How Much Do Households Value The Future? Evidence from the Adoption of Photovoltaic Systems*

Olivier De Groote and Frank Verboven†

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Abstract

The adoption of green technologies depends on how households value future benefits relative to investment costs. We formulate a strategy to identify a discount factor in household investment decisions where households consider postponing adoption, show a simple regression framework to estimate dynamic discrete choice models using market data and apply this to solar panel adoption in Flanders (Belgium) to evaluate its subsidy policy. We also add local market data to control for richer forms of heterogeneity and use this to confirm our results. We find significant undervaluation, making the chosen subsidy policy that focused on increasing future benefits very expensive (JEL C51, Q48, Q58).

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†De Groote: University of Leuven and Ph.D. fellow of the Research Foundation Flanders (FWO), email: olivier.degroote@kuleuven.be. Verboven: University of Leuven and CEPR, frank.verboven@kuleuven.be. Acknowledgements: we would like to thank Frederic Vermeulen, Stef Proost, Jo Van Biesebroeck and other members of our department for their useful comments. Further we like to thank participants of the LCM workshop 2014 in Riberão Preto and of the ECORES summer school 2015 in Brussels. Finally, we thank Guido Pepermans for his help in collecting and geocoding the PV data and Iris Grant for helping with the price data.

1 Introduction

The adoption of green technologies involves a fundamental trade-off between the immediate investment costs and the future benefits from energy cost savings. The successful adoption of these technologies therefore depends on how much households discount future benefits. If consumers are forward looking and capital markets function well, one may expect that consumers use market interest rates in their adoption decisions. However, if households are credit constrained or myopic, they tend to underinvest so that investment in energy saving technologies is delayed. In a seminal article, Hausman (1979) considered the adoption of air conditioners and found that consumers discount the future too much, i.e. use implicit interest rates that are well above market rates. More recently, work has focused on the car market, and found evidence ranging from moderate undervaluation to correct valuation, see for example Allcott and Wozny (2013) and Busse, Knittel and Zettelmeyer (2013).

Implicit discount factors or interest rates are typically estimated from choice models where utility depends on current costs and expected future benefits. One can then infer the discount factor from household responses to variation in the relative costs and future benefits across products and over time. This work typically ignores the timing decision of adoption: it assumes that households make an investment decision without accounting for the option value of waiting. This approach may be reasonable in mature markets where technologies do not change significantly. However, it is unrealistic in new markets, when new energy-saving technologies are just introduced, when prices are quickly decreasing and quality is increasing. In these circumstances, consumers do not only face a traditional investment problem, but must also decide on the timing of their investment decision as it can be beneficial to postpone adoption, even if it is already profitable to invest now.

In this paper, we first show how to infer the discount factor in a dynamic discrete choice model where households may postpone their investment. We subsequently propose a novel approach to estimate the dynamic model based on aggregate market data on adoption rates, investment costs and expected benefits. Next, we apply this framework to the adoption of photovoltaic systems in the region of Flanders (Belgium) during 2006-2012 and discuss the subsidization policy that was implemented. Finally, we propose a more elaborate model that controls for richer forms of heterogeneity using data of local markets to show the robustness of our results. We summarize these four steps in turn.

First, our dynamic discrete choice model of technology adoption is an optimal stopping problem in the spirit of Rust (1987). The discount factor now plays a double role. On the one hand, it influences how much households value the future benefits from their investment. On the other hand, it influences how much households are prepared to wait for better investment opportunities. The first is inherent in every investment decision but does not necessitate the use of a dynamic model as the problem can be solved as a static model with discounted benefits. The second is particularly important for new technologies as they are often characterized by increasing quality and decreasing prices. This aspect does require a dynamic model. Households therefore face the trade-off between investing now to gain benefits quickly, or waiting for a better technology to receive higher benefits in the future. We show how we can infer the discount factor from variation in the investment costs and expected benefits across product varieties and over time, as in traditional investment situations where households do not face an option value of waiting. Although this is common in static choice models, it has not yet been applied on dynamic models where the discount factor plays this double role.

Second, we propose a novel method to estimate the dynamic choice model with aggregate market data on adoption rates, investment costs and future benefits. We make use of Hotz and Miller's (1993) inversion approach , which writes the dynamic discrete choice model as a static one with a correction term. This not only makes it easy to write down and estimate a dynamic model, it also allows us to limit the assumptions we have to make about household expectations of the evolution of prices and subsidies (Arcidiacono & Ellickson 2011). We then show how to bring the data to the model, using a similar approach as in Berry (1994) for static choice models. For a given discount factor, this gives rise to a linear regression equation, where the adoption rate depends on current and future prices, as well as future adoption rates. Similar to Berry (1994), one can estimate the model using OLS or 2SLS. This approach can be applied in a variety of other dynamic discrete choice models, provided that there is a terminating state (technology adoption in our case). To estimate the discount factor in our application, the model becomes similar but nonlinear such that Generalized Methods of Moments (GMM) is used. The existence of a future benefit component in the utility of adoption is crucial to provide valid instruments for this estimator.

Third, we apply our model to the adoption of residential photovoltaic systems (PVs) in the region of Flanders (Belgium). Residential PVs involve an investment for at least 20 years, and are characterized by decreasing prices for a given capacity because of rapid technological progress. Apart from these market factors, government policies have played a crucial role in the evolution of the costs and benefits of PVs, as they are looking for alternative renewable energy sources to meet CO_2 targets. The Flemish government has set up a particularly generous subsidy program for PVs, which has made it a region with one of the highest number of PVs per capita.[1]

The major subsidy program for PVs was introduced in 2006. It consisted of a commitment that PV installers would not only receive the benefits of producing their own electricity, but would also receive Green Current Certificates (GCCs) they could sell at a fixed price for a guaranteed term. Interestingly, the GCC subsidy system was very generous, and the conditions (price and term) were revised many times at pre-announced dates. The considerable variation in the GCC subsidy system enables us to identify the discount factor in a reliable way. In principle, identification could also be obtained from variation in electricity prices (i.e. changing opportunity costs from installing PVs). However, this is less reliable for several reasons: (i) the variation in electricity prices is much smaller than that in GCC subsidies; (ii) there is considerable uncertainty regarding future electricity prices, which puts more weight on the impact of modelling assumptions about households' expectations; (iii) subsidies are financed through higher electricity prices, which implies some reverse causality issues.

We obtain the following main findings. First, households use a real monthly discount factor of 0.9828, which is equivalent to a yearly discount rate of 0.81 or an implicit interest rate of 23%. The 90% confidence interval is between 17% and 29%. This is above the real market interest rate of $\pm 3\%$. Hence, despite the spectacular success of the subsidy program, there is considerable undervaluation of the future benefits.

These findings raise specific policy concerns, at least from a budgetary perspective. The GCC subsidy program was very generous, and it involves substantial committed subsidies for 20 years, so that future payments to households extend to at least 2032. Since households undervalue these future benefits, the government could have reached the same number of PV adopters by borrowing money and giving the entire subsidy to households at the time of the investment. We find that this would have led to a budgetary saving of 64% or € 2.4 billion on GCC subsidies during the years 2006-2012.

To show the robustness of our results, we add rich forms of heterogeneity to our model by including

[1] Belgium ranked 3th in the European Union with a total installed capacity of 240 Watt peak/capita at the end of 2012 (Eurobserv'er 2013). Most of this is due to the adoption in the region of Flanders (Northern part of Belgium). According to our own calculations, total installed capacity in Flanders reached 318 Watt peak/capita at the end of 2012, which is the second highest after Germany which had 399.5 Watt peak/capita.

local market data. Most dynamic models on aggregate data, including the one we proposed earlier, assume heterogeneity is uncorrelated across product varieties and over time. Alternatively, they estimate a dynamic BLP model to allow for correlation through random coefficients (see Melnikov (2013) and Gowrisankaran and Rysman (2012)). We show that a simpler estimator can be found if local market data is available. We control for several sociodemographic variables at the local market level (295 households on average) by including interactions with the utility of adoption, the capacity choice and the price sensitivity. Although these controls are important in explaining adoption behavior, the discount factor, and therefore also the policy evaluation, remains almost identical to the model that uses only aggregate data.

The rest of the paper is structured as follows. Section 2 describes the PV technology and the most important policy measures regarding PVs in Flanders. Section 3 describes the data we use on PVs in Flanders. Section 4 specifies the model that can be used with only aggregate market data. Section 5 discusses the results from this model and its policy implications. In section 6 we extend the model with richer forms of heterogeneity using local market data. We then discuss identification in section 7 and conclude in section 8.[2]

2 Photovoltaic systems

In this section we describe the PV technology from an economic perspective. We look at the benefits through its electricity production and at the investment cost by the price evolution. Further, we show how the subsidization policy in Flanders contributed to the value of a PV investment.

2.1 Technology and benefits from electricity production

Our focus is on grid-connected PV systems, limited to 10 kilowatt (kW). These are the solar panels that are very popular among Flemish households, mainly because of a very generous subsidization scheme but also because of the way electricity production can be sold easily to the distribution system operator (DSO) due to net metering. The PV is usually installed on top of a roof and can produce electricity for the household. In Flanders, a PV of 1 kW produces on average about 0.85 MWh (=MegaWatt hour) a year (CREG 2010). As individual households electricity consumption and production are not always synchronized, the connection to the grid offers a very beneficial alternative to using batteries. The electricity bill for households is simply the difference between their yearly production and yearly consumption.[3] Therefore the electricity price is the opportunity cost of a PV. In our model, we use Eurostat data on electricity prices in Belgium for domestic consumers as benefit component.[4]

2.2 Evolution of investment cost

We constructed a price index for PVs of different capacities, measured in kilowatt. We obtained offers made to consumers using two independent sources: an internet forum, zonstraal.be, where consumers posted the offers they received and historical data from a website that tracks prices: comparemysolar.be. We then discretize the capacity choice in five categories between 2 and 10kW and look at the price evolution of each

[2] External sources that were used for the policy overview and the database creation are listed in the appendix.

[3] It requires a different, less beneficial contract with the grid operator to produce more on a yearly basis than the own consumption.

[4] Since this is half-yearly data, we need to transform it to monthly data in order to be able to use it in our model. Therefore we use a cubic spline interpolation to fill in the missing values.

of these sizes by calculating the median price per watt of the actual power of the system and multiplying it with the discretized size. We could also look at the overall median price per Watt but this would ignore possible increasing returns to scale. We do however need to impose some structure due to data limitations. Although we have data on 2659 offers from May 2009 until the beginning of 2013, there is insufficient data to construct a price index based on median values for each size in each month. Therefore we only use the median price if there were at least ten observations to calculate the median from. Other prices are predicted from a quantile regression model on the median price per watt using month fixed effects, size fixed effects and an interaction term of the discretized size with a linear time trend. This puts a limited amount of structure on the prices: prices per Watt are allowed to differ between time periods and between sizes but their interaction can be explained by a linear time trend. We need to use these predictions primarily for less popular size choices like 8 and 10kW. Because we expect a time lag between posting offers on line and installing a PV, we use the offers that were posted two months before to construct the index. In some cases, especially when subsidies would drop in the near future, the expected waiting time was mentioned by consumers when they posted their offer on line. In these cases we use this announced waiting time instead of our assumption. The resulting price index can be found in Figure 1.

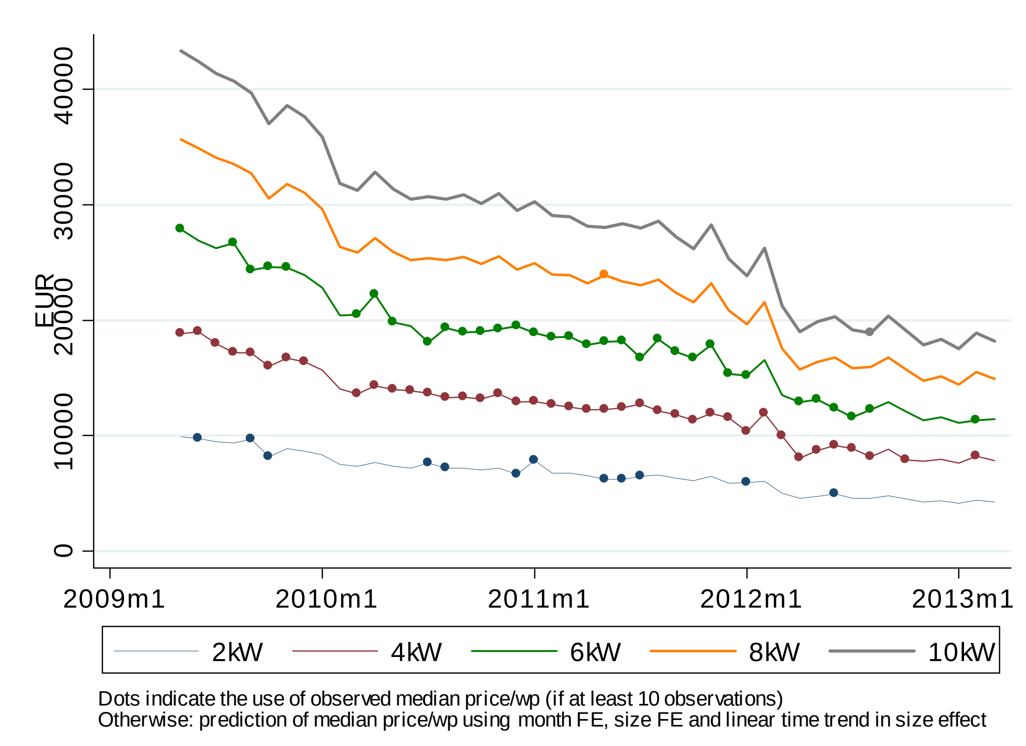


Figure 1: 2009-2013: PV prices without VAT

We see that PV prices decreased substantially during the observation period. For a 4kW system we see that prices dropped from € 18853 in May 2009 to € 7850 in March 2013, a drop of 58%. We also see some increasing returns to scale as the average price of a 10kW systems is only 4.27<5 times as large as the price of a 2kW.

2.3 Support measures in Flanders

We restrict our attention to the support relevant for our model. We want to evaluate the support policies from 2006 until 2012 for household adoption of PVs in Flanders. We start in 2006 because it was the start of the Flemish Green Current Certificates (GCCs) policy which has been one of the most important subsidy components and contributed a lot to the diffusion of PVs in Flanders. Moreover, during the time that GCCs were used, we have reliable adoption data as we receive it from the VREG[5] database that is used to distribute these certificates. We stop our analysis at the end of 2012 because there was a drastic change in policy that made adoption much less beneficial, leading to very few adoption from 2013 on. We will only briefly discuss this change and focus on the 2006-2012 policy. Note that GCCs were not the only measure that was taken to support the adoption process. In this section, we summarize the most important policy measures during 2006-2012. Table 1 provides an overview. In the appendix we cite the sources we used to construct this policy overview.

Table 1: PV support policy Flanders: 2006-2013/06

Date of investment	**GCC**		**Subsidy**	**Tax cut on investment**	
	Price (EUR)	**Duration (years)**		**Percentage**	**Ceiling (EUR 1988)**
2006	450	20	10%	40%	1000
2007	450	20	10%	40%	2600*
2008	450	20	0%	40%	2600
2009	450	20		40%	2600 x 4**
2010	350	20		40%	2600 x 4**
2011/01-2011/06	330	20		40%	2600 x 4**
2011/07-2011/09	300	20		40%	2600 x 4**
2011/10 - 2011/12	270	20		40%***	2600 x 4***
2012/01 - 2012/03	250	20		0%	0
2012/04 - 2012/06	230	20			
2012/07	210	20			
2012/08 - 2012/12	90	10			
2013/01-2013/06	21.39****	15			

*Announced as 2000 but changed to 2600. New announcement made: 18 March 2007.
** If house > 5years old, the tax cut could be spread over 4 years. Announced March 2009.
*** Contract had to be signed before 28 November 2011. Announced on the same date.
**** Corrected for banding factor

Electricity production support: Green Current Certificates (GCCs)

One way of promoting PVs, was to subsidize its electricity production. The VREG delivered GCCs to owners of PV for every MWh they produced, regardless of the fact that they used the electricity themselves or sold it to others. From 2006 until the end of 2012, the PV investors where promised a certain minimum price and duration for these GCCs at the moment of adoption. Since market prices for GCCs have always been lower, the minimum price was binding. For PVs first deployed in 2013 and later, the number of GCCs

[5] Vlaamse Regulator voor de Energie- en Gasmarkt (=Flemish Regulator of the Electricity and Gas market)

given for every MWh had to be multiplied by a banding factor. This banding factor could vary over time and depended on the 'unprofitable top' of an investment in PV. This means that the banding factor alters the amount of GCCs given, such that the investment in PV generates a Net Present Value (NPV) just above 0. This banding factor could change over time and thus it was no longer perfectly known ex ante how many GCCs the investors would receive. However, given the construction of the banding factor, it looked reasonable to assume that it would remain constant. Nevertheless, in February 2014 this banding factor led to the stop of the subsidization program as, according to the government agency VEA[6], the NPV became positive without the subsidy, also for installations of 2013.

The fact that this price guarantee in the 2006-2012 policy period was given at the moment of the investment is very important in the calculation of the net present value and in the estimation of the structural model because it provides a certain benefit component that does not depend on future subsidization policies or price changes.

The guaranteed price and duration have lowered a lot from 2010 on. From € 450 during 20 years at the beginning of the program in 2006 to € 90 and 10 years for new investments at the end of 2012. The policy in 2013 was even less beneficial because of the introduction of the banding factor.

Another aspect of the policy is that it was very unstable. Because of the high popularity of this measure, public support began to decline a lot once the public started noticing the high subsidy costs. Plans to lower the support have been announced, enacted and changed several times. We will see that this does not influence the way we estimate the parameters (including the discount factor) of our model if the changes were announced at least one month before households decide on adoption. However, it could still influence counterfactual analyses that require predictions from a structural model as we would need to model the expectations multiple years ahead. We avoid this by performing a counterfactual analysis where we keep utility constant but change the composition of future versus direct benefits by replacing the GCC subsidies with an investment subsidy that makes households indifferent. This analysis only requires a consistent estimate of the discount factor.

Note that the GCC subsidies were not paid directly by the Flemish government. Nevertheless, the subsidy cost is directed to the population in two ways. First, the local DSO buys GCCs at the minimum price but has to sell them at market price to the electricity suppliers and hereby makes a loss. This cost is redirected to the electricity consumers of the serving distributor. Second, the electricity suppliers have to buy enough GCCs to comply to a quote. This cost is eventually also shifted to electricity consumers. The extent to which the subsidy cost is eventually paid for by the electricity consumers depends on price elasticities but also on market and legal structures and is outside the scope of this paper. We will only look at the loss of giving delayed subsidies, regardless of who bears its cost.

Investment support: subsidies and tax reductions

In 2006 and 2007 households could also apply for a subsidy of 10%.[7] Before 2006 this was 50% and it was also available to companies. The sudden drop is explained by the new system of electricity production support instead of investment support, discussed in the previous subsection.

Next to the Flemish government, the Belgian, federal government also supported the adoption of PVs. They granted a tax reduction of 40%[8], limited to an indexed maximum amount. The maximum amount, in

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

[7] With a maximum cost to be subsidized of 7000 EUR/kiloWatt peak (kW) (VAT excl.) and recalculated to a PV of 3kW if the PV was larger than this.

[8] The subsidy of the Flemish government did not have to be subtracted from this amount.

prices of 1988, was raised in 2007 from 1000 to 2000 and later that year to 2600 retroactively for all new investments in 2007. Since 2009, households could transfer the remaining amount to the following three years if they lived in a house that was at least five years old. This was formally possible from 2009 on but it was in practice already possible to split bills over 2 or 3 years. At the end of 2011, the new government decided to abolish the tax reduction immediately for the year 2012 and following but households that already installed a system could still spread the tax cut over future years.

Another support measure was the VAT rate. Households, living in houses of at least five years old, could benefit from a reduction of the VAT rate so they have to pay 6% instead of 21%. This was not a specific measure for PVs but applied to all construction works.

3 PV data

We hereby discuss the data we obtained from the Flemish government agency VREG on PV adoptions and compare this to price and subsidy data.

3.1 Aggregate market data

To isolate the residential solar panels, we drop PVs that are larger than 10 kW.[9] At the end of June 2013 we found that there were 222077 residential PVs installed[10] with a total capacity of 1065 MW. Since we know there are about 2.6 million households, we obtain an adoption rate of 8.5%. Figure 2 shows the monthly data of new PVs that were declared to the VREG between January 2006 and June 2013. Since the VREG granted the GCCs, we can infer that it contains at least all PVs installed during this period. It took some time after the introduction of the GCCs before households started adopting PVs. Although we do not have price data for the beginning of the GCC program, we expect the main reason was that investment costs were still too high. Another reason could be the uncertainty about the new policy that was not very well known in the beginning. Also noticeable from this figure is the large increase in adoptions right before a drop in GCC subsidies. The results are most clear from the first drops as there is some time span between them. We see that the first drop in the GCC price in 2010 resulted in an increasing number of adoptions at the end of 2009. The same happened towards the end of 2010 before the second drop. We then see large changes in adoptions from the end of 2011 on which corresponds to the volatility of the GCC price then. This indicates two aspects of household behavior: they care about the future benefits of the investment and they care about future benefits of investing in the future. This is because, by construction, the GCC policy in the next month does not influence the benefits that will be given if households decide to adopt now. The fact that households still take this into account, can be explained by dynamic considerations. By choosing to invest in a certain month, households lose the opportunity to do the investment in the future (= the option value of not adopting) as it is unlikely that they install more than one panel or can sell it without significant transaction costs. When GCC subsidies decrease over time, the option value decreases the closer is the drop in the GCC price. Therefore the choice for adoption becomes more likely. Only a dynamic model can explain this behavior.

Figure 3 gives more insight in the different channels that affect both adoption decision and capacity choice. We discretize the choice decision by creating five groups for each increase in size of 2 kW. We see

[9] This is a commonly used cut-off point for distinguishing between residential and non-residential PVs (see e.g. Kwan (2012)).

[10] Since we focus on adoption between 2006 and 2012, it is worth mentioning that at the end of 2012 the total number was not very different: 221925.

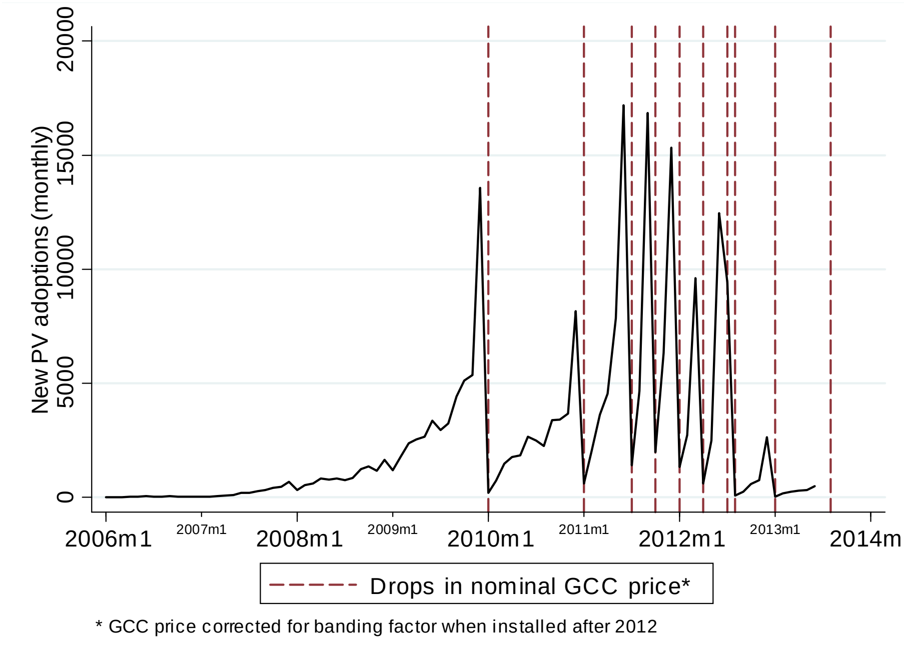


Figure 2: 2006-2013: Time series of new PV adoptions and drops in nominal GCC price

that prices and subsidies move in a very similar way. This suggests that an important part of the subsidy is captured by PV installers and not only by consumers but it might as well come from the fact that the government decided to lower the subsidies once investing in PVs became more profitable. There is often also an increase in the price when subsidies are about to drop. This could be the result of increased demand because households still want to benefit from the better subsidy scheme. This is another indication that dynamic considerations by households play an important role.

We also see that 4 kW and 6 kW systems were the most popular choices for a PV. The popularity of these systems can be explained by the fact that we do not expect households to install PVs of which the yearly production exceeds their own consumption (see previous section). As an average household uses 3.5 MWh/year and a 4 kW system produces about 3.4 MWh/year, we expect to see a higher probability to adopt around this capacity range. Note also that households chose more powerful systems over time. As prices per Watt and subsidies move in a very similar way over time, it is difficult to identify a discount factor from time series variation only. The changes in capacity choices among adopters will therefore help in its estimation. Finally, we see that the large drops in subsidies at the end of 2012 stopped the expansion of solar panels as there was almost no increase in the number of PVs in 2013.

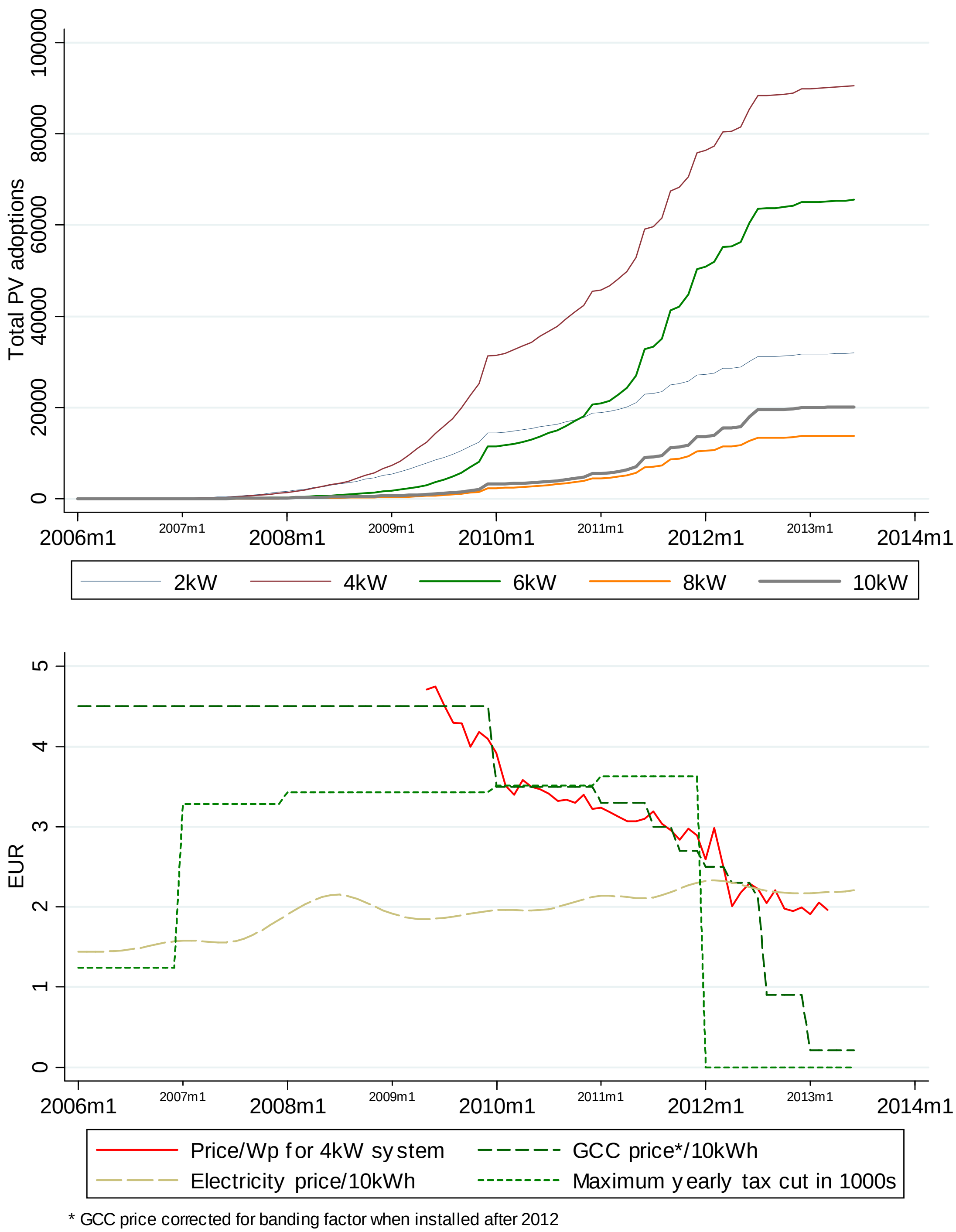
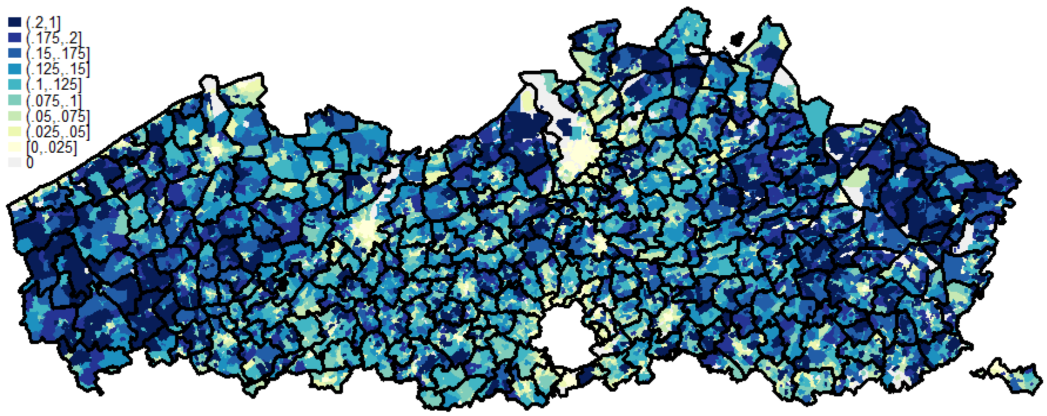


Figure 3: PV adoptions, costs and benefits (nominal values)

3.2 Local market data

Although the discount factor is identified from aggregate market data only, we will be able to control for richer forms of heterogeneity by using local market data. The local markets are the "statistical sectors" defined by ADSEI[11]. Flanders contains 9182 statistical sectors, that can be grouped in 308 municipalities. The data of the VREG were geocoded to match with the definition of these statistical sectors. We use this data to control for unobservables at the municipality level that drive adoption decisions and we use census data of 2011 on sociodemographic variables on the statistical sector level that allow for heterogeneity in the utility of adoption, the preference for the capacity of a PV and the price sensitivity. This data is recently made available publically by ADSEI. Figure 4 illustrates how adoption rates differ within Flanders, also the borders of municipalities are drawn.



Adoption data: VREG, household data: ADSEI census 2011

Figure 4: PV adoption rates in Flanders

4 Model using aggregate data

In this section we specify the structural model for PV adoption. This model only requires aggregate market data to estimate. After discussing the results, we explain and discuss the results of a model that makes use of local market data to control for richer forms of heterogeneity.

We start by describing a simple binary choice model to adopt a PV or not in each month. Next, we extend the model to use the variation we have on different capacity choices of PVs.

4.1 The adoption decision

Every month t, each household $i = 1, ..., N$ either adopts ($j = 1$) or they do not adopt ($j = 0$). A key feature of the model is that adopting is a terminating state, after which no decision has to be made anymore. Not adopting gives the option of adopting at a later stage, when the price for a given size may have decreased, or extra financial benefits (GCC subsidies and electricity prices) may have become higher or lower.

Define $v_{i,j,t}$ to be the conditional value function of j, net from an iid, extreme value type 1 (EV1) error term $\varepsilon_{i,j,t}$. $v_{i,j,t} + \varepsilon_{i,j,t}$ then represents the expected lifetime utility from choosing j at time t. Let $\delta_{j,t}$ be

[11] Algemene Directie Statistiek en Economische Informatie (= Directorate-General Statistics and Economic Information).

the component of $v_{i,j,t}$ that is common to all households and which we will refer to as mean utilities. In this version of the model, we assume heterogeneity only enters through $\varepsilon_{i,j,t}$. Therefore $v_{i,j,t} = \delta_{j,t}$.

We now describe the conditional value function of both options separately.

Conditional value of adoption ($j = 1$)

The conditional value functions and thus also the mean utilities can be summarized as follows:

$$v_{i,1,t} = \delta_{1,t} = -\alpha p_t + \xi_1 + \xi_t \tag{1}$$

Where ξ_1 is a constant, ξ_t are demands shocks and p_t is the price.[12] ξ_1 and α are parameters to be estimated with $\alpha > 0$ representing the marginal utility of income. Because the action is terminal, we can write the mean utilities as if all future benefits are collected immediately, after being discounted. Therefore, the price variable is more general than the investment cost, it is the present value of all future costs and benefits. Note that this can be positive or negative[13]:

$$p_t \equiv p_t^{INV} - \rho \left(p_t^{GCC} + p_t^{EL} \right) \tag{2}$$

with p_t^{INV} the upfront investment cost (net of upfront subsidies), p_t^{GCC} and p_t^{EL} are flow variables, monthly benefits from GCCs and electricity savings, and

$$\rho \equiv \frac{1 - \beta^P}{1 - \beta}$$

is a capitalization coefficient if the technology lasts P periods, with β the real, monthly discount factor. Note that in this formula, only the current prices influence the total benefits. This means we assume households expect a random walk in real electricity prices.[14] In the estimation we also correct for the fact that GCC prices are not constant in real prices but in nominal prices only and we make ρ more flexible to control for deterioration and differences in P (see appendix section A.2).

Conditional value of not adopting ($j = 0$)

The mean indirect utility from not adopting is the flow utility without the technology $u_{0,t}$, plus the option value from waiting.

$$v_{i,0} = \delta_{0,t} = u_{0,t} + \beta V_{t+1}^e \tag{3}$$

where V_{t+1}^e is the expected value function, i.e. the continuation value from behaving optimally from period $t + 1$ onwards. Note that an option value was not included for $j = 1$ because we assume households can only adopt once. Note also that this does not depend on i because we assume heterogeneity is uncorrelated over time.

With an EV1 distribution for $\varepsilon_{i,j,t}$, V_{t+1}^e is given by the logit logsum formula:

$$V_{t+1}^e = \gamma + \ln \left(\exp \delta_{0,t+1}^e + \exp \delta_{1,t+1}^e \right) \tag{4}$$

With γ the Euler constant and $\delta_{j,t+1}^e$ the expected value at time t about $\delta_{j,t+1}$. We assume households can perfectly forecast the future one month ahead such that $\delta_{j,t+1}^e = \delta_{j,t+1}$. As explained in section 2, this is a

[12] This utility specification does not include other observed product characteristics as they are not relevant in this application but such an extension is straightforward.

[13] Note also that we use real prices in the model. We set al monetary variables in prices of January 2013 by using the HICP.

[14] We find almost identical results for different assumptions on expectations about electricity prices (see appendix). This is mainly because our identification approach focuses primarily on investment costs and GCC subsidies and not on electricity prices.

reasonable assumption as changes in policies where announced more than one month ahead. Substituting (4) in (3), we obtain the mean utility of choosing not to adopt:

$$\delta_{0,t} = u_{0,t} + \beta\left(\gamma + \ln\left(\exp\delta_{0,t+1} + \exp\delta_{1,t+1}\right)\right) \tag{5}$$

Hotz and Miller (1993) show that we can compute the logsum term directly from the next period conditional choice probability (CCP). With aggregate data and perfect foresight, this can be approximated by the market share of a particular option. This is

$$S_{1,t+1} = \frac{\exp\delta_{1,t+1}}{\exp\delta_{0,t+1} + \exp\delta_{1,t+1}}$$

Rewrite and take logs:

$$\ln\left(\exp\delta_{0,t+1} + \exp\delta_{1,t+1}\right) = \delta_{1,t+1} - \ln S_{1,t+1}$$

This can be substituted in the mean utilities for not adopting (5):

$$\delta_{0,t} = u_{0,t} + \beta\left(\gamma + \delta_{1,t+1} - \ln S_{1,t+1}\right) \tag{6}$$

We see that the mean utility of not adopting is equal to the flow utility $u_{0,t}$ added by some constant $\beta\gamma$, the value of adopting in the next period $\delta_{1,t+1}$ and a nonnegative correction term $-\ln S_{1,t+1}$ to correct for the fact that $j = 1$ might not be the optimal choice in the next month and the utility can thus be higher than one would obtain from adoption.

4.2 Estimation

Berry (1994) shows how to estimate static models using aggregate data. We can use the same inversion but use a different specification of the conditional value function of the outside option to correct for dynamic considerations. Just like in the static logit case, we obtain a closed form solution for the market shares $S_{j,t}$:

$$\begin{aligned} S_{1,t} &= \frac{\exp\delta_{1,t}}{\exp\delta_{0,t} + \exp\delta_{1,t}} \\ S_{0,t} &= \frac{\exp\delta_{0,t}}{\exp\delta_{0,t} + \exp\delta_{1,t}} \end{aligned}$$

We divide both and take logs:

$$\ln\frac{S_{1,t}}{S_{0,t}} = \delta_{1,t} - \delta_{0,t} \tag{7}$$

Substitute the expressions for the mean utilities (1) and (6) in (7), rewrite and normalize $u_{0,t} + \beta\gamma = 0$:

$$\ln\frac{S_{1,t}}{S_{0,t}} = -\alpha\left(p_t - \beta p_{t+1}\right) + \beta\ln S_{1,t+1} + (1-\beta)\xi_1 + \xi_t - \beta\xi_{t+1} \tag{8}$$

For more intuition, we can bring the dynamic correction term to the left-hand side:

$$\ln\frac{S_{1,t}/S_{1,t+1}^{\beta}}{S_{0,t}} = -\alpha\left(p_t - \beta p_{t+1}\right) + (1-\beta)\xi_1 + \xi_t - \beta\xi_{t+1}$$

This results in a pseudo-differenced regression equation with a dynamic correction term. The regression equation has an intuitive interpretation. It shows that the ratio of current to next period adopters is small when the expected price drop is large. Note that if a certain value for β is imposed and prices are exogenous, it would be possible to estimate this model using OLS by regressing the left-hand side with market share data[15] on a simple transformation of the price data: $(p_t - \beta p_{t+1})$ and by rescaling the result for the constant. Note that if observable product characteristics are available, they would enter in a similar fashion as the price variable. If we expect demand shocks to be correlated with the price, a 2SLS regression can be considered.

For the estimation of the discount factor, look again at equation (8) as now all parameters are back to the right hand side. Note also from (2) that the price variable itself depends on the discount factor. This makes the regression nonlinear. Furthermore, estimating the discount factor causes an additional source of correlation of the regressors with the regression residual. The extra source of endogeneity comes from the dynamic correction term $\ln S_{1,t+1}$. The regression residual $\xi_t - \beta\xi_{t+1}$ depends on the demand shocks of technology $j = 1$ in the next period: ξ_{t+1}. It will therefore be correlated with its market share in the next period such that $\ln S_{1,t+1}$ is not an exogenous regressor.

We therefore apply Generalized Method of Moments (GMM) (Hansen 1982) on this model by calculating the residual, conditional on the unknown parameters ξ_1, α and β and multiplying it with a vector of instruments z_t to create the standard exogeneity condition. We match the following moments:

$$\begin{aligned} E[z_t(\xi_t - \beta\xi_{t+1})] &= 0 \\ E[z_t(\ln \frac{S_{1,t}}{S_{0,t}} - \beta \ln S_{1,t+1} + \alpha\,(p_t - \beta p_{t+1}) - (1-\beta)\xi_1)] &= 0 \end{aligned} \tag{9}$$

As investment costs cannot be used as a valid instrument because of possible correlation with the demand shocks, we use a price index of Chinese PV modules on the European market[16]. As these are the most important cost components of PVs, they provide a strong instrument and we can assume that demand only depends on it through its translation in the investment costs, making it a valid instrument. For the identification of the discount factor, we cannot use $\ln S_{1,t+1}$ as an instrument as it will be correlated to the error term. We can however use the fact that the price variable not only depends on the investment costs, but also on the future benefits (see equation (2)). We therefore use the GCC subsidy as an instrument that allows us to identify the discount factor. Since the price variable enters both in the current and next period, we also add current and next period values of the investment costs and GCC subsidies to the set of instruments. Further we add a vector of ones to identify the constant. Since we use both current and next period values, the model will be overidentified but the GMM two-step optimal weight matrix will optimally weigh all the moments.

The GCC subsidies are very useful in identifying the discount factor because they provide a lot of variation, even in the very short run as they discontinuously drop in several months. The estimation is helped a lot by the large variation over time of the investment costs but also of the GCC subsidies. Changes in electricity prices could also have been used as an instrument. However, this is less reliable for several reasons: (i) the variation in electricity prices is much smaller than that in GCC subsidies; (ii) there is considerable uncertainty regarding future electricity prices, which puts more weight on the impact of modelling assumptions about households' expectations; (iii) subsidies are financed through higher electricity prices, which implies some reverse causality issues. In the appendix we show that this approach makes our results robust for different assumptions on electricity price expectations.

[15] To know the market share we need to define the potential market. We use the total number of households, subtracted by households that already adopted. Our results for the discount factor however are robust against large changes in the definition of the potential market because it is identified on different behavior among adopters.

[16] Source: pvXchange

4.3 The capacity choice

Extending this binary choice model to a discrete choice model is straightforward. Households now not only choose between adopting ($j = 1$) or not ($j = 0$) but between different capacities $j \neq 0$ and not adopting. Each capacity choice is terminal so the Hotz-Miller inversion can be applied on an arbitrary one. We therefore maintain the $j = 1$ option as the arbitrary terminal choice. For $j \neq 0$, we include $J = 5$ alternatives: a 2kW, 4kW, 6kW, 8kW and 10kW PV. Note that prices and subsidies are therefore also different as larger systems cost more but also generate more benefits.

The mean utilities can now be summarized as follows:

$$\begin{aligned} \delta_{j,t} &= -\alpha p_{j,t} + \xi_j + \xi_{j,t} \text{ for } j \neq 0 \\ \delta_{0,t} &= u_{0,t} + \beta V^e_{t+1} \end{aligned}$$

with

$$\begin{aligned} p_{j,t} &\equiv p^{INV}_{j,t} - \rho \left(p^{GCC}_{j,t} + p^{EL}_{j,t} \right) \\ \rho &\equiv \frac{1-\beta^P}{1-\beta} \end{aligned}$$

Again the Hotz-Miller (1993) inversion can be applied, this time on an arbitrary choice $j \neq 0$, we choose $j = 1:$

$$\delta_{0,t} = u_{0,t} + \beta \left(\gamma + \delta_{1,t+1} - \ln S_{1,t+1} \right)$$

Now apply the Berry (1994) inversion:

$$\begin{aligned} \ln \frac{S_{j,t}}{S_{0,t}} &= \delta_{j,t} - \delta_{0,t} \text{ for } j \neq 0 \\ &= -\alpha \left(p_{j,t} - \beta p_{1,t+1} \right) + \beta \ln S_{1,t+1} + \xi_j - \beta \xi_1 + \xi_{j,t} - \beta \xi_{1,t+1} \end{aligned}$$

This looks similar to the binary choice model but now current state values have subscript j, while future state variables and adoption rates are specific to the arbitrary terminal choice $j = 1$. Dummy variables for each capacity choice will capture the $\xi_j - \beta \xi_1$ term to control for unobserved differences in time-invariant capacity preferences. The residual is now $\xi_{j,t} - \beta \xi_{1,t+1}$.

We can also add common demand shocks by estimating a time fixed effect ξ_t. Interestingly, a time fixed effect also captures the entire dynamic correction term which simplifies the estimating equation substantially:

$$\begin{aligned} \ln \frac{S_{j,t}}{S_{0,t}} &= -\alpha \left(p_{j,t} - \beta p_{1,t+1} \right) + \beta \ln S_{1,t+1} \qquad (10) \\ &\quad + \xi_j - \beta \xi_1 + \xi_t - \beta \xi_{t+1} + \xi_{j,t} - \beta \xi_{1,t+1} \\ &= -\alpha p_{j,t} + \xi_j + \xi'_t + \xi_{j,t} \\ \text{with } \xi'_t &= \alpha \beta p_{1,t+1} + \beta \ln S_{1,t+1} - \beta \xi_1 + \xi_t - \beta \xi_{t+1} - \beta \xi_{1,t+1} \end{aligned}$$

To estimate the model without time fixed effects, we use a similar GMM estimator as before, but now the instruments are also $j-$specific. The monthly GCC subsidies are larger for larger PVs and the module prices, which are expressed in a price/kW, are multiplied by the kW of the capacity choice. We match the following moment conditions:

$$
\begin{aligned}
E[z_{j,t}(\xi_{j,t} - \beta\xi_{1,t+1})] &= 0 \\
E[z_{j,t}(\ln \frac{S_{j,t}}{S_{0,t}} + \alpha\,(p_{j,t} - \beta p_{1,t+1}) - \beta \ln S_{1,t+1} - \xi_j + \beta\xi_1)] &= 0
\end{aligned}
$$

The model with time fixed effects can be estimated by demeaning the linear terms in the regression equation, the same holds for the instruments. Since the future values of the terminal choice are identical for each observation in the same time period, they are dropped as instruments, making the GMM estimator an exactly identified method of moments estimator. We denote demeaned values by a tilde:

$$
E[z_{j,t}(\widetilde{\ln \frac{S_{j,t}}{S_{0,t}}} + \alpha\tilde{p}_{j,t} - \tilde{\xi}_j)] = 0
$$

5 Results

We start by discussing the results of the estimation. We then use the estimated discount factor to look at the effect on the NPV of an investment in PV and on the efficiency of the GCC subsidization policy.

5.1 Structural parameters

We show the results for four regressions in Table 2. We build up from a static model (1) where the adoption decision is only between not adopting and adopting a PV. We use the sum of the adoption rates over all capacity choices and we use the costs and benefits of our benchmark 4kW system. In (2) we make the model dynamic, (3) adds the capacity choice and finally (4) adds month fixed effects.

Although we are interested in the entire 2006-2012 policy period, we only estimate the model from June 2009 on because we do not have older price data. This still captures all the variation in GCC prices and a large majority of adoptions from 2006 until the end of 2012.

The regression results of the binary choice model are unreliable as we are not able to significantly estimate the marginal utility of income. Moreover, the standard error of the discount factor in the dynamic model is large. Adding the capacity choice leads to more precise estimates and adding time fixed effects shows that too much of the time trend in adoption behavior is captured by price changes. The effect on the discount factor is more subtle but still substantial if we extrapolate the result to yearly discounting behavior.

We see that the estimate for the real monthly discount factor β in our preferred model (4) is 0.9828. As it is more intuitive to look at yearly discounting behavior, we apply the delta method to retrieve its yearly counterpart. We also calculate the implicit interest rates, i.e. the rate of return that households want to have from installing a PV, over one month and over one year to gain more intuition. These results and confidence intervals can be found in Table 3. We see that our estimation results imply a real yearly discount factor of 0.81 or an implicit interest rate of 23%. We see that the commonly assumed discount factor in dynamic choice models of 0.9 lies far outside the 90% interval. The estimate is also significantly lower than one would expect from comparing with risk-free investments like savings accounts or government bonds.

A low discount factor can have different explanations. A rational interpretation is that the discount factor reflects intertemporal preferences and therefore we infer that households value utility in the future much less than utility today. The problem with this interpretation is that it excludes the possibility to mitigate this by borrowing money. This is especially surprising in this application because between 2009 and the end of 2011,

Table 2: Results

	(1) Static Rep. PV=4kW	(2) Dynamic Rep. PV=4kW	(3) Dynamic 5 alternatives	(4) Dynamic 5 alternatives + FE
MU income (x1000 EUR) (= α)	2.4484	1.0195	1.2451***	0.3848***
	(1.7237)	(1.0248)	(0.2652)	(0.1307)
Monthly discount factor (= β)	0.9843***	0.9998***	0.9897***	0.9828***
	(0.0021)	(0.0080)	(0.0012)	(0.0023)
Choice specific constants				
2kW			3.5093***	-1.6446***
			(0.6311)	(0.1417)
4kW			*Benchmark*	
6kW			-5.0151***	0.1746
			(0.6613)	(0.1697)
8kW			-11.2678***	-0.8797***
			(1.3242)	(0.3102)
10kW			-16.1110***	-0.3617
			(2.0210)	(0.4175)
Constant ($x(1-\beta)$ if dynamic)	-1.4483	-0.1285	-0.2181*	
	(5.9625)	(0.1501)	(0.1298)	
Time fixed effects	NO	NO	NO	YES
Observations (JxT)	43	43	215	215

Standard errors in parentheses, moments clustered within time period
*** p<0.01, ** p<0.05, * p<0.1

the federal government subsidized loans for environmentally friendly investments.[17] A possible explanation is that households were credit-constrained or credit-aversed.

A second explanation for finding a low discount factor is irrational behavior. It is possible that households were unable to calculate the benefits from adoption and make systematic mistakes. Allcott (2013) studies this type of irrational behavior in the car market by looking how well consumers calculate the financial benefits from fuel economies of different cars. He finds that most households correctly or only slightly underestimate the value of fuel economy. Since PVs are in the same price range as cars, we could expect households to devote similar effort in their decision. Moreover, in contrast to PVs, the benefits of a car are more diverse than only future savings. Therefore we expect households to spend even more effort on calculating the benefits in the PV case, further reducing the impact of irrationalities on the estimated discount factor. However, we do see signs of irrational behavior. The discussion on the profitability of a PV is often about their "payback period" rather than their return on investment. This is problematic because it ignores all benefits that can be collected after the payback period is reached. Because of the high subsidies, there were times that the payback period was only 4 years. This means that 16 years of GCC subsidies is ignored when households make a decision based on this alone. This behavior could therefore explain the low discount factor because

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

Table 3: Discount factor and implicit interest rate implied by model (6)

	Monthly	**Yearly**
Real discount factor	$\beta = 0.9828$	$\beta^{12} = 0.8122$
	[0.9790 ; 0.9866]	[0.7741 ; 0.8502]
Real implicit interest rate	$1/\beta - 1 = 1.7487\%$	$1/\beta^{12} - 1 = 23.13\%$
	[1.3515% ; 2.1459%]	[17.36% ; 28.90%]

90% Confidence intervals between brackets

Confidence intervals of implicit interest rates and yearly discount factor calculated using delta-method

not all future benefits are valued.

A third explanation is that households are risk-averse and therefore prefer current money over future money because it is more certain. This is doubtful for this application as the GCC subsidies, our source to identify the discount factor, were guaranteed over the entire investment period. Nevertheless, mistrust in the government or a concern that the PV is of bad quality can still result in a low discount factor. By estimating the discount factor three years after the program started, we do believe that mistrust in the government was limited as it already built up some confidence in the first years of the program. Also a lack of information about the policy is therefore doubtful.

5.2 Implications for NPV

Knowing the discount factor, we can look at the NPV of a PV investment (see Figure 5).

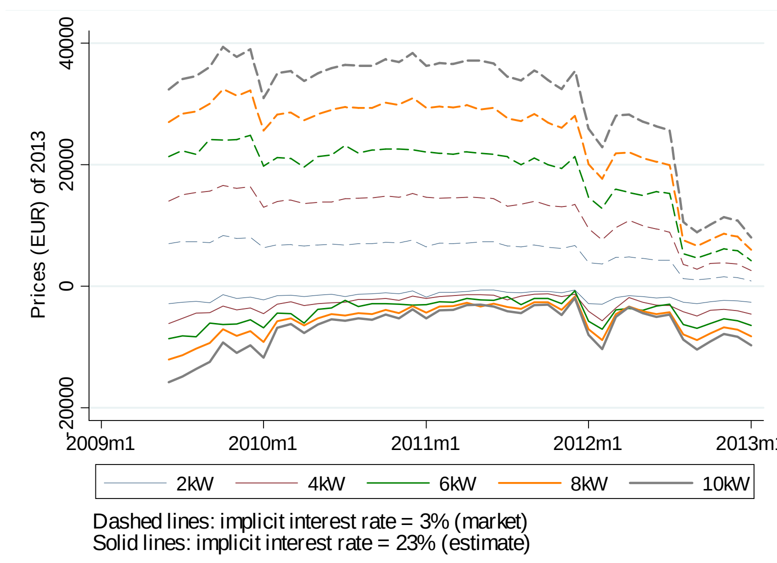


Figure 5: NPV of PVs during 2006-2012 at real, yearly interest rates: market rate and estimate of implicit rate

We look at two scenarios. In the first scenario we calculate the NPV with an implicit interest rate of 3%. This corresponds to a commonly used value of a risk-free interest rate. The second scenario looks at the NPV at the estimated implicit interest rate of 23%. While the first scenario shows a very profitable investment in all time periods, especially in the beginning, the second scenario always leads to a negative NPV. This figure shows that PVs were strongly over-subsidized if households would discount the future at market interest rates but if we take into account the discount factor that was actually used by households, the high subsidies were required to achieve this number of adoptions because of the use of a subsidy scheme that focused on increasing future benefits.

Since the NPV at the estimated discount factor is close to 0, one could argue that our estimate simply reveals the rate of return of the PV investment. This however is coincidental. Our structural model takes into account both financial and non-financial costs and benefits from adopting a PV. Since the NPV we find is even slightly negative, it suggests some non-financial benefits like environmental preferences could have persuaded households in their decision. Moreover, the estimated model also makes use of the observed adoption rates. Therefore the discount factor is identified from responses to price and subsidy shocks and not just by equalizing costs and benefits to find the rate of return in each month.

5.3 Policy implications

The fact that we find an implicit real interest rate (23%) that is much higher than interest rates on savings or government bonds is not surprising and confirms what is often seen in empirical studies. What is more surprising is that policy makers did not take this fact into account when they designed the GCC policy as it implies large losses, at least from a budgetary perspective. These losses imply that the government behaved even more myopic than households. Knowing the value of the discount factor, we can calculate the loss by giving subsidies in the future instead of at the moment of adoption. If the discount factor reflects intertemporal preferences, we can consider this to be efficiency losses. The reason is that the institute that gives the subsidy, regardless if it is a government or DSO, is expected to be able to borrow at much lower rates than 23%. In general it is assumed that the long run government bond real interest rate is around 3%. By borrowing this amount and giving it straight to the PV investor instead of spreading it over 10 or 20 years, the same adoption rates could have been achieved by granting the same utility to households but at a much lower cost. This is because direct and future costs and benefits are inefficiently distributed as households value direct benefits relatively more, leading to a Pareto-inefficient situation. Note that, in order to discuss Pareto-efficiency, we implicitly assume here that the discount factor reflects the intertemporal preferences of households and is not the result of irrational behavior as discussed in section 5.1. Without this assumption, the discussion is more about equity rather than efficiency as subsidies are transfers from all households to PV adopters, which have higher incomes in general.

At the estimated discount factor, we find that the same adoption rates could have been achieved at only 36.26% of the costs that were made now. We find that this efficiency loss of the 2006-2012 GCC policy, when actualized to 2013, amounts to € 2.387 billion. In the appendix section A.5 we show the details of these calculations. Note that we only calculated the loss for residential PVs ($\leq 10kW$) so the total loss might be much larger if companies also discount the future strongly. Note also that this is a different approach to estimating over-subsidization than is commonly done by government agencies like CREG[18] and VITO[19]. They often use non-estimated but predefined discount factors and calculate how much the subsidies should have been in order to bring the NPV to zero (CREG 2010). We keep the NPV constant (which at the estimated discount factor is often even slightly negative, see Figure 5) but change the subsidy scheme from an increase in future beneftis to a decrease in investment costs. By keeping the NPV constant, we guarantee

[18] Commissie voor de Regulering van de Elektriciteit en het Gas (=Regulatory Commission for Electricity and Gas).

[19] Vlaamse Instelling Voor Technologisch Onderzoek (=Flemish Institute for Technological Research).

the same adoption rates and the same household utility but at a lower cost and can therefore discuss efficiency losses. In the calculations of CREG and VITO, the expected decrease in adoptions when subsidies fall is not taken into account. They implicitly assume households will react in the same way once a certain threshold of profitability is reached but this is not in line with a utility function that is monotonically increasing in income as a decrease in subsidies will always lead to a decrease in adoptions unless an adoption rate of 100% can be reached at the low subsidies.

6 Model with local market data

In this section we discuss the model that uses local market data to control for richer forms of heterogeneity. Recall that in the model on aggregate data, heterogeneity only entered through an EV1 iid error term. This means that heterogeneity was uncorrelated over alternatives and uncorrelated over time. We maintain this assumption on the error term but add sociodemographic differences between local markets to control for heterogeneity that is allowed to be correlated. We estimate the effect of sociodemographic variables on the utility of adopting a PV, on the capacity choice and on the the price sensitivity. An alternative solution would have been to estimate random coefficients, which would result in a dynamic BLP model, similar to Gowrisankaran and Rysman (2012). We believe our approach is more suitable because it allows us to exploit more observed data, estimation is less tedious and we can use Hotz & Miller's CCP method with the weak one month ahead assumptions about future state variables.

6.1 Setup

The choice set is still $j = 0, 1, ..., J$ with $j = 0$ the option not to install a PV and $j = 1, .., J$ being different capacity choices of PVs. We estimate three new parameter vectors: $\boldsymbol{\mu}_{bench}$ will measure how the utility of a benchmark PV ($j = 1$) depends on local variables D_m. In the application we choose $j = 1$ to be the PV of 4kW. $\boldsymbol{\mu}_{kw}$ will measure how this effect changes with the capacity (measured in kW) for a subset D_m^{kW} of D_m. Finally, the subset D_m^{α} of D_m measures how local variables influence the marginal utility of income through $\boldsymbol{\mu}_{\alpha}$. For the mean utilities, we assume that the unobserved product characteristics are additively separable in an alternative specific constant ξ_j, a common demand shock ξ_t and a residual $\xi_{j,t}$.

Conditional value function of adoption ($j \neq 0$)

$$\begin{aligned} v_{i,j,t} &= \delta_{j,t} + \boldsymbol{\mu}_{bench} D_m + \boldsymbol{\mu}_{kw} D_m^{kW}(kW_j - kW_1) - \boldsymbol{\mu}_{\alpha} D_m^{\alpha} p_{j,t} \quad (11) \\ & \quad \text{with } i \text{ living in local market } m \\ \text{with } \delta_{j,t} &= -\alpha p_{j,t} + \xi_j + \xi_t + \xi_{j,t} \quad (12) \end{aligned}$$

Conditional value function of not adopting ($j = 0$)

$$v_{i,0,t} = u_{m,0,t} + \beta V_{m,t+1}^e \quad (13)$$

Note that the m subscript appears for the value of behaving optimally in the future as expected heterogeneity on the local market level no longer disappears in the future. However, since our EV1 assumption on $\varepsilon_{i,j,t}$ has not changed, the expected value function $V_{m,t+1}^e$ is still given by the logit logsum formula. We then obtain the following expression:

$$V^e_{m,t+1} = \gamma + \ln\left(\sum_{j'=0}^{J} \exp(v^e_{i,j',t+1})\right)$$

Substituting this in (13):

$$v_{i,0,t} = u_{m,0,t} + \beta\left(\gamma + \ln\left(\sum_{j'=0}^{J} \exp(v^e_{i,j',t+1})\right)\right) \tag{14}$$

Again we apply the Hotz-Miller inversion with $j = 1$ as our arbitrary terminal choice. Note that $\boldsymbol{\mu}_{kw} D^{kW}_m (kW_j - kW_1) = 0$ for $j = 1$. The adoption rate is given by:

$$S^e_{m,1,t+1} = \frac{\exp(\delta^e_{1,t+1} + \boldsymbol{\mu}_{bench} D_m - \boldsymbol{\mu}_\alpha D^\alpha_m p^e_{1,t+1})}{\sum_{j'=0}^{J} \exp(v^e_{i,j,t+1})}$$

Rewriting and taking logs:

$$\ln \sum_{j'=0}^{J} \exp(v^e_{i,j',t+1}) = \delta^e_{1,t+1} + \boldsymbol{\mu}_{bench} D_m - \boldsymbol{\mu}_\alpha D^\alpha_m p^e_{1,t+1} - \ln S^e_{m,1,t+1} \tag{15}$$

Substituting (15) in (14):

$$v_{i,0,t} = u_{m,0,t} + \beta\left(\gamma + \delta^e_{1,t+1} + \boldsymbol{\mu}_{bench} D_m - \boldsymbol{\mu}_\alpha D^\alpha_m p^e_{j,t+1} - \ln S^e_{m,1,t+1}\right)$$

Again we normalize $u_{m,0,t} + \beta\gamma = 0$ and impose assumptions on expectations:

$$\begin{aligned} v_{i,0,t} &= \beta\left(\delta^e_{1,t+1} + \boldsymbol{\mu}_{bench} D_m - \boldsymbol{\mu}_\alpha D^\alpha_m p^e_{1,t+1} - \ln S^e_{m,1,t+1}\right) \\ &= \beta\left(\delta_{1,t+1} + \boldsymbol{\mu}_{bench} D_m - \boldsymbol{\mu}_\alpha D^\alpha_m p_{1,t+1} - \ln S^e_{m,1,t+1}\right) \end{aligned} \tag{16}$$

Like in the model with only aggregate data, we assume that households can perfectly forecast the next period state variables such that $\delta^e_{1,t+1} = \delta_{1,t+1}$ and $p^e_{1,t+1} = p_{1,t+1}$. Note that the CCP $S^e_{m,1,t+1}$ can no longer be approximated with the market share in the next month but has to be predicted in a first stage. Since next month states are known, we can immediately predict the CCPs by using a nonparametric estimation method.[20]

6.2 Estimation

Estimation of the model is more complicated because we need to include micro data. We do this by supplementing the macro-moments we found with the aggregated data, with micro-moments that will identify the effect of the demographic data. This resembles methods for static discrete choice models on market data, supplemented with micro-moments as has been done by Petrin (2002) and Berry *et al.* (2004) and applied to local market data in Nurski and Verboven (2013).

Note that the distributional assumption implies the standard logit probabilities:

[20] We use a Gaussian kernel estimator using the technique of Racine and Li (2003) to smooth over continuous and dummy variables to obtain predicted values $\widehat{S}$, we do not smooth over the time periods but apply the kernel in each time period separately.

$$s_{i,j,t} = \frac{\exp(v_{i,j,t} - v_{i,0,t})}{1 + \sum_{j'=1}^{J} \exp(v_{i,j',t} - v_{i,0,t})}$$

From (11) and (16) it follows that

$$\begin{aligned} v_{i,j,t} - v_{i,0,t} &= \delta_{j,t} - \beta\delta_{1,t+1} \\ &+ (1-\beta)\boldsymbol{\mu}_{bench} D_m + \boldsymbol{\mu}_{kw} D_m^{kW}(kW_j - kW_1) - \boldsymbol{\mu}_\alpha D_m^\alpha (p_{j,t} - \beta p_{1,t+1}) + \beta \ln S^e_{m,1,t+1} \end{aligned}$$

The macro-moments are very similar to the moments of our estimator that used aggregated data. Note from (12) that:

$$\begin{aligned} \delta_{j,t} - \beta\delta_{1,t+1} &= -\alpha(p_{j,t} - \beta p_{1,t+1}) + \xi_j - \beta\xi_1 + \xi_t - \beta\xi_{t+1} + \xi_{j,t} - \beta\xi_{1,t+1} \\ \delta_{j,t} &= -\alpha p_{j,t} + \xi_j + \xi_t^{''} + \xi_{j,t} \\ \text{with } \xi_t^{''} &= \alpha\beta p_{1,t+1} - \beta\xi_1 + \xi_t - \beta\xi_{t+1} - \beta\xi_{1,t+1} + \beta\delta_{1,t+1} \end{aligned}$$

If we make the same assumption that $\xi_{j,t}$ is uncorrelated with a set of demeaned instruments $\widetilde{z_{j,t}}$, we obtain:

$$\begin{aligned} E[\widetilde{z_{j,t}}\xi_{j,t}] &= 0 \\ E[\widetilde{z_{j,t}}(\tilde{\delta}_{j,t} + \alpha\tilde{p}_{j,t} - \tilde{\xi}_j)] &= 0 \end{aligned}$$

Which can be matched by the data using:

$$\sum_{j,t} \widetilde{z_{j,t}}(\tilde{\delta}_{j,t} + \alpha\tilde{p}_{j,t} - \tilde{\xi}_j) = 0$$

and

$$\sum_m N_{m,t}(S_{m,j,t} - s_{m,j,t}) = 0 \text{ for each } j,t$$

With $N_{m,t}$ the number of households in local market m that have not yet adopted a PV before time t. Note that $s_{m,j,t} = s_{i,j,t}$ because of the distributional assumption. The latter moment is imposing the Berry (1994) inversion. This is necessary to retrieve the mean utilities as they are no longer given by a simple transformation of the aggregate adoption data. Like in the model with only aggregate data, we use the GCC price x monthly electricity production, PV module prices x kW and dummy variables for each $j \neq 1$ as instruments to identify the model.

The micro-moments we add to the model are necessary to find $\boldsymbol{\mu}$. We therefore add the following moments:

$$\begin{aligned} \sum_{m,j,t} N_{m,t}(S_{m,j,t} - s_{m,j,t}) D_{m,t} &= 0 \\ \sum_{m,j,t} N_{m,t}(S_{m,j,t} - s_{m,j,t}) D_m^{kW}(kW_j - kW_1) &= 0 \\ \sum_{m,j,t} N_{m,t}(S_{m,j,t} - s_{m,j,t}) D_m^\alpha (p_{j,t} - \beta p_{1,t+1}) &= 0 \end{aligned}$$

The micro-moments have an intuitive explanation. The first matches the observed mean of each demographic variable, conditional on the choices made. The two others are similar, interacting the demographic variables with capacity choices and prices in the way they enter the conditional value functions. In the appendix we show that these micro-moments follow from the scores of an underlying maximum likelihood estimation on observing the local adoption rates.

To estimate the model, we stack the five sets of moments and minimize the GMM objective function, subject to our nonparametric estimate of the CCP:

$$\begin{aligned} \left\{\hat{\alpha}, \hat{\beta}, \hat{\boldsymbol{\delta}}, \hat{\boldsymbol{\mu}}\right\} &= \arg\min_{\alpha,\beta,\boldsymbol{\delta},\boldsymbol{\mu}} B'WB \\ \text{st } S^{e}_{m,1,t+1} &= \widehat{S}_{m,1,t+1} \\ \text{with } B &= \begin{pmatrix} \sum_{j,t} \widetilde{z_{j,t}}(\tilde{\delta}_{j,t} + \alpha\tilde{p}_{j,t} - \tilde{\xi}_j) \\ \sum_m N_{m,t}(S_{m,j,t} - s_{m,j,t}) \text{ for each } j,t \\ \sum_{m,j,t} N_{m,t}(S_{m,j,t} - s_{m,j,t}) D_{m,t} \\ \sum_{m,j,t} N_{m,t}(S_{m,j,t} - s_{m,j,t}) D^{kW}_m (kW_j - kW_1) \\ \sum_{m,j,t} N_{m,t}(S_{m,j,t} - s_{m,j,t}) D^{\alpha}_m (p_{j,t} - \beta p_{1,t+1}) \end{pmatrix} \end{aligned} \tag{17}$$

Since our estimator is exactly identified, any positive semidefinite weight matrix W is allowed and $\min_{\boldsymbol{\mu},\boldsymbol{\delta},\alpha,\beta} B'WB = 0$ such that each moment is matched exactly. To correct for the fact that within a local market observations are not independent over time, we cluster the moments in the calculation of the covariance matrix. We also cluster the macro moments within time periods.

6.3 Results

The results of the model with local market data can be found in Table 4. Most importantly, we see that the discount factor is almost identical. The marginal utility of income however has changed. This can be explained by the interaction of median income with the price variable. Since price sensitivity decreases with income and incomes are always positive, it must be that the estimate of α increases. Most other results have intuitive signs. Adopting a PV becomes less likely in areas with high population density, more foreign nationals and, surprisingly, bigger houses. Positive effects are found for households size, income, the percentage of house owners and of highly educated people. The interaction with the capacity choice shows how the results change as the capacity of the PV increases. We see that it becomes less likely to install a large PV in dense areas and more likely when houses or households increase in size. The other coefficients indicate that some of the effects we found for a benchmark PV model, become less important when the size of a PV increases.

Although the sociodemographic variables are important in explaining heterogeneity in adoption behavior, we find that the discount is not influenced. This can be explained by the fact that it is identified mainly from time variation in the difference between future benefits and upfront costs which are identical for each household. We might obtain different results if we interact the discount factor with sociodemographic variables but this complicates the estimation and is therefore left for further research.

Table 4: Results micro data

	(4) Dynamic 5 alternatives + FE		(5) Dynamic + micro data 5 alternatives + FE	
MU income (x1000 EUR) (= α)	0.3848***	(0.1307)	0.5191***	(0.1317)
Monthly discount factor (= β)	0.9828***	(0.0023)	0.9827***	(0.0024)
Choice specific constants				
2kW	-1.6446***	(0.1417)	-1.5818***	(0.2027)
4kW		*Benchmark*		
6kW	0.1746	(0.1697)	0.0262	(0.2296)
8kW	-0.8797***	(0.3102)	-1.2344***	(0.4313)
10kW	-0.3617	(0.4175)	-0.9726	(0.6089)
Effect on benchmark PV (4kW) x(1 − β)				
Population density (inhabitants/m^2 x10000)			-0.1364***	(0.0462)
Average house size (number of rooms)			-0.1236***	(0.0195)
Average household size			0.4805***	(0.0348)
Median yearly income x10000			0.2364***	(0.0267)
% house owners			0.4437***	(0.0744)
% higher education degree			0.2810***	(0.0959)
% foreign			-2.0893***	(0.1830)
Municipality dummy variables			YES	
Interaction with capacity choice				
Population density (inhabitants/m^2 x10000)			-0.6986***	(0.0195)
Average house size (number of rooms)			0.0646***	(0.0055)
Average household size			0.0933***	(0.0108)
Median yearly income x10000			-0.1458***	(0.0184)
% house owners			-0.0470*	(0.0258)
% higher education degree			-0.1791***	(0.0267)
% foreign			0.2982***	(0.0292)
Interaction with price variable				
Median yearly income x10000			-0.0605***	(0.0071)
Time fixed effects	YES		YES	
Observations/clusters macro moments (JxT/T)	215/43		215/43	
Observations/clusters micro moments (NxT/N)	0		394826/9182	

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

7 Identification

The identification of discount factors in dynamic discrete choice models is usually difficult to establish. The intuition behind the identification problems is that a static model is observationally equivalent to a dynamic choice model (Manski 1993). Rust (1994) shows that the discount factor is therefore in general not identified.

Our identification strategy follows from the additional information we have about how households value the future. The economic model implies that future costs and benefits in the utility of adoption must be valued identically to upfront costs and benefits, after correction by the discount factor. Therefore this discount factor is already identified in a static choice model. Examples of this strategy can be found in static models of the car market where fuel efficiencies are traded off against higher car prices (see Verboven (2002), Allcott and Wozny (2013) and Busse, Knittel and Zettelmeyer (2013)). The extension to a dynamic model is straightforward by restricting the discount factor in the valuation of future values to be the same to the discount factor in the valuation of future costs and benefits. This identification strategy carries over to all models of investment choices as they always involve a trade-off between upfront costs and future benefits. This strategy differs substantially from previous propositions in dynamic models that rely on exclusion restrictions (Magnac & Thesmar 2002), stated choice data (Dube *et al.* 2012), unexpected shocks in expectations about future states (Bollinger 2013) or choices in both static and dynamic contexts (Yao *et al.* 2012). The paper in the dynamic literature that is closest to our approach is Lee (2013) who uses the time until new games arrive to infer the discount factor from the decision to adopt video game consoles. This is because games that are currently unavailable are a future benefit component of the game console.

8 Conclusion

The contribution of this paper is four-fold. First, we formulated a strategy to identify discount factors in household investment decisions where adoption might be postponed to wait for better opportunities. Second, we showed how to estimate dynamic choice models using aggregate data on adoption rates or market shares in a simple linear regression framework. Third, we estimated the discount factor in an application on PV adoption in Flanders and we used the estimates to evaluate the GCC subsidy policy during 2006-2012. Finally, we showed how to incorporate local market data to allow for richer forms of heterogeneity and use this model to confirm our results using aggregate data only.

We found that households discount significantly more than expected from market interest rates. We find an implicit real interest rate of 23%. Because we can assume that subsidy providers can borrow at cheaper rates, Pareto-improvements would have been possible by subsidizing households directly when they invested in PVs instead of paying for the electricity they generate. We find that the same adoption rates could have been achieved, resulting in the same utility for households but at a much lower total cost. We find an efficiency loss of 64% or € 2.387 billion.

In future work, we want to exploit the local market data more by estimating a distribution of the discount factor, conditional on sociodemographic data to look at distributional effects of the subsidization policy. Another path of research is to extend the model to control for peer effects. In this paper we only looked at the differential effect of the timing of subsidies for a given moment of adoption. We see however that governments lower subsidies for new investments over time. One of the rationales behind this strategy is that subsidies are only necessary to start the diffusion of a new technology but local spillovers can trigger further adoption. Therefore there will be some optimal path of declining subsidies.

Another extension would be to incorporate unobserved heterogeneity using a finite mixture of unobserved types, similar to Arcidiacono and Miller (2011). Since our results were robust for rich forms of observed heterogeneity, we do not expect important differences but alternative policy questions might benefit from this approach.

Finally, it would be interesting to look at adoption decisions of large companies, rather than households. Recall that we excluded all systems that were larger than 10kW to focus on households only. A similar model could be used for larger systems to see if big investors value the future differently.

References

Allcott H (2013). The Welfare Effects of Misperceived Product Costs: Data and Calibrations from the Automobile Market, *American Economic Journal: Economic Policy* **5**(3), 30–66.

Allcott H & Wozny N (2013). Gasoline prices, fuel economy, and the energy paradox, *Review of Economics and Statistics* (Forthcoming).

Arcidiacono P & Ellickson P B (2011). Practical Methods for Estimation of Dynamic Discrete Choice Models, *Annual Review of Economics* **3**, 363–394.

Arcidiacono, P. & Miller, R. A. (2011). Conditional Choice Probability Estimation of Dynamic Discrete Choice Models With Unobserved Heterogeneity, *Econometrica* **79**(6), 1823–1867.

Audenaert A, De Boeck L, De Cleyn S, Lizin S & Adam J F (2010). An economic evaluation of photovoltaic grid connected systems (PVGCS) in Flanders for companies: A generic model, *Renewable Energy* **35**(12), 2674–2682.

Berry S, Levinsohn J & Pakes A (2004). Differentiated Products Demand Systems from a Combination of Micro and Macro Data: The New Car Market, *Journal of Political Economy* **112**(1), 68–105.

Berry S T (1994). Estimating Discrete-Choice Models of Product Differentiation, *The RAND Journal of Economics* **25**(2), 242.

Bollinger B (2013). Technology adoption in regulated industries: An empirical study of the southern california garment cleaning industry, *Working paper* .

Busse, Meghan R., Knittel, Christopher R. & Zettelmeyer, Florian (2013). Are Consumers Myopic? Evidence from New and Used Car Purchases, *American Economic Review* **103**(1), 220–56.

CREG (2010). De verschillende ondersteuningsmechanismen voor groene stroom in Belgie, Technical report.

Dube J P H, Hitsch G J & Jindal P (2012). The Joint Identification of Utility and Discount Functions From Stated Choice Data: An Application to Durable Goods Adoption, *Working paper* .

Eurobserv'er (2013). Photovoltaic Barometer, Technical report.

Gowrisankaran G & Rysman M (2012). Dynamics of Consumer Demand for New Durable Goods, *Journal of Political Economy* **120**(6), 1173–1219.

Hansen L P (1982). Large Sample Properties of Generalized Method of Moments Estimators, *Econometrica* **50**(4), 1029.

Hausman J A (1979). Individual Discount Rates and the Purchase and Utilization of Energy-Using Durables, *The Bell Journal of Economics* **10**(1), 33.

Hotz V J & Miller R A (1993). Conditional choice probabilities and the estimation of dynamic models, *The Review of Economic Studies* **60**(3), 497–529.

Kwan C L (2012). Influence of local environmental, social, economic and political variables on the spatial distribution of residential solar PV arrays across the United States, *Energy Policy* **47**, 332–344.

Lee R S (2013). Vertical Integration and Exclusivity in Platform and Two-Sided Markets, *American Economic Review* **103**(7), 2960–3000.

Magnac T & Thesmar D (2002). Identifying dynamic discrete decision processes, *Econometrica* **70**(2), 801–816.

Manski C F (1993). Dynamic choice in social settings: Learning from the experiences of others, *Journal of Econometrics* **58**(1), 121–136.

Melnikov O (2013). Demand For Differentiated Durable Products: The Case Of The U.S. Computer Printer Market, *Economic Inquiry* **51**(2), 1277–1298.

Nurski L & Verboven F (2013). Exclusive dealing as a barrier to entry? Evidence from automobiles, *Working paper* .

Petrin, Amil (2002). Quantifying the Benefits of New Products: The Case of the Minivan, *Journal of Political Economy* **110**(4).

Racine J & Li Q (2004). Nonparametric estimation of regression functions with both categorical and continuous data, *Journal of Econometrics* **119**(1), 99–130.

Rust J (1987). Optimal Replacement of GMC Bus Engines: An Empirical Model of Harold Zurcher, *Econometrica* **55**(5), 999.

Rust J (1994). Structural estimation of Markov decision processes, *Handbook of econometrics* **4**(4).

Verboven F (2002). Quality-based price discrimination and tax incidence: evidence from gasoline and diesel cars, *RAND Journal of Economics* pp. 275–297.

Yao S, Mela C, Chiang J & Chen Y (2012). Determining consumers' discount rates with field studies, *Journal of Marketing Research, Forthcoming* .

A Appendix

A.1 Details on sources of PV support measures

Policy of Flemish government

Details about the GCC policy were found on the website of the VREG (www.vreg.be) and in official documents: the Flemish Energy Decree, changed 6 July 2012, KB 10 February 1983, changed by the Flemish government in 15 July 2005, 16 June 1998: "Besluit van de Vlaamse Regering tot wijziging van het koninklijk besluit van 10 februari 1983 houdende aanmoedigingsmaatregelen voor het rationeel energieverbruik." The latter also included information about the investment subsidies of which more information was found in a government brochure "Subsidieregeling voor elektriciteit uit zonlicht" (2005).

Note that in the first years of the GCC program, it was expected that GCCs were given over the whole lifetime of the PV, only the price was guaranteed during a limited number of years. This changed in the renewal of the energy decree in 2012 (Flemish Energy Decree, changed 30 July 2012). The emission of GCCs has since been limited to the same amount of years as the minimum price, also for already installed PVs. This would however not change much in adoption behavior since the life expectancy of PVs was about 20 years. The same number of years that was given as guarantee.

The main reason for changing the banding factor that led to an effective stop of the GCC subsidy program was the abolishment and repayment of the newly introduced grid fee because of a judgement by the Court of Appeal on 27 November 2013. Since 2013 all PV owners were obligated to pay a yearly grid fee. This measure was contested a lot, some electricity suppliers did not charge it and it was uncertain if it would eventually be abolished.

The financial details about the GCC policy were found in CREG (2010).

Announcements of new subsidy policies were found in newspapers. The first change in policy was announced in February 2009 (De Standaard, 7 February 2009, p2) for PVs installed from 2010 on. The second change was announced in June 2011 (De Standaard, 6 June 2011, Economie p12) for PVs from July 2011 on. The third change was announced in May 2012 (De Standaard, 26 May 2012) for PVs installed from August 2012 on and the final change was in July 2012 (Degree proposal amending the Energy Decree of 8 May 2009 (6 July 2012) and Energy decree 8 May 2009, changed 30 July 2012) for PVs installed from 2013 on.

Policy of federal government

Economic recovery plan Federal Government (March 2009) announced the possibility to spread tax cuts over multiple years but this was already possible by splitting bills over multiple years as announced in newspaper articles: Gazet Van Antwerpen: Zonnepanelen zijn tot drie keer fiscaal aftrekbaar, 19 Mei 2008; Het Nieuwsblad: Belastingvoordeel klanten nekt installateurs zonnepanelen, 13 December 2008. Details about the abolishment of the tax cut were found on the official website of the finance department of the federal government.[21] Also the VAT rules can be found on this website.[22] Between 6 and 16 December 2006 energiesparen.be (website maintained by government agency VEA) announced that it was very likely that the tax cut ceiling would be doubled. The official document "programmawet" of 28 December 2006 confirmed this. Between 1 and 21 March 2007, the same website announced the increase from 2000 to 2600 EUR. Historic copies of the website were consulted using Internet Archive[23].

A.2 Construction of the price variable for the adoption of PV in Flanders

We hereby discuss the construction of the price variable $p_{j,t}$ in more detail for the PV application. Recall:

$$\begin{aligned} p_{j,t} &\equiv p_{j,t}^{INV} - \rho\left(p_{j,t}^{GCC} + p_{j,t}^{EL}\right) \\ \text{with } \rho &\equiv \frac{1-\beta^P}{1-\beta} \end{aligned}$$

The intuition of the impact of the discount factor β on this term was clear from the paper as future electricity prices and future GCC subsidies decrease $p_{j,t}$ with a rate ρ that depends on β. Here we specify how exactly the policy in Flanders can be implemented using this model.

Net investment cost

We first discuss the investment cost $p_{j,t}^{INV}$. This price component consists of the cost that households have to pay for the PV, subtracted by the subsidy (10% in 2006 and 2007) and the tax cuts they receive for this investment. Since the subsidy was abolished before the start of the estimation sample, we ignore it here. To calculate the VAT rate, we use a weighted average of 6% and 21% with the number of households in Flanders that qualify for the 6% rate (91% according to ADSEI) as weight. Note that from 2006 to 2011 there was tax cut of 40% with an indexed maximum amount that was increased in 2007. From 2009 on, it

[21] http://www.minfin.fgov.be/portail2/nl/current/spokesperson-11-11-30.htm, consulted 14 May 2014.
[22] http://minfin.fgov.be/portail2/nl/themes/dwelling/renovation/vat.htm, consulted 14 May 2014.
[23] https://web.archive.org

was possible to transfer the remaining tax cut to the following three years. We can summarize the investment cost as follows:

$$p_{j,t}^{INV} = \text{cost}_{j,t} - \beta^{12} taxcut_{j,t+12} - \beta^{24} taxcut_{j,t+24} - \beta^{36} taxcut_{j,t+36} - \beta^{48} taxcut_{j,t+48}$$

Note that the discount factor β not only appears in ρ but also in the investment cost term $p_{j,t}^{INV}$. This is not standard in an investment problem but is just due to the specific nature of the tax cut policy where the tax cut is not collected immediately and therefore has to be discounted. As it involves some time to collect subsidies and tax cuts, we assume that it takes at least one year before the first tax cut is collected. Given the data, we can now calculate $p_{j,t}^{INV}$ up to an unknown discount factor β only.

Benefits from electricity generation

We now focus on the negative part of the price variable: $\rho\left(p_{j,t}^{GCC} + p_{j,t}^{EL}\right)$. These are the benefits from generating electricity from PVs. We make this model more flexible by allowing a different ρ for the benefit component related to GCC subsidies and the one related to the opportunity cost of having to buy electricity. Furthermore, we do not let them depend only on the discount factor and the duration but correct for some specific aspect of a PV investment. Note first that nominal GCC prices were constant for a given installation. Therefore the real prices (all prices in the model are real) decrease with the monthly inflation rate π. For electricity prices we assume a random walk in real prices such that they do not need a correction but we can use the real price at t as the expected price for all remaining periods. We also correct for monthly decreases in the production of PVs by including an extra parameter for the monthly deterioration rate λ. We obtain the following expression for the price variable:

$$p_{j,t} \equiv p_{j,t}^{INV} - (\rho^{GCC} p_{j,t}^{GCC} + \rho^{EL} p_{j,t}^{EL})$$

with

$$\begin{aligned}
\rho^{EL} &= \frac{1 - [(1-\lambda)\beta]^{240}}{1 - (1-\lambda)\beta} \text{ (we assume } PV\text{s last 240 months (CREG 2010))} \\
\rho^{GCC} &= \frac{1 - [(1-\pi)(1-\lambda)\beta]^{240}}{1 - (1-\pi)(1-\lambda)\beta} \text{ when GCCs were given for 240 months} \\
\rho^{GCC} &= \frac{1 - [(1-\pi)(1-\lambda)\beta]^{120}}{1 - (1-\pi)(1-\lambda)\beta} \text{ when GCCs were given for 120 months}
\end{aligned}$$

If we assume the expected inflation rate $\pi = 0.17\%$ and the deterioration rate $\lambda = 0.01^{1/12}$ (Audenaert *et al.* 2010), we have defined ρ up to only the discount factor β.

From the choice of j and the observed price data, we can immediately calculate $p_{j,t}^{GCC}$ and $p_{j,t}^{EL}$. To see this, note first that the benefits of PVs, installed at a given time period t, differ only in their total production, expressed in MWh (Megawatt hour). We make the usual assumption that the relation between size and monthly production is as follows: $0.07\frac{MWh}{kW}$(CREG, VEA and 3E (CREG 2010)). The nominal GCC price for each MWh is observed in the policy announcements. The price variable then only has to be corrected for inflation by using a price index.[24]

We have now specified the entire price variable $p_{j,t}$ up to observable variables and one parameter: the discount factor β. These expressions can be substituted in the GMM moment conditions such that the structural parameters, including β, can be estimated.

[24] The HICP is used to transform all nominal prices into prices of January 2013.

A.3 Robustness checks

These graphs show the results of changing one assumed parameter on the estimate of the discount factor in our preferred model. Since the model is estimated almost instantly, it allows us to show graphs that summarize hundreds of regressions at once. Note that changed parameters also include unrealistic values. Within realistic bounds, the estimate is very stable. The first graph shows changes in the expected lifetime of a PV. We see that the estimates stabilize from around 15 years of expected life time which is a very low number. Next to this graph, we show what happens if households expect an increase in the real electricity price on top of the price they observe today. We see that the estimate remains very stable until a yearly increase of about 25%, which is very high. The reason for the robustness to this results is that the identification of the discount factor does not come from time series variation in electricity prices but from variation in the GCC policy. The third graph adds a parameter to measure the valuation of tax cuts. In the model we assumed all costs and benefits enter the utility function in the same way. However one can be concerned that some aspects of policies where not very well known. An extra parameter on the tax cuts allows for some extra flexibility but there is insufficient data to estimate this parameter in a reliable way, we therefore show robustness of the discount factor to changes of this parameter. We see that the discount factor increases if we account for undervaluation of tax cuts but even in the extreme case of zero valuation of the tax cut, we find a low discount factor. The last graph changes the assumption on the yearly deterioration rate λ (see section A.2), again we see that for a en extreme value of 5% yearly deterioration, the discount factor is still very low.

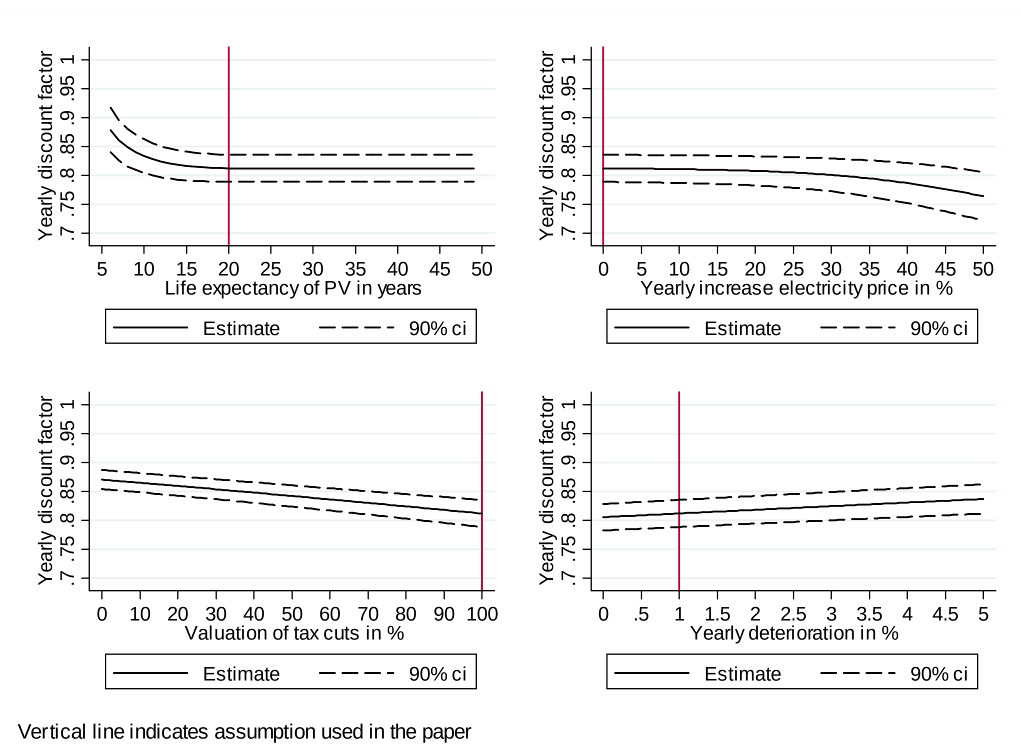


Figure 6: Results from FE model without heterogeneity under different assumptions

Note also that the definition of the relevant market is irrelevant if month fixed effects are used. Therefore look again at regression equation (10):

$$
\begin{aligned}
\ln \frac{S_{j,t}}{S_{0,t}} &= -\alpha p_{j,t} + \xi_j + \xi'_t + \xi_{j,t} \\
\text{with } \xi'_t &= -\beta\xi_1 + \alpha\beta p_{1,t+1} + \beta \ln S_{1,t+1} + \xi_t - \beta\xi_{t+1} - \beta\xi_{1,t+1}
\end{aligned}
$$

We assumed the relevant market to be all households that have not yet adopted. Another extreme is to only consider households that adopted. This would strongly increase $S_{j,t}$ and reduce $S_{0,t}$, making the LHS much larger but this change will be absorbed by the time fixed effect. To see this:

$$
\begin{aligned}
\ln \frac{S_{j,t}}{S_{0,t}} &= \ln S_{j,t} - \ln S_{0,t} \\
&= \ln S_{j,t}N_t/N_t - \ln S_{0,t}N_t/N_t \\
&= \ln S_{j,t}N_t - \ln N_t - \ln S_{0,t}N_t + \ln N_t \\
&= \ln S_{j,t}N_t - \ln S_{0,t}N_t
\end{aligned}
$$

With N_t the total relevant market at time t. If we change the potential market, only $\ln S_{0,t}N_t$ is affected since the number of adopters $S_{j,t}N_t$ remains the same. Since $\ln S_{0,t}N_t$ enters the regression equation (and thus the moment condition) linearly and identically for each capacity choice, it will be absorbed by the time fixed effect.

A.4 Estimation details micro-data

We observe the market shares in each month for $M = 9182$ local markets in Flanders, containing on average 295 households.

In practice we do not directly estimate the GMM model given in the paper but estimate the model in two parts: a maximum likelihood approach for the micro-data and a GMM model on the mean utilities and the macro-data. This gives good starting values for the GMM model that then estimates the complete model. An alternative procedure would be to add a contraction mapping to obtain the mean utilities instead of estimating them. It also shows the origin of the micro moments we added to the model.

In summary, the estimation consists of two parts. First, we maximize the likelihood of observing the local market data, given local market variables where we allow for fixed effects for each j, t combination to estimate the effects of local market variables and the mean utilities. Next, we regress these fixed effects on prices and subsidies using a moment condition similar to equation (9). Because the discount factor enters both parts of the estimation and to obtain consistent standard errors, we will however propose a single GMM estimator to find all parameters at once.

Intuition and sequential estimation

Assume first that we had individual data and the discount factor is known. The likelihood to observe the data is then simply the likelihood function of a conditional/multinomial logit:

$$L(\boldsymbol{\mu}, \boldsymbol{\delta}) = \prod_{i,t} s_{it}(\boldsymbol{\mu}, \boldsymbol{\delta}) \tag{18}$$

With $s_{it}(\boldsymbol{\mu}, \boldsymbol{\delta})$ the probability predicted by the model for the chosen option of i. The EV1 error assumption results in the following predicted probabilities for all options j:

$$s_{i,j,t} = \frac{\exp v_{i,j,t}}{\sum_{j'=0}^{J} \exp v_{i,j',t}} = \frac{\exp(v_{i,j,t} - v_{i,0,t})}{1 + \sum_{j'=1}^{J} \exp(v_{i,j',t} - v_{i,0,t})} \tag{19}$$

Using the expressions for the conditional value functions (16) and (11) in (19) we obtain:

$$\begin{aligned} v_{i,j,t} - v_{i,0,t} &= \overset{\circ}{\delta}_{j,t} + (1-\beta)\boldsymbol{\mu}_{bench} D_m + \boldsymbol{\mu}_{kw} D_m^{kW}(kW_j - kW_1) - \boldsymbol{\mu}_{\alpha} D_m^{\alpha}(p_{j,t} - \beta p_{1,t+1}) + \beta \ln S^e_{m,1,t+1} \\ \text{with } \overset{\circ}{\delta}_{j,t} &= \delta_{j,t} - \beta\delta_{1,t+1} \end{aligned}$$

Since $s_{i,j,t}$ does not depend on variables that are i-specific, we can write $s_{m,j,t}$ instead. Define now $N_{m,t}$ to be the number of households in the local market and $S_{m,j,t}$ the observed local market share. (18) can then be written using local market data only as follows:

$$\begin{aligned} L(\boldsymbol{\mu}, \boldsymbol{\delta}) &= \prod_{m,t} \prod_{j} s_{m,j,t}(\boldsymbol{\mu}, \boldsymbol{\delta})^{N_{m,t} S_{m,j,t}} \\ \ln L(\boldsymbol{\mu}, \boldsymbol{\delta}) &= \sum_{m,j,t} N_{m,t} S_{m,j,t} \ln s_{m,j,t}(\boldsymbol{\mu}, \boldsymbol{\delta}) \end{aligned}$$

This loglikelihood function can now be maximized if we know the CCPs $S^e_{m,1,t+1}$ and the discount factor β. Since next month states are known, we can immediately predict the CCPs by using a nonparametric estimation method. We use a Gaussian kernel estimator using the technique of Racine and Li (2003) to smooth over continuous and dummy variables to obtain predicted values $\widehat{S}$, we do not smooth over the time periods but apply the kernel in each time period separately. If we impose a value for β, we can find estimates for all $\overset{\circ}{\delta}_{j,t}$, μ_{bench}, $\boldsymbol{\mu}_{kW}$ and $\boldsymbol{\mu}_{\alpha}$:

$$\begin{aligned} \left\{\hat{\boldsymbol{\mu}}, \hat{\boldsymbol{\delta}}^{\circ}\right\} &= \arg\max_{\boldsymbol{\mu},\delta} \ln L(\boldsymbol{\mu}, \boldsymbol{\delta}^{\circ}) \\ \text{st } S^e_{m,1,t+1} &= \widehat{S}_{m,1,t+1} \\ \beta &= \bar{\beta} \end{aligned} \tag{20}$$

The estimated values for $\boldsymbol{\delta}^{\circ}$ can now be used to recover α and β using a GMM estimator, similar to the estimator we used in the model with only aggregate data. To see this, note from (12) that:

$$\overset{\circ}{\delta}_{j,t} \equiv \delta_{j,t} - \beta\delta_{1,t+1} = -\alpha(p_{j,t} - \beta p_{1,t+1}) + \xi_j - \beta\xi_1 + \xi_t - \beta\xi_{t+1} + \xi_{j,t} - \beta\xi_{1,t+1} \tag{21}$$

To control for time fixed effect ξ_t, we demean the linear terms within each month. Note again that time fixed effects also capture the entire dynamic correction term (each element in the above expression with subscript $j = 1$) as it is constant within a time period. To avoid perfect collinearity, we do not estimate ξ_j for the benchmark $j = 1$. The residual $\xi_{j,t}$ is then interpreted as the unobserved product characteristic that changes over time. Its interactions with the demeaned set of instruments $\widetilde{z_{j,t}}$ will be the GMM moment condition to identify α and β. We refer to demeaned values using a tilde:

$$\begin{aligned} E[\widetilde{z_{j,t}}\xi_{j,t}] &= 0 \\ \text{with } \xi_{j,t} &= \widetilde{\overset{\circ}{\delta}}_{j,t} + \alpha\tilde{p}_{j,t} - \tilde{\xi}_j \\ &= \widetilde{\delta}_{j,t} + \alpha\tilde{p}_{j,t} - \tilde{\xi}_j \end{aligned} \tag{22}$$

Like in the model with only aggregate data, we use the GCC subsidies (GCC price x monthly electricity production), PV module prices x kW and dummy variables for each $j \neq 1$ as instruments to identify the model.

Joint estimation

There are two problems with this sequential approach. First, the discount factor β we find by matching the moment condition (22) might not be consistent with the one we used as a constraint in the likelihood function (20). Second, we do not correct standard errors in the second step for the fact that mean utilities δ° are estimated values from the first step. A solution for both problems is to estimate the two parts simultaneously. We can do this by adding the scores of the likelihood function to the GMM objective function.

The scores are given by:

$$\frac{\partial \ln L(\boldsymbol{\mu}, \boldsymbol{\delta}^{\circ})}{\partial(\boldsymbol{\mu}, \boldsymbol{\delta}^{\circ})} = \sum_{m,j,t} N_{m,t}(S_{m,j,t} - s_{m,j,t})\mathbf{w}_{m,j,t} = 0$$

With $\mathbf{w}_{m,j,t}$ a vector containing the regressors in the likelihood function: $D_{m,t}$, $D_m^{kW}(kW_j - kW_1)$, $D_m^{\alpha}(p_{j,t} - \beta p_{1,t+1})$ and dummy variables for each j,t combination. We then obtain the following GMM estimator that we also showed in the paper:

$$\begin{aligned}
\left\{\hat{\alpha}, \hat{\beta}, \hat{\boldsymbol{\delta}}, \hat{\boldsymbol{\mu}}\right\} &= \arg\min_{\alpha,\beta,\boldsymbol{\delta},\boldsymbol{\mu}} B'WB \\
\text{st } S^e_{m,1,t+1} &= \widehat{S}_{m,1,t+1} \\
\text{with } B &= \begin{pmatrix}
\sum_{j,t} \widetilde{z_{j,t}}\xi_{j,t} \\
\sum_m N_{m,t}(S_{m,j,t} - s_{m,j,t}) \text{ for each } j,t \\
\sum_{m,j,t} N_{m,t}(S_{m,j,t} - s_{m,j,t})D_{m,t} \\
\sum_{m,j,t} N_{m,t}(S_{m,j,t} - s_{m,j,t})D_m^{kW}(kW_j - kW_1) \\
\sum_{m,j,t} N_{m,t}(S_{m,j,t} - s_{m,j,t})D_m^{\alpha}(p_{j,t} - \beta p_{1,t+1})
\end{pmatrix}
\end{aligned}$$

Note that we do not estimate μ_{bench} directly but we estimate $(1-\beta)\mu_{bench}$ instead. This reduces the way in which the discount factor enters both the micro and macro moments. This is also the reason why we defined μ_{bench} as the impact on the terminal choice $j = 1$ and not as a common effect on all sizes of PVs. Moreover, the results of $\boldsymbol{\mu}_{kw}$ do not have to be rescaled to be interpreted, we only need a simple correction on the results of $(1-\beta)\mu_{bench}$ by dividing it by $(1-\beta)$.

A.5 Efficiency gain from directly subsidizing PVs

We hereby show how low discount factors (high implicit interest rates) lead to efficiency losses if subsidies are given with a delay. Take $\beta_{\text{households}}$ to be the discount factor of households and β_{govt} the be the discount factor of the provider of the subsidy. If households yearly receive an amount A during P periods, their NPV from this subsidy will be:

$$NPV(A, P, \beta_{\text{households}}) = A\left(\sum_{\tau=0}^{P} \beta^{\tau}_{\text{households}}\right)$$

The provider of the subsidy wants to make sure that the NPV for the households is $A\left(\sum_{\tau=0}^{P}\beta^{\tau}_{\text{households}}\right)$ to achieve a certain adoption rate but he can choose between borrowing at a yearly interest rate of $r = \frac{1}{\beta_{\text{govt}}} - 1$ to give the money directly to the households or to spread the subsidy over P periods. The (discounted) costs of the provider to achieve a pre-specified adoption rate is then $A\left(\sum_{\tau=0}^{P}\beta^{\tau}_{\text{households}}\right)$ if he decides to give the subsidy right away and $A\left(\sum_{\tau=0}^{P}\beta^{\tau}_{\text{govt}}\right)$ if he decides to spread it over P periods. It is clear that if $\beta_{\text{govt}} > \beta_{\text{households}}$, the subsidy provider will have lower costs if it gives the subsidy directly. Moreover, households will have the same utility as their NPV does not change. Nevertheless, we observed that the government chose to spread a large part of the subsidies over a finite number of time periods. The achieve the same effect on adoption, they could have done this with $\frac{A\left(\sum_{\tau=0}^{P}\beta^{\tau}_{\text{households}}\right)}{A\left(\sum_{\tau=0}^{P}\beta^{\tau}_{\text{govt}}\right)}100\% = \frac{\sum_{\tau=0}^{P}\beta^{\tau}_{\text{households}}}{\sum_{\tau=0}^{P}\beta^{\tau}_{\text{govt}}}100\% = \frac{1-[\beta_{\text{households}}]^{P}}{1-\beta_{\text{households}}}\frac{1-\beta_{\text{govt}}}{1-[\beta_{\text{govt}}]^{P}}100\%$ of the costs that they made now.

Note that GCC subsidies were sometimes granted during 20 years and 10 years[25] and the efficiency loss obviously depends on this duration and the number of households that adopted during each of these periods. Moreover we need to take into account that the amount a household got (A) was not constant but lowered because of inflation and the deterioration of the PVs. To have an overall estimate of the efficiency loss, we therefore calculate at each month t the total discounted value of the GCC subsidy cost for new systems using the formula we used to calculate the individual GCC benefits in the utility function but we use the total production of all PVs installed at t. We calculate this at two discount rates: $\beta_{\text{households}}$ and β_{govt}, actualize their values to the beginning of 2013 and compare. The costs of subsidies at $\beta_{\text{households}}$ is what the government could have paid as an investment subsidy because households are indifferent between future and direct subsidies at this discount factor. The cost of subsidies at β_{govt} is the cost the government has actually paid.

We find that for $\beta_{\text{households}} = 0.9828$ and $\beta_{\text{govt}} = 0.9974$, a direct subsidy from 2006 until 2012 would have cost 36.26% of the costs that where made today, which means a loss was made of € 2.387 billion. Note that we only looked at PVs that were not bigger than 10kW. This is because we cannot use the results of our model to infer anything about discounting behavior of larger investors and companies. They will probably discount less than households so it would be misleading to extrapolate our results to these systems. Nevertheless, if these investors also have discount factors smaller than β_{govt}, additional efficiency gains are possible. Note also that we restricted the calculations until 2012 because the banding factor that is applicable to newer installations makes it possible to change the future subsides ex-post such that these calculations no longer hold. The qualitative implications of the new GCC policy however were still the same as it also involved a promise for future subsidies instead of direct support.

[25] After 2012 for 15 years.