.286*	(0.120)	0.031	(0.152)
Occup: self-employed	0.116	(0.123)	0.202	(0.130)	0.101	(0.123)	0.173	(0.127)	-0.074	(0.147)
Occup: public sector	0.365*	(0.125)	0.388*	(0.130)	0.337*	(0.124)	0.350*	(0.128)	0.241	(0.171)
House age: before 1971	0									
House age: 1971-1980	0.320*	(0.057)	0.311*	(0.057)	0.311*	(0.056)	0.300*	(0.056)	0.156	(0.103)
House age: 1981-1990	0.484*	(0.061)	0.513*	(0.065)	0.477*	(0.060)	0.502*	(0.062)	0.265*	(0.111)
House age: 1991-2000	0.566*	(0.068)	0.530*	(0.072)	0.571*	(0.068)	0.535*	(0.073)	0.552*	(0.124)
House age: after 2000	1.055*	(0.077)	1.026*	(0.087)	1.066*	(0.081)	1.037*	(0.093)	0.751*	(0.191)
House size <45m2	0									
House size 45-64m2	1.340*	(0.377)	1.199*	(0.360)	1.389*	(0.368)	1.292*	(0.347)	-0.255	(0.502)
House size 65-104m2	1.675*	(0.362)	1.593*	(0.348)	1.700*	(0.359)	1.651*	(0.346)	-0.277	(0.450)
House size 105-184m2	2.281*	(0.358)	2.155*	(0.343)	2.309*	(0.356)	2.218*	(0.342)	0.237	(0.456)
House size >184m2	2.456*	(0.364)	2.356*	(0.347)	2.479*	(0.364)	2.415*	(0.348)	0.375	(0.461)
House type: detached	0									
House type: semi-detached	0.283*	(0.058)	0.313*	(0.065)	0.283*	(0.058)	0.314*	(0.065)	0.166*	(0.064)
House type: terraced	0.078	(0.057)	0.067	(0.062)	0.064	(0.058)	0.049	(0.063)	0.066	(0.103)
House type: apartment	-0.542*	(0.066)	-0.576*	(0.070)	-0.526*	(0.061)	-0.549*	(0.062)	-0.072	(0.124)
Double glazing	0.344*	(0.075)	0.352*	(0.081)	0.356*	(0.075)	0.375*	(0.082)	0.326*	(0.102)
Roof insulation	-0.441*	(0.070)	-0.384*	(0.079)	-0.449*	(0.068)	-0.398*	(0.077)	-0.374*	(0.126)
Roof: good condition	0.443*	(0.115)	0.437*	(0.118)	0.435*	(0.116)	0.425*	(0.119)	-0.067	(0.170)
Alpha			0.0310*	(0.002)			0.0301*	(0.002)		
Observations	8471		8471		8,471		8,471		8,471	
Loglikelihood	-27419		-26632		-27283		-26519		-26746	

Notes: Results from maximum likelihood estimation with municipality fixed effects. Robust standard errors in parentheses, clustered by municipality. * indicates p<0.05. Dependent variable is total number of PV installations at the end of 2012. Unless otherwise indicated, the explanatory variables are expressed as percentages. 0-values indicate the variable is reference category.

Table 8: comparing different count models

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