Subsidies and Myopia in Technology Adoption: Evidence from Solar Photovoltaic Systems

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Abstract

Many countries have relied on subsidies to promote the adoption of renewable energy technologies. We study a particularly generous program, which promoted the adoption of solar photovoltaic (PV) systems through subsidies on future electricity production. We develop and estimate a tractable dynamic model of technology adoption, also accounting for local market heterogeneity. We exploit rich variation at pre-announced dates in the future production subsidies. Although the program led to a massive adoption, we find that households significantly undervalued the future benefits from the new technology. This implies that an upfront investment subsidy program would have promoted the technology at a much lower budgetary cost, so that the government essentially shifted the subsidy burden to future generations of electricity consumers. (JEL C51, Q48, Q58)

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1 Introduction

Many countries have relied on subsidies to promote the adoption of renewable energy technologies for electricity production, such as wind power and solar photovoltaic (PV) systems. The generous support has often been motivated on the grounds that there is not only an environmental externality (CO_2 emissions from fossil sources), but also a technology market failure (insufficient incentives to innovate and adopt a new technology). The subsidies for the green technologies often consist of a combination of investment subsidies, which are paid upfront at the moment of installation, and production subsidies, which are paid in the future when the systems are producing the electricity (or equivalently, a combination of investment and production tax credits, as reviewed for the U.S. in Murray et al. (2014)).

In this paper we investigate the incentive to adopt a new green technology, and the role played by investment and production subsidies. The adoption decision involves a fundamental trade-off between the immediate investment costs and the future benefits from electricity production. The successful adoption of the new technology thus depends on how much households discount future benefits, and on the extent to which subsidies apply to the upfront investment costs or the future electricity production. We study a particularly generous program for residential solar PV systems, running in the region of Flanders (Northern part of Belgium) during 2006–2012, and responsible for a particularly high adoption rate compared with other countries.[1] The program heavily relied on future production subsidies in the form of Green Current Certificates (GCCs), which were committed for up to 20 years. The program was similar to the German and several other European programs but it differed from the U.S. programs, which mainly relied on upfront subsidies or rebates.[2] Interestingly, the GCC subsidy program revised its conditions many times at pre-announced dates. The considerable variation in the subsidies enables us to identify the households' discount factor in a reliable way. Because the program mainly consisted of future production subsidies, it potentially enabled the government to shift the financial burden to future electricity consumers and we will assess to which extent this was the case.

To estimate the impact of the subsidy program, we develop a dynamic discrete choice

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

[2] In the U.S. there were federal tax credits of 30%, and several states took additional measures. For example, the famous California Solar Initiative (CSI) had a budget of $2.2 billion and aimed to install 1.9GW of solar PV capacity. Combined with the federal tax credits, the investment subsidies could amount to 50% of the cost of a solar PV system. Source: https://en.wikipedia.org/wiki/California_Solar_Initiative.

model, where in each period households face the decision to adopt the new technology or to postpone their investment. We propose a novel approach to estimate the dynamic model based on aggregate, country-level data on adoption rates, investment costs and expected future benefits. We also show how to extend the model to account for rich forms of local market heterogeneity in a tractable way.

We obtain the following main findings. First, although the program led to a massive adoption of solar PV systems, households significantly undervalued the future benefits from the new technology. They use a implicit real interest rate of 13% in evaluating these future benefits, which is much above the real market interest rate of about 3%. This implies a considerable undervaluation of the future benefits from electricity production, as consumers are only willing to pay 0.53 Euro upfront for one Euro of discounted future benefits from electricity production. Our finding of undervaluation is robust with respect to various assumptions, such as political uncertainty on the program. The considerable consumer myopia in technology adoption raises specific policy concerns, at least from a budgetary and distributional perspective. The government could have saved 47% or € 1.8 billion by giving upfront investment subsidies instead of future production subsidies. This is a saving of almost € 700 per household, a very large number given that only 8.5% of the households had adopted a PV at the end of the program. We conclude that the government essentially shifted the subsidy burden to future households, as both adopters and non-adopters pay for the subsidy through higher electricity prices.

Our paper makes several contributions. First, we contribute to the empirical intertemporal choice literature, which studies how consumers value future payoffs. Much of this work focuses on the important question whether there is consumer myopia or inattention in the valuation of future energy cost savings, as this could be responsible for the so-called energy efficiency gap (Allcott and Greenstone (2012)). After Hausman's (1979) seminal contribution, the recent evidence ranges from moderate undervaluation to correct valuation, see for example Allcott and Wozny (2013) and Busse, Knittel and Zettelmeyer (2013). All this evidence is based on energy-saving investments of existing, mature technologies (such as cars). This paper instead focuses on the decision to adopt an entirely new technology, which aims to obtain a shift from traditional energy sources to renewables. Our evidence suggests that consumer myopia is much stronger in this case, with important implications for policy programs.

Second, because we focus on the adoption decision of a new technology we also make a methodological contribution. Other empirical work on consumers' valuation of future payoffs typically ignored the timing dimension of adoption. It focuses on the decision of how much to invest in energy cost savings, without accounting for the option value of waiting. This approach may be reasonable for mature technologies where households simply replace their current products. 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. They also must decide on the timing of their investment, as it can be beneficial to postpone adoption even if it is already profitable to invest now.

To incorporate the timing decision, we develop a dynamic discrete choice model that captures the optimal stopping problem in the spirit of Rust (1987). The discount factor now plays a double role: it influences both how much households value the future benefits of their investments, and how much they 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 it can treated 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. The dynamic discrete choice literature has stressed that the discount factor is not identified without additional restrictions; see Manski (1993), Rust (1994) and Magnac and Thesmar (2002). In our setting we obtain identification by assuming the discount factor that weigh investment costs against future benefits is the same as the discount factor for the timing decision to adopt. We thus obtain identification from variation in the investment costs and future 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 in dynamic models where the discount factor plays this double role. Our particular identification strategy relies on the large variation in investment costs, combined with the considerable variation in the GCC subsidies, which were revised many times on pre-announced dates.

Third, we contribute by proposing a novel method to estimate a dynamic choice model with aggregate data on adoption rates, investment costs and future benefits, and we also show how to extend the model to account for local market heterogeneity in a tractable way. We follow several steps. In a first step, 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 simplifies estimation, but also allows us to limit the assumptions about household expectations of the evolution of prices and subsidies (Arcidiacono & Ellickson 2011). In a second step, we show how to invert the demand model to solve for the unobserved error term, using a similar approach as in Berry (1994) for static choice models. Conditional on the discount factor, this gives rise to a linear regression equation, where the current adoption rate depends on current and future prices, as well as the next period adoption rate. One can use a standard nonlinear GMM estimator to also estimate the discount factor and account for the endogeneity of several variables. In a third step, we also account for rich forms of household heterogeneity at a very disaggregate local market level (with on average only 295 households per local market).[3] We include household size, income and other demographics, interacted with the constant, price and capacity size, by adding suitable micro-moments to the aggregate moment conditions. Although these controls are important in explaining adoption behavior, they do not affect our conclusions for the discount factor, and our implied policy implications.

The rest of the paper is structured as follows. Section 2 describes the datasets, the solar PV technology, the most important policy measures to promote PV adoption in Flanders, and takes a first look at the evolution of adoption and costs and benefits. Section 3 specifies the model that can be estimated with only aggregate data, and also its extension to account for local market heterogeneity. Section 4 discusses the empirical results, performs a detailed sensitivity analysis and derives policy implications. Finally, we conclude in section 5.

2 Industry background

In this section we describe the market of residential photovoltaic (PV) systems. We begin with a brief description of the available datasets. We then discuss the technology and the various sources of costs and benefits of installing PV systems. Finally, we provide descriptive statistics on the magnitude of the costs and benefits during the considered period, and on the evolution of the number of adopters of the new technology.[4]

2.1 Datasets

Our main dataset contains information of all installed PVs across Flanders during 2006–2012. We will analyze this dataset at the monthly frequency, first at the aggregate level of Flanders (covering about 2.7 million households) and in an extension at the disaggregate local area level (which divides the entire region in 9,182 statistical sectors, with an average of 295 households per statistical sector).

[3]Other dynamic adoption models with aggregate data have ignored persistent heterogeneity (Melnikov 2013), or allowed for it through random coefficients (Gowrisankaran and Rysman (2012)) or unobservable types in the population (Scott 2013).

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

We combine the information from this main dataset with several additional datasets. First, we collected information on the prices of PV systems from May 2009 until December 2012. Second, we have information on the benefits from adopting PVs, including the public support measures in the form of Green Current Certificates (GCCs), electricity cost savings, and tax benefits. Finally, for our extension to the disaggregate local area level, we collected detailed socio-demographic information, such as income, household and house characteristics. In the Appendix we provide further details on the data sources and the data construction.

2.2 Technology and public support measures

A PV system consists of solar panels, which absorb sunlight and convert this into electricity. One can distinguish between residential and commercial PV systems. Residential PV systems are usually installed on top of a roof and typically have a capacity size no larger than 10 kilowatt (kW). Commercial PV systems may also be on the top of a roof or they may be grount-mounted, and they generally reach much larger capacity sizes than residential PV systems.

Our focus is on residential PV systems, with capacity limited to 10 kW. In Flanders, a PV system produces 0.85 MWh per year for each kW of capacity (CREG 2010). All residential PV systems are connected to the grid, so that households do not need to synchronise their electricity consumption and production, or use batteries to store excess production. Households pay an upfront investment price for a PV system, and they receive two main sources of future benefits from installing a PV system: Green Current Certificates (GCCs) and electricity bill savings from net-metering. We discuss these elements in turn.

Investment price The investment price is the price households have to pay for a PV system, including all additional costs. This mainly depends on the capacity, measured in kW. In 2006 and 2007 households could apply for a 10% investment subsidy for PV installations.[5] Furthermore, there was a general tax credit of 40% for renewable energy investments, including PV installations. The maximum allowed tax credit varied over the period, ranging from 2,600€ in 2008 to 3,600€ in 2011 (and since 2009 households could transfer the remaining amount to the following three years if their house was built at least five years ago). In 2012 the tax credits for PV installations were abolished. Finally, PV installations that were built in houses of at least five years old also benefited from a reduced VAT rate of 6% instead of 21%.

[5]The subsidizable investment cost was capped at 7000€ per kWp and a maximum subsidizable capacity of 3kW.

Subsidies from Green Current Certificates (GCCs) The Flemish government has actively promoted the adoption of PV systems through the program of tradable GCCs. Households obtained a GCC for each MWh of electricity production through their PV system, and they could sell these to the distribution system operators (DSOs) at a guaranteed price for a fixed number of years. This guaranteed price was substantially above the market price of GCCs. At the start in 2006, the program was very generous, paying €450 per MWh for 20 years. The program became less favourable in 2010, and was subsequently gradually phased out. By the end of 2012, new PV systems only received a guaranteed price of €90 per MWh for a period of 10 years. In January 2013, the government introduced a so-called banding factor. This restricted the number of GCCs per MWh, and effectively led to an abolishment of the entire GCC system in February 2014.[6]

From the point of view of PV adopters, the GCCs are a subsidy for future electricity production. The DSOs were responsible to buy these GCCs at the contracted price. They subsequently resell them at the prevailing market price to the electricity suppliers, who are required to purchase a sufficient amount every year to meet their renewable energy sources requirements. The GCCs are thus a cost to both the DSOs and the electricity suppliers, and these costs are eventually passed on to retail electricity prices. As such, the GCC subsidy scheme is not financed through taxes, but rather through increased electricity prices to all consumers.

Electricity bill savings from net-metering Households with a PV system with a capacity limited to 10 kW benefit from a net-metering principle. This means that they only have to pay for their net annual electricity consumption, i.e. their consumption after subtracting the annual electricity production generated by their PV system and transmitted on the grid.[7] Hence, in addition to the subsidies from GCCs, a second main source of benefits from installing a PV system is given by the annual electricity bill savings, i.e. the PV's annual electricity production multiplied by the retail price of electricity.

Access to the grid was initially offered without any charge. In July 2015, the DSOs were able to introduce an annual grid fee of around 100€/kW. This came after a long public debate and several legislative procedures. The grid fee enabled the DSOs to partly finance their cost of the GCC subsidies, aiming to avoid further electricity price increases to all

[6] The idea of the banding factor was to limit the number of GCCs for every produced MWh, in such a way that the net present value of installing a PV would essentially be zero at the prevailing market prices of PV systems. Since the prices of PV systems continued to drop, the net present value soon became positive even without GCCs, so that GCCs were effectively abolished in February 2014.

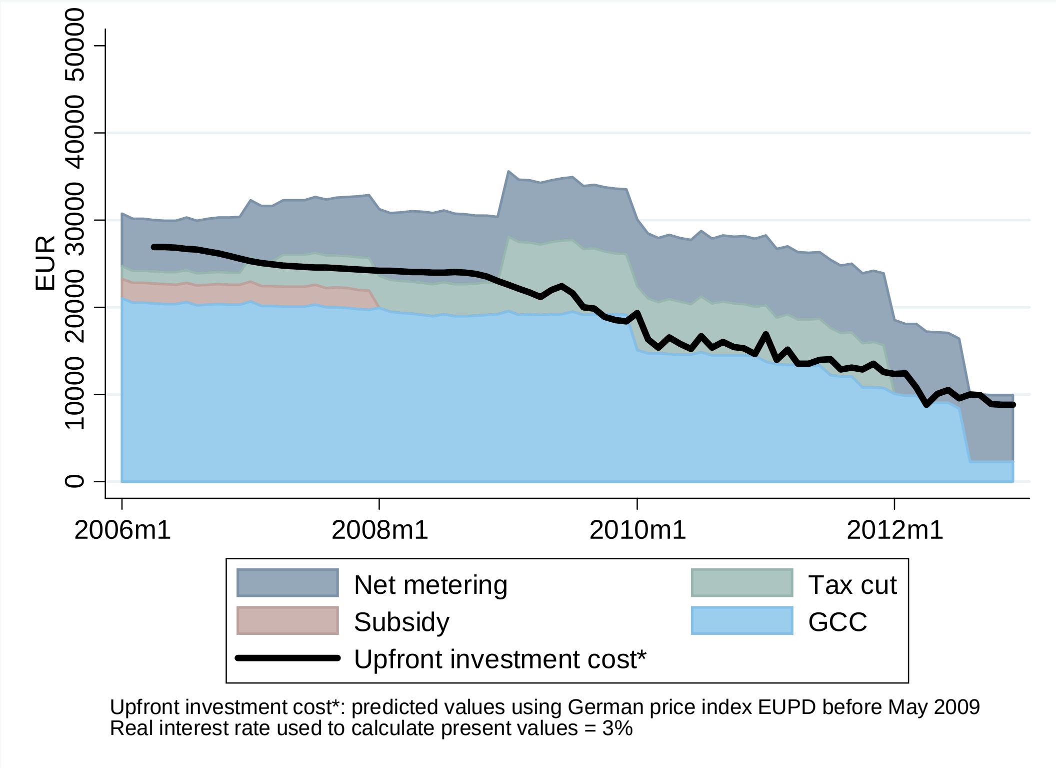
[7] Note that there is no reimbursement in case a household would produce more electricity than it consumes on an annual basis.

consumers.

2.3 Evolution of costs, benefits and adoption

Figure 1 summarizes of the costs and benefits of a PV system of 4kW. We calculate future

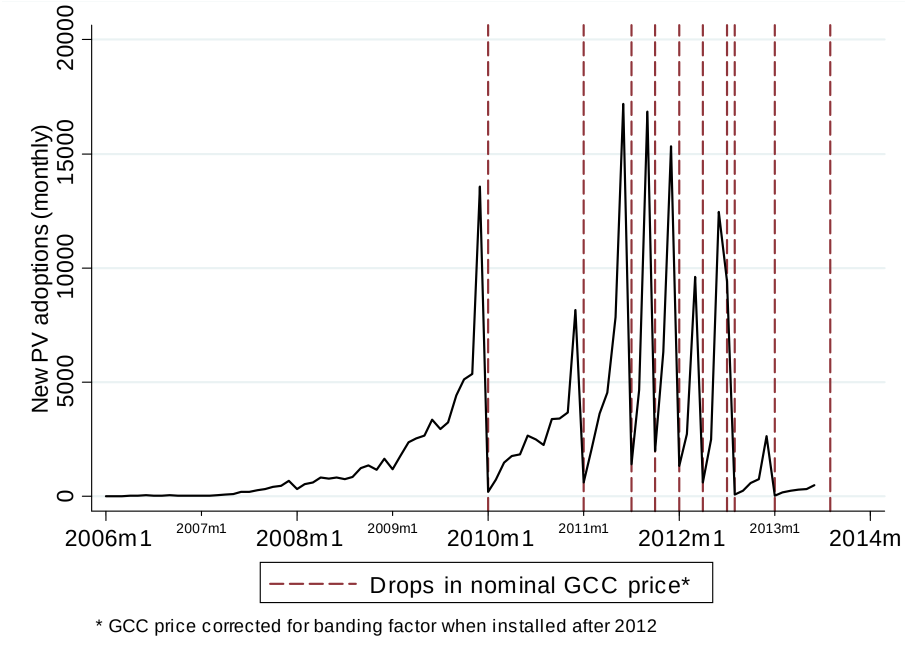
Figure 1: Costs and benefits of 4kW PV in EUR 2013, discounted at market interest rate



benefits in present value terms using a real interest rate of 3% and an expected life time of 20 years and we convert all prices to 2013 prices. The gross purchase price (net of any investment tax cuts) dropped from € 21,700 in May 2009 to € 8,791 at the end of 2012. The present value of future benefits was highest in 2009 and rapidly decreased afterwards. The most important benefits came from the GCCs. They provided a present value of € 20,000 until January 2010, and subsequently declined until they almost disappeared at the end of 2012. Benefits from tax cuts were also high, especially from 2009 on, but they were removed in 2012. Finally, the benefits from net-metering (i.e. electricity cost savings) formed a fairly stable source of benefits. These benefits became the most important reason to adopt PVs since the end of 2012, but only because other benefit components decreased over time.

Figure 2 shows the evolution of the monthly number of new adopters between January 2006 and June 2013. Vertical lines indicate drops in the GCC prices, as typically announced

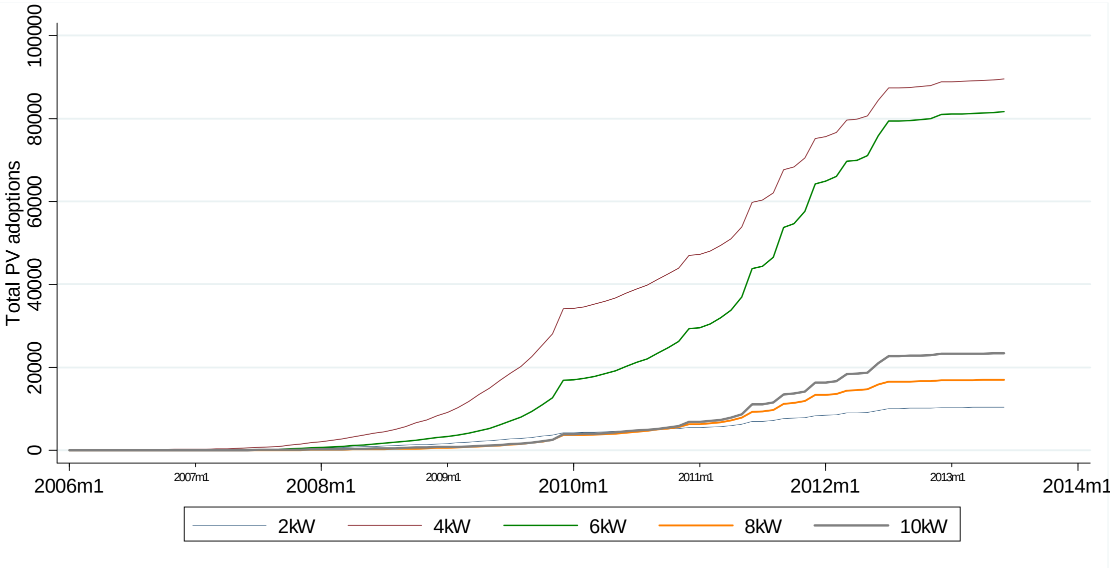
Figure 2: 2006-2013: Time series of new PV adoptions and drops in nominal GCC price



a few months in advance. The number of new adopters remained very low until 2009, which may be because households did not fully value the benefits or because they postponed their adoption in anticipation of better future investment opportunities. From 2009 onwards the number of new adopters started to increase to reach a sharp peak just before the first announced drop in the GCC price in January 2010. There was again a gradual increase in the number of adopters in 2010 with a new peak just before the second drop in the GCC price in January 2011. The same pattern of gradual increases and peaks just before a next announced drop in the GCC price has been repeated several times until the beginning of 2013 when the GCC policy changed drastically and became less generous. This adoption pattern illustrates the dynamic nature of the households' decision problem to adopt a PV installation. Households take into account the announced drops in the GCC price, and they may speed up their purchases to avoid falling under a less advantageous future subsidy scheme.

Figure 3 shows the cumulative number of adopters over the considered period, broken down into five groups of capacity size: 2kW, 4kW, 6kW, 8kW and 10kW. This shows a gradual long-term increase in the number of adopters, with several kink points around the

Figure 3: 2006-2013: Time series of total adoption of PVs of different capacity



time of new GCC schemes. The 4kW and 6kW systems were the most popular choices for a PV. This is because households only benefit from net-metering for the production that is below their household consumption. In practice, an average household consumes 3.5MWh per year, while a 4kW system produces about 3.4 MWh per year, so that larger PV systems are only of value for households that are sufficiently larger than average. Nevertheless, there is a modest shift during the period towards PV systems of larger capacity: whereas in January 2010 the market share of PV systems of 8kW and 10kW was only 12%, it reached 18 % by 2013.

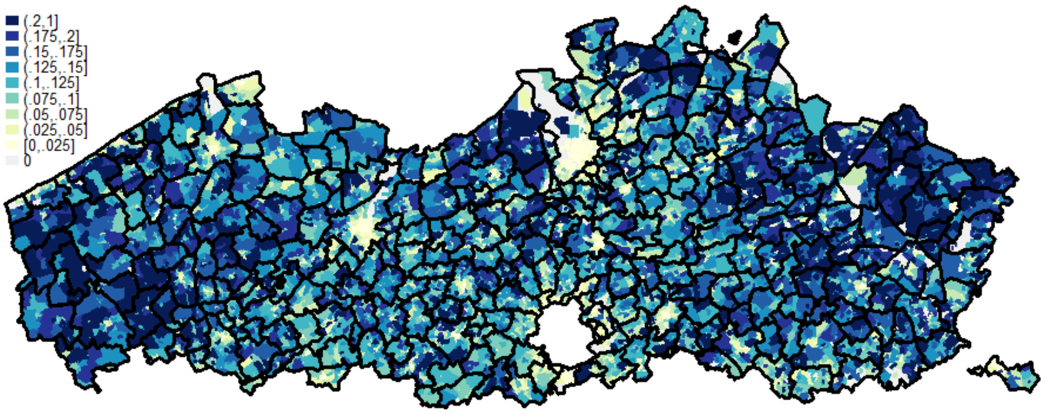
By the end of June 2013, the cumulative number of adopters had reached 222,077, amounting to an adoption rate of 8.5% of the households (and an identical 8.5% of the number of buildings). The total capacity of residental PV systems had at that time reached 1,065MW, or 5.1% of total electricity capacity in Belgium.[8]

Adoption rates vary widely within the region, as illustrated in Figure 4. Adoption rates are very high (over 20%) in rural areas often in the west and east parts of the region. Conversely, adoption rates are extremely small in cities such as Ghent (west of center) and Antwerp (north of center), or the areas around Brussels (south of center). Various socio-demographic factors may explain this variation, such as average household size, house size and income. In an extension of our aggregate demand model, we will take into account the

[8] According to the US Energy Information Administration, Belgium had a total installed electrical capacity of 21 000 MW in 2012.

role of these socio-demographic characteristics.

Figure 4: PV adoption rates in Flanders



Adoption data: VREG, household data: ADSEI census 2011

3 The model of technology adoption

We first specify a dynamic model that can be estimated with aggregate market data: we describe to adoption decision (subsection 3.1), derive the estimating equation (subsection 3.2) and discuss estimation and identification (subsection 3.3). We subsequently show how to extend the appraoch to estimate the model at a highly disaggregate local market level. This makes it possible to account for heterogeneity across households (subsection 3.4).

3.1 The adoption decision

In a given period t a household $i = 1, \ldots, N$ may either choose not adopt a PV, $j = 0$, or it may choose to adopt one of the available PV alternatives, $j = 1, \ldots, J$. In our application, the PV alternatives refer to systems with different capacity sizes. A key feature of the model is that the adoption decision ($j > 0$) is a terminating state. Not adopting gives the option of adopting at a later period, when the price for a given size may have decreased, or when the financial benefits may have increased or decreased.

In each period a household obtains a random taste shock $\varepsilon_{i,j,t}$, which we assume to follow a type I extreme value distribution. Let $v_{i,j,t}$ be the conditional value of household i for alternative j at period t, i.e. the expected discounted utility from choosing j at t before the realization of the random taste shock $\varepsilon_{i,j,t}$. In general, one can decompose $v_{i,j,t} = \delta_{j,t} + \mu_{i,j,t}$, where $\delta_{j,t}$ is the mean utility and $\mu_{i,j,t}$ is the individual-specific utility. In this section, we set

$\mu_{i,j,t} = 0$, so that $v_{i,j,t} = \delta_{j,t}$. Household heterogeneity then only enters through the extreme value term $\varepsilon_{i,j,t}$.

Assume that in each period t households choose the alternative j that maximizes random utility $v_{i,j,t} + \varepsilon_{i,j,t}$. This will give rise to a choice probability, or approximately an aggregate market share, for each alternative j in each period t. Before deriving this, we first describe the conditional value of adoption ($v_{i,j,t}$, $j = 1, \ldots, J$) and the conditional value of not adopting ($v_{i,0,t}$) in period t.

Conditional value of adoption ($v_{i,j,t}$, $j = 1, \ldots, J$)

The conditional value of adoption is particularly simple because it is the expected discounted utility in a terminating state, after which the household no longer takes any actions. We specify $v_{i,j,t}$ as follows:

$$v_{i,j,t} = \delta_{j,t} = x_{j,t}\gamma - \alpha p_{j,t} + \xi_{j,t}, \tag{1}$$

where $x_{j,t}$ is a vector of characteristics of alternative j at period t, $p_{j,t} = p_{j,t}(\beta)$ is the price variable as a function of the monthly discount factor β, and $\xi_{j,t}$ is the unobserved quality of alternative j at period t. In our specification, $x_{j,t}$ will contain a set of fixed effects for the alternatives. The price variable is the sum of the upfront investment price ($p_{j,t}^{INV}$) and the discounted future flow benefits from GCC subsidies ($p_{j,t}^{GCC}$) and electricity cost savings ($p_{j,t}^{EL}$):

$$p_{j,t} = p_{j,t}(\beta) \equiv p_{j,t}^{INV}(\beta) - \underbrace{\frac{1 - \left(\beta^G\right)^{S_t^G}}{1 - \beta^G}}_{\rho_t^G} p_{j,t}^{GCC} - \underbrace{\frac{1 - \left(\beta^E\right)^{S^E}}{1 - \beta^E}}_{\rho^E} p_{j,t}^{EL}, \tag{2}$$

where β^G and β^E are monthly adjusted discount factors:

$$\begin{aligned} \beta^G &= (1-\lambda)(1-\pi)\beta \\ \beta^E &= (1-\lambda)(1+\vartheta)\beta, \end{aligned} \tag{3}$$

i.e. the monthly discount factor β adjusted for the depreciation parameter λ, the inflation rate π and the trend in real electricity prices ϑ. We now discuss the three terms in (2) in more detail.

The first term in (2), $p_{j,t}^{INV}$, is the real upfront net investment price of the PV system j at period t, i.e. the real gross investment price minus the tax cuts:

$$p_{j,t}^{INV}(\beta) = p_{j,t}^{GROSS} - \sum_{\tau=1}^{4} \beta^{12\tau} taxcut_{j,t+12\tau}. \tag{4}$$

The tax cuts were capped at an indexed maximum amount. But since 2009 any remaining tax cuts could be shifted to the following three years for houses that were built at least five years ago, so that the last three terms in the summation in (4) become non-zero.[9]

The second and third terms in (2) capture the discounted future benefits from electricity production: $p_{j,t}^{GCC}$ and $p_{j,t}^{EL}$ are flow variables measuring the monthly benefits from the fixed subsidies from the GCCs and the electricity savings associated with the PV system. Both $p_{j,t}^{GCC}$ and $p_{j,t}^{EL}$ are essentially prices per kW at period t (p_t^{GCC} and p_t^{EL}), multiplied by the capacity size k_j of the alternative j (in kW) and a factor that translates PV capacity in monthly electricity production ($\frac{0.85}{12}MWh/kW$).[10] The parameters ρ_t^G and ρ^E are capitalization factors that convert the monthly benefits for S_t^G months of GCCs and S^E months of electricity savings into present value terms using the adjusted monthly discount factors β^G and β^E. According to (3), these are the monthly discount factor β net of any depreciation. The parameter λ captures physical deterioriation of electricity production, whereas π is the monthly inflation rate (because GCC are fixed in nominal prices, while our model is in real prices) and ϑ captures a trend in real electricity prices. As we make several assumptions in constructing the price variable, we provide a detailed sensitivity analysis in section 4.2.[11]

Conditional value of not adopting ($v_{i,0,t}$)

The conditional value of not adopting is the flow utility in period t, $u_{0,t}$, plus the option value of waiting. More precisely,

$$v_{i,0,t} = \delta_{0,t} = u_{0,t} + \beta E_{\delta_{t+1}} \overline{V}_{t+1} \tag{5}$$

where $\overline{V}_{t+1}$ is the ex ante value function, i.e. the expected continuation value from behaving optimally from period $t+1$ onwards. This expectation integrates over uncertainty about the next period mean utilities $\delta_{t+1} = (\delta_{0,t+1}, \delta_{1,t+1}, ..., \delta_{J,t+1})$. With a type I extreme value distribution for the random taste shocks $\varepsilon_{i,j,t}$ the ex ante value function $\overline{V}_{t+1}$ has the well-

[9] The VAT on the gross investment price is reduced from 21% to 6% for houses older than 5 years. Furthermore, the possibility to shift tax cuts to the next three years is only possible for houses older than 5 years. We account for this by taking a weighted average of the VAT rate and tax cuts over new and old houses (where 91% is the fraction of old houses).

[10] We follow CREG, VEA and 3E (2010).

[11] In our main specification we assume a yearly physical deterioration rate of 1%, $\lambda = 1.01^{1/12} - 1$ (following Audenaert et al., 2010), a yearly inflation of 2%, $\pi = 1.02^{1/12} - 1$, and estimate a yearly growth in electricity prices of 3.4%, $\vartheta = 0.0028148$. We assume $S^E = 240$ months (the expected life time of a PV, following CREG, 2010), and based on the GCC schemes announced by the government we set $S_t^G = 240$ months for January 2006 - July 2012, $S_t^G = 120$ for August 2012 - December 2012, and $S_t^G = 180$ months for January 2013.

known closed form logsum expression:

$$\overline{V}_{t+1} = 0.577 + \int \ln \sum_{j=0}^{J} \exp(\delta_{j,t+1})\, d\delta_{t+1} \tag{6}$$

where 0.577 is Euler's constant (the mean of the extreme value distibution).

With random utility maximization and a type I extreme value distribution for the random taste shocks $\varepsilon_{i,j,t}$, we obtain the following choice probability, or approximately the aggregate market share, for each alternative $j = 0, \ldots, J$ at period t:

$$s_{j,t} = \frac{\exp(\delta_{j,t})}{\sum_{j'=0}^{J} \exp(\delta_{j',t})}. \tag{7}$$

The aggregate market share for alternative $j = 1, \ldots, J$ at period t is measured as $s_{j,t} = q_{j,t}/N_t$, i.e. the actual number of adopters of j at t, $q_{j,t}$, divided by the potential number of adopters at period t, N_t. Since adoption is a terminating state, the potential number of adopters is the total number of households N minus the number of households that adopted in the past, $N_t = N - \sum_{\tau=1}^{t-1} \sum_{j=1}^{J} q_{j,\tau}$.

3.2 Estimating equation

The aggregate market share equation (7) involves two complications. First, the conditional value for not adopting $\delta_{0,t}$ involves the expected future $\overline{V}_{t+1}$, which is recursively defined by (6). Second, the error term $\xi_{j,t}$ enters nonlinearly. We now show how to solve both complications, by combining Hotz and Miller's (1993) conditional choice probability (CCP) approach to deal with dynamic discrete choice problems, and Berry's (1994) market share inversion to deal with aggregate choice data (market shares).

CCP approach

The first step is to compute the conditional value or mean utility for not adopting $\delta_{0,t}$. Substituting (6) in (5), the mean utility from not adopting is:

$$\delta_{0,t} = u_{0,t} + \beta \left(0.577 + \int \ln \sum_{j=0}^{J} \exp(\delta_{j,t+1})\, d\delta_{j,t+1} \right). \tag{8}$$

Hotz and Miller's (1993) insight is to compute the next period logsum expression directly from the next period conditional choice probability (CCP) of a terminating choice, $j = 1, \ldots, J$. Any arbitrary terminating choice can be taken, so we take $j = 1$. The conditional choice probability of alternative $j = 1$ in the next period $t + 1$ is given by

$$\Pr(j_{t+1} = 1 | \delta_{t+1}) = \frac{\exp(\delta_{1,t+1})}{\sum_{j=0}^{J} \exp(\delta_{j,t+1})}$$

After rewriting and taking logs:

$$\ln \sum_{j=0}^{J} \exp\left(\delta_{j,t+1}\right) = \delta_{1,t+1} - \ln \Pr(j_{t+1} = 1|\delta_{t+1})$$

this can be substituted in the mean utility from not adopting (8) to obtain:

$$\begin{aligned} \delta_{0,t} &= u_{0,t} + \beta \left(0.577 + \int \left(\delta_{1,t+1} - \ln \Pr(j_{t+1} = 1|\delta_{t+1})\right) d\delta_{j,t+1} \right) \\ &= \beta \int \left(\delta_{1,t+1} - \ln \Pr(j_{t+1} = 1|\delta_{t+1})\right) d\delta_{j,t+1} \end{aligned} \tag{9}$$

where the second equality follows from normalizing $u_0 + \beta 0.577 = 0$. As discussed in Arcidiacono and Ellickson (2011), expression (9) has an intuitive interpretation. The conditional value of not adopting is essentially equal to the present value of choosing option $j = 1$ in the next period and the CCP correction term $-\ln \Pr(j_{t+1} = 1|\delta_{t+1}) \geq 0$. The correction term adjusts for the fact that $j = 1$ may not be optimal in the next period so that the expected utilility is generally higher than that of adopting $j = 1$ (unless $\Pr(j_{t+1} = 1|\delta_{t+1}) = 1$).

We now impose an assumption on households' expectations about mean utilities in the next month: we assume that households can perfectly predict the mean utilities of all alternatives in the next month. We do not need to make an assumption on how they expect the future to evolve after that. This allows us to write the last expression without uncertainty, so that the CCP correction term is equal to the aggregate market share of alternative 1 in the next period, i.e. $\Pr(j_{t+1} = 1|\delta_{t+1}) = s_{1,t+1}$:

$$\delta_{0,t} = \beta\left(\delta_{1,t+1} - \ln s_{1,t+1}\right) \tag{10}$$

The benefit of this approach is that we do not need to predict the mean utilities or the CCP before estimation, as we simply observe the variables in $\delta_{1,t+1}$ and the next period market share $s_{1,t+1}$ in the data.

Market share inversion

The second step follows Berry's (1994) approach to estimate static choice models with aggregate market share data. Using the market share expressions (7), we can divide $s_{j,t}$ for each $j = 1, \ldots, J$ by $s_{0,t}$ and take logs to obtain

$$\ln s_{j,t}/s_{0,t} = \delta_{j,t} - \delta_{0,t}, \quad j = 1, \ldots, J \tag{11}$$

Substitute the expressions for the mean utilities (1) and (10) in (11), and rewrite to obtain the following main estimating equation:

$$\ln s_{j,t}/s_{0,t} = \left(x_{j,t} - \beta x_{1,t+1}\right)\gamma - \alpha\left(p_{j,t} - \beta p_{1,t+1}\right) + \beta \ln s_{1,t+1} + \widetilde{\xi}_{j,t}. \tag{12}$$

where $\widetilde{\xi}_{j,t} \equiv \xi_{j,t} - \beta \xi_{1,t+1}$ is the econometric error term. In the static case where $\beta = 0$, this is Berry's standard aggregate logit regression for the number of new adopters on current prices and other control variables. To gain further intuition when $\beta > 0$, assume there is only one adoption alternative $j = 1$. The estimating equation can then be written as:

$$\ln \frac{s_{1,t}/s_{1,t+1}^{\beta}}{s_{0,t}} = x_{1,t}\gamma - \beta x_{1,t+1}\gamma - \alpha \left(p_{1,t} - \beta p_{1,t+1}\right) + \xi_{1,t} - \beta \xi_{1,t+1}.$$

With β close to 1, this is essentially a regression for the change in the number of new adopters on the change in price and possibly other characteristics. Intuitively, with forward-looking consumers one may expect that the number of current period adopters is small relative to the next period adopters when the expected price drop is large.

3.3 Estimation and identification

The estimating equation (12) contains the price variable $p_{j,t}$, which is given by (2). This depends on the upfront investment price $p_{j,t}^{INV}$, the future financial benefits from GCCs $p_{j,t}^{GCC}$ and electricity savings $p_{j,t}^{EL}$, and it is a non-linear function of the discount factor β.

To fix ideas, first consider the case in which β is known and all variables are exogenous, i.e. uncorrelated with the error term $\widetilde{\xi}_{j,t}$. In this case, it is possible to estimate (12) using a simple linear OLS regression for the differenced adoption variable $\ln s_{j,t}/s_{0,t} - \beta \ln s_{1,t+1}$ on the differenced product characteristics $x_{j,t} - \beta x_{1,t+1}$ and the differenced price variable $p_{j,t} - \beta p_{1,t+1}$.

Now consider the more general case where β has to be estimated and the upfront investment price $p_{j,t}^{INV}$ may be correlated with the error term $\widetilde{\xi}_{j,t}$. Notice first that the estimating equation (12) is non-linear in β because it enters the price term (2) non-linearly, so a non-linear regression is necessary. Several variables in equation (12) give rise to endogeneity concerns. First, $p_{j,t}$ may be correlated with the error term as it contains the investment price variable $p_{j,t}^{INV}$, so we need an instrument to identify the price coefficient α. Second, $p_{j,t}$ also contains the electricity price variable $p_{j,t}^{EL}$, which may be endogenous because GCC subsidies were financed through higher electricity prices. Third, the next period adoption share $\ln s_{1,t+1}$ may be correlated with the error term, since it contains a next period unobservable $\widetilde{\xi}_{j,t} \equiv \xi_{j,t} - \beta \xi_{1,t+1}$. We therefore also need an instrument to identify the discount factor β.

To account for these problems we construct an instrument vector $z_{j,t}$ and apply the moment conditions $E\left(z_{j,t}\widetilde{\xi}_{j,t}(\theta)\right) = 0$ with $\theta = (\alpha, \beta, \gamma)$. More specifically, we include the following variables in our instrument vector $z_{j,t}$. First, we include a price index of Chinese PV modules on the European market, $p_{j,t}^{MOD}$. Since these modules are the most important cost component of PV installations, the price index $p_{j,t}^{MOD}$ is expected to be correlated with the endogenous upfront investment price $p_{j,t}^{INV}$, and as a cost shifter it is reasonable to assume it does not directly influence demand. Hence, the price index of Chinese PV modules provides a strong instrument to identify the price coefficient α. Second, we include the future benefits from the GCC subsidies $p_{j,t}^{GCC}$ as an instrument. This variable refers to the main source of future benefits from adopting a PV. There is considerable variation in $p_{j,t}^{GCC}$ across alternatives and over time, even in the short run as the benefits showed discontinuous drop in several months. This variation is therefore helpful to identify how households trade off upfront investment costs with future benefits. Third, we use the oil price as an instrument, as this may be correlated with the endogenous electricity price variable. Note however that the GCC subsidies are a much more important source of variation of future benefits than the electricity cost savings. These instruments are sufficient to identify the model, but further efficiency gains are possible by using Chamberlain's (1987) optimal instruments, as applied in static aggregate discrete choice models by Berry, Levinsohn and Pakes (1999) and Reynaert & Verboven (2014). We explain this in Appendix A.2.

The dynamic discrete choice literature has stressed that the discount factor is not identified without additional restrictions; see (Manski 1993), Rust (1994) and (Magnac & Thesmar 2002). In our setting we obtain identification by assuming the discount factor that weighs the upfront investment cost with future benefits (i.e. the discount factor that enters $p_{j,t}$ through (2)) is the same as the discount factor for the timing decision to adopt (i.e. the discount factor that directly enters (12)). This then gives rise to traditional instruments coming from variation in the determinants of the upfront investment costs and future flow benefits. As such, our identification approach for estimating the discount factor is the same as "static" models of intertemporal choice, which abstract from the timing decision and only focus on the investment decision. For example, a detailed literature on the car market focuses on how households trade off future fuel cost savings against higher upfront purchase prices, without explicitly modeling the timing of the purchase decision; see Verboven (2002), Allcott and Wozny (2013) and Busse, Knittel and Zettelmeyer (2013)). Lee (2013) uses a related identification approach in an application on the timing of hardware purchases (video game consoles) when there are future benefits from new software (games). He makes use of variation in the time until new games arrive, and assumes the discount factor for the timing of adoption is the same as that for the valuation of investment costs versus future benefits.[12]

[12] Related approaches to identify the discount factor in dynamic choice problems have relied 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).

3.4 Accounting for local market heterogeneity

The previous subsections provided a framework to study the adoption of PV systems at the aggregate country level. In this subsection we show how to extend the empirical analysis to account for rich observed heterogeneity across 9,182 local markets, where each market m consists on average of 295 households. We match information on the number of adopters in each market m for each alternative j in each period t to several demographic characteristics. This enables us to include a rich set of demographics and interact this with a constant, price and capacity size in the utility specification. An alternative approach to account for heterogeneity would be to estimate random coefficients, similar to Gowrisankaran and Rysman (2012), or estimate a finite mixture of unobserved types in the population as in Scott (2013), based on the EM algorithm of Arcidiacono and Miller (2011).

The basic set-up is as before, except that we now observe adoption decisions at the local market level m and we can match this with an $H \times 1$ vector of household demographics D_m. In each period t a household i living in market m chooses its preferred alternative $j = 0, 1, \ldots, J$, where $j = 0$ is the option not to adopt (yet).

The conditional value of adoption $v_{i,j,t}$ $(j = 1, \ldots, J)$ is the sum of the mean utility $\delta_{j,t}$ and an individual-specific component $\mu_{m,j,t}$, which depends on demographics in the local market m. We specify:

$$\begin{aligned} v_{i,j,t} &= \delta_{j,t} + \mu_{m,j,t} \\ &= \delta_{j,t} + w_{j,t}\lambda_m, \end{aligned} \tag{13}$$

where $\delta_{j,t}$ was given earlier by (1), and $w_{j,t}$ is a $1 \times K$ vector of characteristics of the PV alternatives (which is allowed to differ from $x_{j,t}$ entering $\delta_{j,t}$). We specify the $K \times 1$ vector $\lambda_m = \Lambda D_m$, where Λ is a $K \times H$ parameter matrix with interaction effects to be estimated. The vector of characteristics $w_{j,t}$ will include a constant, the additional capacity to a reference capacity (we take j=1, which is the 4kW alternative), and the price variable. The vector of household demographics D_m includes income, household size, house size, etc. We will not estimate all the interaction effects in Λ, so we constrain some of these coefficients to be zero.

The conditional value of not adopting $v_{i,0,t}$ is

$$v_{i,0,t} = u_{m,0,t} + \beta \overline{V}_{m,t+1}.$$

where the ex ante value function is now specific to market m and given by

$$\overline{V}_{m,t+1} = 0.577 + \ln \sum_{j=0}^{J} \exp(v_{i,j,t+1})$$

Finally, the logit choice probabilities in market m are

$$s_{m,j,t} = \frac{\exp(v_{i,j,t})}{\sum_{j'=0}^{J} \exp(v_{i,j',t})}. \tag{14}$$

As before, one could in principle consider to set the choice probabilities equal to the observed local market shares $s_{m,j,t} = q_{m,j,t}/N_{m,t}$, where $q_{m,j,t}$.is the actual number of adopters in market m of alternative j at period t and $N_{m,t}$ is the potential number of adopters, $N_{m,t} = N_m - \sum_{\tau=1}^{t-1} \sum_{j=1}^{J} q_{m,j,\tau}$ (with N_m is the total number of households). In principle, we could then take similar steps as for the country-level aggregate model to obtain a regression equation at the local market, parallel to (12). In practice, however, this regression approach is not possible because we observe many zero market shares at the disaggregate local level ($q_{m,j,t} = 0$), so that the logarithmic expressions in the Hotz-Miller and Berry inversions are not defined. We therefore take an alternative approach, which essentially amounts to combining the moment conditions from the aggregate model with a set of micro-moments that consist of the score vector from the likelihood function of the model. We outline the details of this procedure in Appendix A.3.

4 Empirical results

We first discuss our main findings with a focus on the estimated discount factor (subsection 4.1). To interpret these findings more thoroughly, we then perform a detailed sensitivity analysis with respect to alternative assumptions about how future payoffs enter utility (subsection 4.2). Finally, we use the parameter estimates to consider the budgetary impact of an alternative policy to promote PV adoption (subsection 4.3).

4.1 Main findings

Table 1 provides summary statistics of the included variables and instruments for the sample on which we estimate the model (May 2009 – December 2012).

The first panel shows summary statistics for the number of adopters. At the aggregate country level, we observe the number of adopters for 5 levels of capacity during 44 months, resulting in 220 observations. At the disaggregate level, we observe the number of adopters for 9,182 local markets, resulting in more than 2 million observations. The average number of adopters per capacity level is 894 at the country level, and it has always been positive for every capacity and month. At the local market level, the average number of adopters is evidently much smaller at 0.10. Because of the highly disaggregate level, the number of adoptions is zero for many local markets. The median number of adopters for a capacity level/month/local market is actually zero.

The second panel presents information on the components of the price variable. This shows for example that the investment price of a PV has on average been 20,700€, with a large standard deviation both because of falling prices over time and large differences depending on the capacity size. The third panel shows the excluded instruments, i.e. the variables that do not enter the model directly but are correlated with the endogenous investment cost and electricity price.

The fourth panel shows information on the household characteristics for the cross-section of 9,182 local markets. This shows for example that the household size is on average 2.47, but varies between 1 and 6. Similarly, median yearly income is on average $24,000$ EUR, and varies between $4,800$ and $51,800$ across the statistical sectors.

Table 1: Summary statistics

Variable	Notation	Mean	Std. Dev.	Min	Median	Max	Obs.
Adoptions							
Country level	$q_{j,t}$	894.17	1297.26	4	311	7164	220
Local level	$q_{m,j,t}$	0.10	0.41	0	0	26	2,020,040
Price variable (in 10^3 EUR)							
Investment cost	$p_{j,t}^{GROSS}$	20.70	10.85	48.20	19.61	50.82	220
Monthly GCC subsidies	$p_{j,t}^{GCC}$	0.14	0.08	0.01	0.13	0.35	220
Monthly electricity bill savings	$p_{j,t}^{EL}$	0.09	0.04	0.03	0.09	0.17	220
Tax cut year 1	$taxcut_{j,t+12}$	2.63	1.62	0	3.69	3.69	220
Tax cut year 2	$taxcut_{j,t+24}$	1.83	1.57	0	2.44	3.36	220
Tax cut year 3	$taxcut_{j,t+36}$	1.20	1.50	0	0	3.36	220
Tax cut year 4	$taxcut_{j,t+48}$	0.55	1.11	0	0	3.36	220
Excluded instruments							
Module price (10^3 EUR)	$p_{j,t}^{MOD}$	7.81	5.01	10.60	6.56	2.33	220
Oil price (EUR / barrel)	p_t^{OIL}	68.37	12.10	40.69	71.20	88.37	44
Local market variables (N_m and D_m)							
Households	N_m	295.26	320.88	1	191	3608	9,182
Pop. density (10^4 inhab / m^2)		0.16	0.24	0.00	0.09	2.89	9,182
Average house size		5.93	0.64	1.85	5.96	9	9,182
Average household size		2.47	0.34	1	2.49	6	9,182
Median income (10^4 EUR)		2.40	0.36	0.48	2.40	5.18	9,182
% home owners		0.77	0.17	0	0.82	1	9,182
% higher education		0.26	0.11	0	0.25	1	9,182
% foreign		0.06	0.09	0	0.03	1	9,182

Notes: The total number of observations is 2,020,040 = 44 time periods x 5 capacity choices x 9,182 local markets. All prices are corrected for inflation using the HICP and set to prices of January 2013. Half-yearly electricity prices extrapolated using cubic spline interpolation, missing values on local market level replaced by averages within the 308 municipalities (642 markets for median income and between 0 and 146 markets for other variables).

Table 2 shows the empirical results. We begin with a discussion of specification (1) and (2), which are estimated with country-level data and do not account for household heterogeneity. Both specifications include fixed effects for each capacity size using the most popular 4kW system as the base. Specification (2) in addition includes several time variables: seasonal dummies and a trend.

The investment price coefficient is negative and statistically significant, meaning that consumers responded positively to the declining investment prices of PV systems. The mag-

Table 2: Empirical results

	(1) Dynamic		(2) + time controls		(3) + micro-moments	
Price sensitivity in 10^3 EUR ($-\alpha$)	-0.470***	(0.097)	-0.438***	(0.115)	-0.547***	(0.116)
Monthly discount factor (β)	0.9884***	(0.0025)	0.9896***	(0.0016)	0.9900***	(0.0016)
Annual real interest rate ($r \equiv \frac{1}{\beta^{12}} - 1$)	15.05%***	(3.44%)	13.37%***	(2.23%)	12.78%***	(2.22%)
Choice-specific constants (ξ_j)						
Common constant	-1.353	(16.465)	-645.698	(1,033.221)	-1013.889	1114.771
2kW	-1.820***	(0.567)	-1.589***	(0.436)	-1.319**	(0.557)
6kW	-0.516	(0.600)	-0.741	(0.476)	-1.107*	(0.594)
8kW	-2.461**	(1.168)	-2.923***	(0.913)	-3.715***	(1.153)
10kW	-2.619	(1.698)	-3.319**	(1.308)	-4.588***	(1.671)
Control variables (γ)						
Linear time trend			1.243	(2.022)	1.485	(2.178)
Spring			-0.177	(0.469)	-0.167	(0.468)
Summer			-0.049	(0.492)	-0.040	(0.493)
Fall			-0.021	(0.357)	-0.028	(0.358)
Local market variables (Λ)						
Interactions with constant						
Pop. density (10^4 inhab / m^2)					2.701	(4.106)
Average house size					-8.856***	(2.439)
Average household size					58.063***	(10.041)
Median income (10^4 EUR)					41.120***	(7.536)
% home owners					99.130***	(17.976)
% higher education					43.036***	(11.957)
% foreign					-292.078***	(50.285)
308 Municipality dummy variables					YES	
Interactions with capacity difference to benchmark 4kW						
Pop. density (10^4 inhab / m^2)					-0.694***	(0.018)
Average house size					0.055***	(0.005)
Average household size					0.085***	(0.011)
Median income (10^4 EUR)					-0.087***	(0.024)
% home owners					-0.059**	(0.026)
% higher education					-0.108***	(0.027)
% foreign					0.272***	(0.030)
Interaction with price						
Median income (10^4 EUR)					0.047***	(0.006)
Obs. macro moments (JxT)	220		220		220	
Obs. micro moments (NxJxT)	0		0		2,020,040	

Notes: Macro moments clustered within 44 time periods, micro moment clustered within 9182 local markets. Instruments are approximations of optimal instruments (Chamberlain, 1987). Standard errors of r, common constant, linear time trend and interaction of local market variables with constant, obtained via delta method. *** p<0.01, ** p<0.05, * p<0.1

nitude of the investment price coefficient is comparable for both specifications (-0.470 and -0.437). The estimated (real) discount factor measures the valuation of the future benefits relative to the investment price. The monthly discount factor is very similar for both specifications (0.988 and 0.990), and differs significantly from 1. It is more informative to convert the monthly discount factor in an annual implicit interest rate. The results show that the real implicit interest rate is 15.1% in the first specification (standard error of 3.4%), and a similar 13.4% in the second specification (standard error of 2.2%). These estimates are much higher than the interest rate on risk-free or moderate risk investments, such as savings accounts or checking accounts. Imperfect capital markets and high market interest rates may in principle be responsible for this, but this is not plausible in this market because between 2009 and 2011 the federal government subsized loans for environmentally friendly investments.[13] This then suggests there is much more consumer myopia in investment decisions for new technologies such as PV installations than has been observed in recent work on mature technologies such as the car industry. Put differently, if consumers would have been more forward looking, the generous GCC subsidy policy would have led to an even faster adoption of PV systems.

In the next subsection, we will investigate the sources of the high interest rates, by investing the sensitivity of the estimates with respect to alternative assumptions.

Before turning to this, we discuss the results of specification (3), which is estimated with local market data and accounts for household heterogeneity. The investment price coefficient increases somewhat (from -0.437 to -0.547), which can be explained by the inclusion of an interaction variable for median income with price. This interaction effect shows that high income households tend to be less price sensitive, so that for the average income household the price coefficient is close to the estimate from the aggregate model.

Most importantly, the estimated discount factor remains almost identical when we account for household heterogeneity. The implied annual implicit interest rate is 12.8% (compared with 13.4% in the model without heterogeneity), so also in the richer model there is evidence of consumer myopia in adopting the new PV technology.

The coefficients for most of the household characteristics have an intuitive interpretation. First consider how the household characteristics influence the valuation for the reference PV with a capacity of 4kW. As expected, this valuation increases with household size, income, home ownership and education level. Furthermore, the valuation for the 4kW PV is lower for foreign nationals and larger houses. Now consider the interaction effects, i.e. how the household characteristics influence the valuation for the capacity size of PVs. A

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

large capacity is especially valued among large households and households living in large houses or in areas with a low population density. The other coefficients indicate that some of the valuations for the reference PV of 4kW become less important when the size of a PV increases. For example, home owners and highly educated households have a positive valuation for the reference PV of 4kW, but this positive valuation becomes less important for larger PV systems.

4.2 Sensitivity analysis

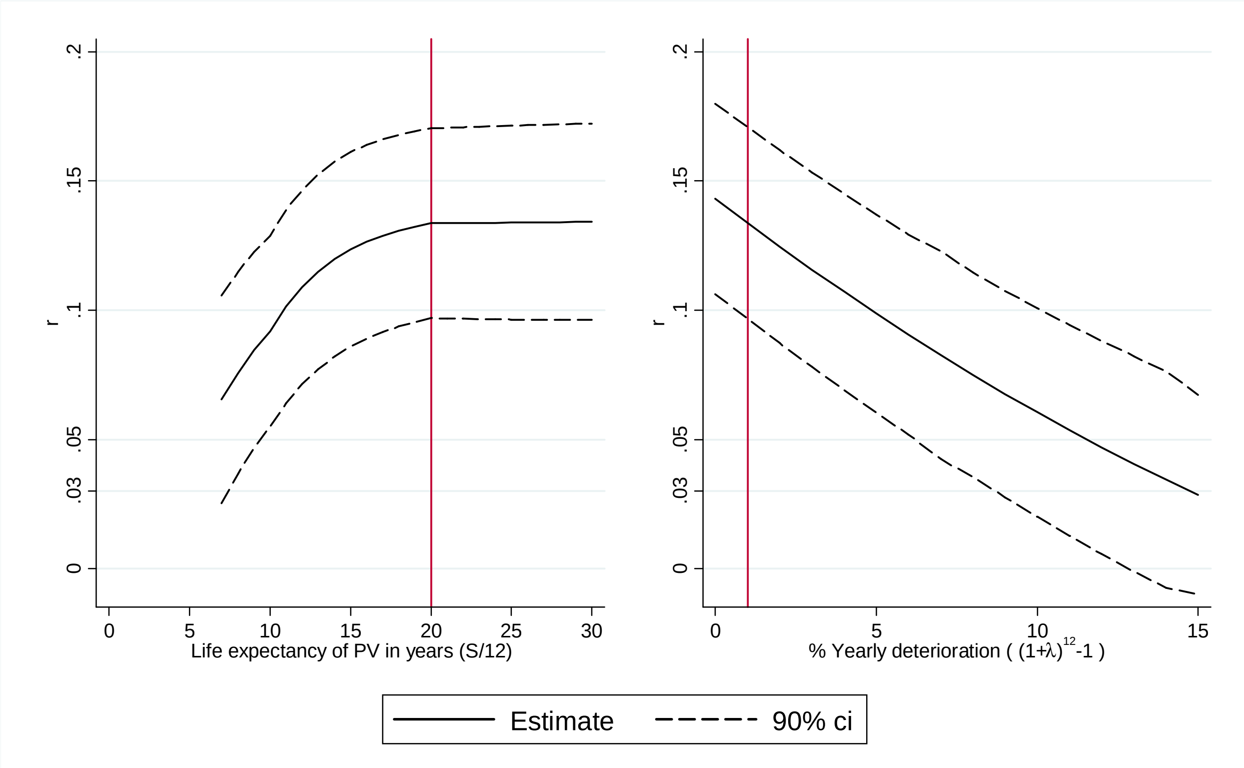
Before turning to the implications for the government's GCC policy, we consider several possible explanations for the high estimate of the real implicit interest rate. We look into this by assessing the impact of the various assumptions we made in section 3.1 when constructing the up-front investment price and the future benefits. As such, this also serves as a sensitivity analysis of our main results. We use the aggregate adoption model, because the estimates of the implicit interest rate were very close to the disaggregate model with household heterogeneity and because it is computationally much faster so that a very detailed sensitivity analysis becomes possible.

We distinguish between three possible explanations for the high implicit interest rate: the durability of the PV technology, consumer expectations about government's commitment, and intrinsic consumer myopia.

Durability of the PV technology A first explanation for the high implicit interest rate is that the durability of the PV technology is lower than assumed in our main specification, so that the future benefits are in practice lower. Figure 5 shows how the estimated implicit interest rate varies as we change the assumptions on the durability of the PV technology: the life expectancy S and the yearly deterioration rate λ. The vertical lines denote the assumptions made in the base model.

Figure 5 shows that the estimated implicit interest rate remains robust if we increase the life expectancy S above the assumed value of 20 years or if we reduce it by several years. We only estimate a low, market-oriented implicit interest rate under unrealistically low values for the life expectancy, say 10 years or shorter. The estimated implicit interest rate decreases as we assume a higher value for the deterioration rate λ in the production of electricity. However, even an unrealistically high deteriation rate of 5% anunally does not bring market interest rate within the confidence interval of our estimates. We conclude that the estimated implicit interest rate would only become close to market interest rates under unrealistic assumptions regarding the durability of the PV technology.

Figure 5: Estimate of annual real interest rate under different investment assumptions



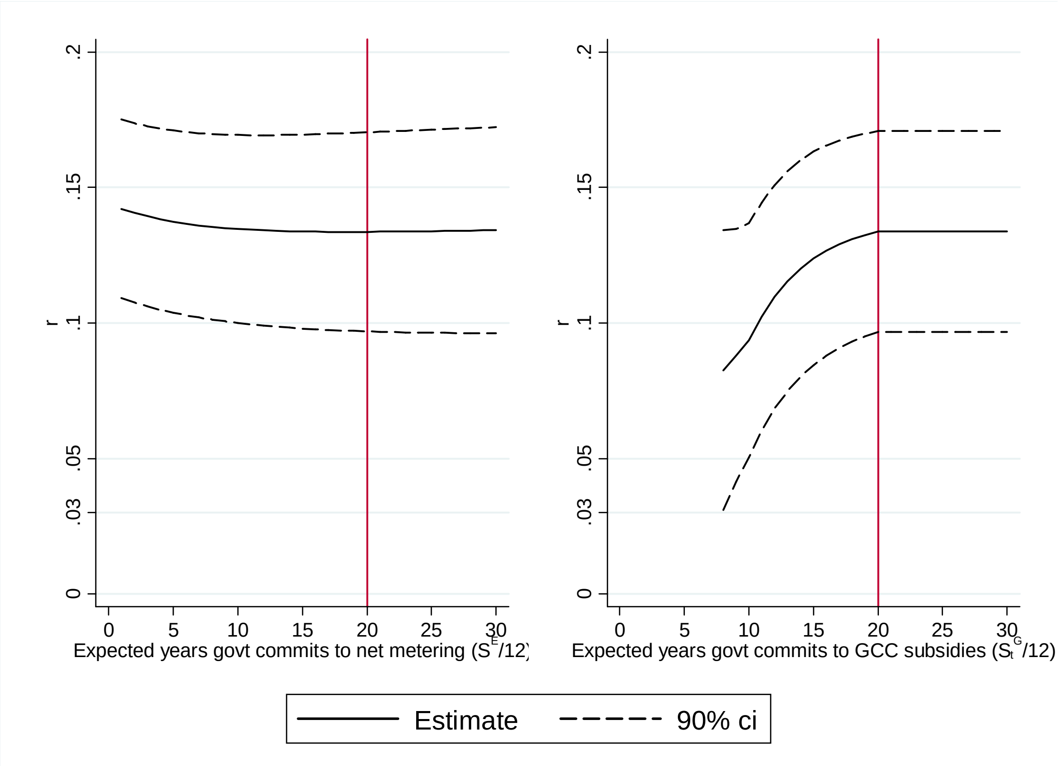
Note: vertical line indicates assumption used in the baseline model

Consumer expectations about government's commitment A second explanation for the high implicit interest rate is that consumers may fear that the government will not fulfill its subsidy policy. The government had guaranteed the net metering principle for the life time of a PV (assumed to be 20 years), and had similarly guaranteed the payment of the GCC subsidies for a fixed number of years (15 or 20 years, depending on the date of installation). Figure 6 shows how the estimated implicit interest rate varies as consumers expect a different duration for net metering benefits or GCC subsidies, i.e. when we either change the value of S^E or S_t^G in (2).[14]

Changes in expectations about net metering does not affect the estimated implicit interest rate. This is interesting, because the government has in practice introduced a fee for using net metering, but any anticipation of this by consumers cannot explain the high implicit interest

[14]A breach in both contracts is equivalent to the change in the lifetime of a PV, which we considered earlier in Figure 5.

Figure 6: Estimate of annual real interest rate under different bliefs in goverment's commitments



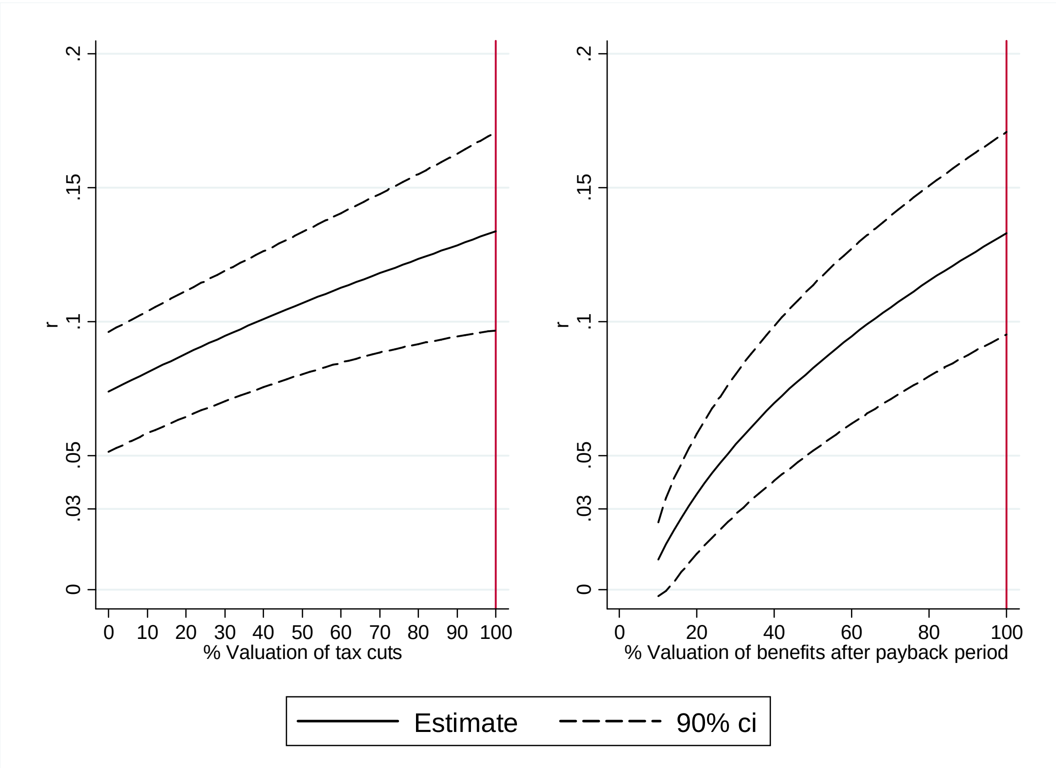
Note: vertical line indicates assumption used in the baseline model

rate. In contrast, a change in expectations about GCC subsidies does have an impact on the results. If consumers fear that the government will remove the 20 year subsidy program already after 5 years, the estimated interest rate comes close to market rates. Hence, one could rationalize consumer behavior if they expect that the government will breach the contract by removing the subsidies after a short period. We note however that such a breach in contract has not actually occurred.

These figures also highlight how identification of the discount factor in our model comes mainly from changes in GCC subsidies, rather than changes in net metering benefits. This can be explained by the larger variation in the GCC price than in the electricity price.

Consumer myopia A remaining explanation for the high implicit interest rate would be that this is evidence for consumer myopia. It is then still interesting to ask where such myopia might come from. A first possibility is that consumers only take into account the future subsidies but fail to take into account the tax cuts. Another possibility is that consumers only correctly value the benefits up to the pay-back period, and undervalue the benefits after that. The pay-back period is that time when all collected beneifts are equal to the investment costs: this number is often quoted in advertizing or media coverage, so it may be an important source of information for households who cannot do a net present calculation. Figure 7 shows how the estimated implicit interest rate varies if consumers do not correctly account for the tax cuts or for the benefits after the pay-back period.

Figure 7: Estimate of annual real interest rate under bounded rationality



Note: vertical line indicates assumption used in the baseline model

To assess the role of an incorrect valuation of the tax cuts, we multiply the tax cut benefits by a parameter between 0 and 100%. The estimated implicit interest rate remains high even for quite severe undervaluation of the tax cuts. Hence, a failure to take into account the tax cuts may partly explain household myopia, but the high interest rate appears to be mainly due to undervaluation of the GCC benefits.

To assess the role of the payback period, we multiply the benefits after the payback period by another parameter between 0 and 100%. The estimated implicit interest rate becomes close to the market interest rate for strong undervaluation after the payback period (at about 40% or lower of the actual benefits).

In sum, our finding of a high implicit interest rate remains robust after using more conservative assumptions regarding the durability of the PV technology. Potential explanations for the high implicity interest rate are consumer distrust in the government's commitment to provide the GCC subsidies for up to 20 years, or intrinsic consumer myopia, for example stemming from a failure to take into account benefits after the payback period.

4.3 Policy implication

Our finding that consumers use a real implicit interest rate of 13% when deciding to adopt a PV system has an important policy implication. One may ask the question whether the government could not have achieved the same level of adoption by removing the future GCC subsidy program and instead paying an equivalent upfront subsidy, and borrowing the required amount on the capital market at the long run government bond real interest rate of 3%. More precisely, according to the utility specification (2) and (3), a household who adopts a PV system j at time t perceives a net present value from the GCC subsidy during $S_t^G = 240$ months of

$$NPV_{j,t} = \frac{1 - ((1-\lambda)(1-\pi)\beta)^{S_t^G}}{1-(1-\lambda)(1-\pi)\beta} p_{j,t}^{GCC},$$

where the estimated monthly discount factor $\beta = 0.9896$ corresponds to an implicit annual interest rate of $r = \beta^{-12} - 1 = 13.7\%$. The government could thus have paid out the amount $NPV_{j,t}$ as an upfront subsidy program. If the government instead spreads the subsidies over the next S_t^G months, the net present value at the government bond interest rate $r_{gov} = \beta_{gov}^{-12} - 1 = 3\%$ amounts to

$$NPV_{j,t}^{ACTUAL} = \frac{1 - \left((1-\lambda)(1-\pi)\beta_{gov}\right)^{S_t^G}}{1-(1-\lambda)(1-\pi)\beta_{gov}} p_{j,t}^{GCC}.$$

Hence, the government could have reached an identical number of adopters with an upfront subsidy $NPV_{j,t}$ and saved the amount $NPV_{j,t}^{ACTUAL} - NPV_{j,t}$ for a household that adopts PV system j at time t. Summing this over all adopters, we find that the cost of the actual subsidy program was € 3.77 billion in net present value terms, while the cost of an upfront subsidy program would have been only € 2.00 billion (actualized to 2013). Hence, the government could have achieved the same adoption rates at only 53.3% of the current subsidy costs, amounting to a saving of € 1.77 billion (with a 90% confidence interval of [€1.46–€2.02] billion.[15] This is a saving of almost € 700 per household, which is a very large number given that only 8.5% of the households had adopted a PV by June 2013. Savings would have been even higher if the government would have abandoned the net metering principle (future benefits through electricity cost savings $p^{EL}_{j,t}$) in favour of an even larger upfront subsidy, or if the government would also have followed an upfront subsidy policy for commercial users (capacity size higher than 10kW).

5 Conclusion

This paper studied the incentives to adopt a new renewable energy technology for electricity production, and the role played by upfront investment and future production subsidies. We considered a generous subsidy program for solar PV adoption, and exploited rich variation at pre-announced dates in the future subsidy conditions. Although the program led to a massive adoption of solar PV systems, we find that households significantly undervalued the future benefits from the new technology, which has important budgetary and distributional implications. The government could have saved 47% or €1.8 billion by giving upfront investment subsidies, and it essentially shifted the subsidy burden to future electricity consumers.

We contribute to the literature on how consumers discount future energy costs. We show that consumers are apparently considerably more myopic in the adoption decision of an entirely new green technology, than in the energy-saving investment decision of existing technologies.

We adopted a tractable dynamic model of technology adoption, and several directions of future work are possible. First, with our data it may be possible to further exploit the local market data and estimate the distribution of the discount factor conditional on sociodemographic characteristics. This would make it possible to further understand the distributional effects of the subsidization policy. Another path of research is to extend the model to account for peer effects, which may provide a rationale for a subsidy path that is declining over time.

Third, it would be interesting to use our framework to study the adoption of new technologies in other applications. Regarding renewables, we focused on residential PV adoption, and further work could investigate whether investment myopia also applies to commercial PV adopters. It would also be interesting to apply our framework to other countries or regions, or other renewable technologies, such as wind power, to analyze how different subsidy schemes may influence the outcomes.

[15] To calculate the confidence interval, we take 1000 draws of β which as a GMM estimate is normally distributed with mean of 0.9896 and standard error of 0.0016. We calculate the government loss for each draw of β to obtain a distribution of this loss.

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A Appendix

A.1 Data construction

As discussed in the text, the main dataset contains information of all installed PVs across Flanders during 2006–2012. We combine this dataset with various additional datasets on prices, investment tax benefits, electricity cost savings, GCCs and socio-demographic data at the local area level.

A.1.1 PV installations

The main dataset comes from VREG, the Flemish regulator of the electricity and gas market. The data records the following three key variables for every new PV installation: the adoption date, the size of the installation and the address of the installation. We aggregate the data to the monthly level, distinguishing between five categories of capacity sizes: 2kW, 4kW, 6kW, 8kW and 10kW. Each category includes all capacity sizes up to the indicated maximum. For example, a capacity size of 6kW refers to all capacity sizes between 4kW and 6kW. To focus on residential solar panels, we exclude all installations with a capacity size larger than 10kW. This is a commonly used cut-off point for distinguishing between residential and non-residential PVs (see e.g. Kwan (2012)). Furthermore, systems of more than 10kW do not qualify from the same public support measures in Flanders.

Our main model aggregates the number of installations to the level of the entire region of Flanders. The extended model considers the highly disaggregate level of the statistical sector, as defined by ADSEI, the Belgian statistical office. The region has 9,182 statistical sectors, with on average slightly more than 600 inhabitants. To organize the data at the level of the statistical sector, we use of a geographic dataset from ADSEI that assigns street addresses of each installation to statistical sectors.

A.1.2 Gross investment price

We obtained price information of PV systems from two independent sources: an internet forum, zonstraal.be, where consumers posted their received offers; and a website, comparemysolar.be, which contains historical data. This resulted in a dataset of 2,659 offers from May 2009 until December 2012. To construct a monthly price index for each of the five capacity size categories (between 2kW and 10kW), we then proceed as follows. For each month and each size category we take the median price per watt, multiplied by the size of the category. If there are less than ten price observations in a given month and category (usually the less popular 8kW and 10kW PVs), we consider the median to be insufficiently accurate. As a price measure for these cases, we use the prediction from a quantile regression model for the median price per watt on monthly fixed effects, capacity fixed effects and capacity interacted with a linear trend.

To combine the price information with the data on PV installations per month and per size category, we assume there was a time lag of two months between the posted prices and the actual installment. In some months, especially when subsidies would drop in the near future, consumers report the expected waiting time together with the posted price offer. If such information on the announced waiting time was available, we use this instead of the assumption of a two month time lag.

A.1.3 Public support measures

We obtained information of public support measures from various sources.

Investment tax credits Tax credits fall under the competence of the Belgian Federal government. Information on a doubling of the tax credit ceilings comes from the official document "Programmawet" of 28 December 2006, and announcements on the the website of the government agency VEA before and after this publication.[16] Information on spreading tax cuts or splitting bills over multiple years comes from newspaper articles[17] and the Economic Recovery Plan of the Federal Government (March 2009). Details about the abolishment

[16] Announcements on the doubling of the tax credit ceiling on 6 and 16 December 2006 and information on the increase from 2000 to 2600€ between 1 and 21 March 2007 on VEA's website energiesparen.be. Historic copies from this website are on Internet Archive (https://web.archive.org).

[17] Gazet Van Antwerpen: "Zonnepanelen zijn tot drie keer fiscaal aftrekbaar", 19 Mei 2008; Het Nieuwsblad: "Belastingvoordeel klanten nekt installateurs zonnepanelen", 13 December 2008

of the tax cut were found on the official website of the finance department of the federal government.[18] Information on the VAT rules also can be found on this website.[19]

We combine this information with the price data to compute the net investment price, as described more formally in the next Appendix.

Electricity cost savings and Green Current Certificates (GCCs) Information on retail electricity prices comes from Eurostat. These data are half-yearly, and we transform it to monthly data using a cubic spline interpolation. We multiply the electricity prices with the expected electricity production to compute the expected electricity cost savings, as described more formally in the next Appendix.

Information on the background and start of the GCC policy relating to PVs in 2006 comes from the website of the Flemish energy regulator VREG (www.vreg.be) and from official documents and government information brochures.[20] The price of a GCC was guaranteed for a fixed period, but it was initially expected that GCCs could continue to be sold at the (much lower) market price for the entire life time of the PV system. The renewal of the energy decree in 2012 (Flemish Energy Decree, 30 July 2012) no longer allowed for the possibility to obtain GCCs after the experation of the fixed period with the guaranteed price. In practice, this does not change much because the life expectancy of PV systems (about 20 years) is close to the fixed period with the guaranteed price.

Information on the financial details of the GCC policy comes from the Belgian energy regulator CREG (2010). Announcements of new subsidy policies were gathered from 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.

Based on the information from these sources, Table A1 provides an overview of the policy support measures during the period 2006–2012. Figure 1 in the text makes use of this

[18]http://www.minfin.fgov.be/portail2/nl/current/spokesperson-11-11-30.htm, consulted 14 May 2014.

[19]http://minfin.fgov.be/portail2/nl/themes/dwelling/renovation/vat.htm, consulted 14 May 2014.

[20]See the Flemish Energy Decree, changed on 6 July 2012, KB 10 February 1983, changed by the Flemish government on 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).

information to express the various subsidies in present value terms.

Table A1: 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	0%	40%	2600 x 4**
2010	350	20	0%	40%	2600 x 4**
2011/01-2011/06	330	20	0%	40%	2600 x 4**
2011/07-2011/09	300	20	0%	40%	2600 x 4**
2011/10 - 2011/12	270	20	0%	40%***	2600 x 4***
2012/01 - 2012/03	250	20	0%	0%	0
2012/04 - 2012/06	230	20	0%	0%	0
2012/07	210	20	0%	0%	0
2012/08 - 2012/12	90	10	0%	0%	0
2013/01-2013/06	21.39****	15	0%	0%	0

*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

A.1.4 Socio-demographic characteristics

For the disaggregate model at the local market level we collected socio-demographic information per statistical sector. This data is freely downloadable from the website of ADSEI, the Belgian Statistics Office. We have population data for each statistical sector in 2011 on the following variables: income, population density, house size (number of rooms), household size, % of house owners, % with a higher education degree and % foreign. For confidentiality reasons, some variables are not reported when the number of households in the statistical sector is very small. This applies to a small subset of statistical sectors. In these cases, we use the average of the municipality to which the statistical sector belongs.

A.2 Optimal instruments

We estimate the model using an approximation of Chamberlain's (1987) optimal instruments. While any set of exogenous instruments leads to consistent estimates, more efficient and stable estimates can be found using approximations to optimal instruments . We focus here on the model that only uses macro data but we use a similar set of instruments to interact with the macro-moments in the model that includes micro-moments.

The conditional moment conditions are

$$E\left(\widetilde{\xi}_{j,t}(\theta)|z_{j,t}\right) = 0$$

where

$$\widetilde{\xi}_{j,t}(\theta) = \ln s_{j,t}/s_{0,t} - \left(x_{j,t} - \beta x_{1,t+1}\right)\gamma + \alpha\left(p_{j,t}(\beta) - \beta p_{1,t+1}(\beta)\right) - \beta \ln s_{1,t+1}$$

Defining the parameter vector $\theta = (\alpha, \beta, \gamma)$, the optimal instrument matrix of Chamberlain (1987) for a single-equation GMM estimator is:

$$\begin{aligned} D_{jt}(z_{jt}) &= \left(E\left[\left. \frac{\partial \widetilde{\xi}_{j,t}(\theta)}{\partial \theta'} \right| z_{jt} \right] \right) \\ &= \left(E\left[\left. \frac{\partial \widetilde{\xi}_{j,t}(\theta)}{\partial \alpha} \right| z_{jt} \right] \quad E\left[\left. \frac{\partial \widetilde{\xi}_{j,t}(\theta)}{\partial \beta'} \right| z_{jt} \right] \quad E\left[\left. \frac{\partial \widetilde{\xi}_{j,t}(\theta)}{\partial \gamma'} \right| z_{jt} \right] \right) \end{aligned}$$

We now derive the optimal instruments for these various parameters. First, for the linear parameter vector γ we simply have:

$$E\left[\left. \frac{\partial \widetilde{\xi}_{j,t}(\theta)}{\partial \gamma'} \right| z_{jt} \right] = -E\left[x_{j,t} - \beta x_{1,t+1}|z_{jt}\right] = -\left(x_{j,t} - \beta x_{1,t+1}\right). \tag{15}$$

The optimal instrument for γ is therefore just a difference term for the exogenous variable $x_{j,t}$, where β is substituted by an estimate $\widehat{\beta}$ in a first stage using non-optimal instruments.

For the other linear parameter α we have

$$E\left[\left. \frac{\partial \widetilde{\xi}_{j,t}(\theta)}{\partial \alpha} \right| z_{jt} \right] = E\left[p_{j,t}(\beta) - \beta p_{1,t+1}(\beta)|z_{jt}\right] = E\left[p_{j,t}(\beta)|z_{jt}\right] - \beta E\left[p_{1,t+1}(\beta)|z_{jt}\right]. \tag{16}$$

In this expression the expected price is

$$\begin{aligned} E\left[p_{j,t}(\beta)|z_{jt}\right] &= E\left[p_{j,t}^{INV}(\beta)|z_{jt}\right] - \rho_t^G(\beta)\, E\left[p_{j,t}^{GCC}|z_{jt}\right] - \rho^E(\beta)\, E\left[p_{j,t}^{EL}|z_{jt}\right] \\ &= E\left[p_{j,t}^{GROSS}|z_{jt}\right] - \sum_{\tau=1}^{4} \beta^{12\tau} E\left[taxcut_{j,t+12\tau}|z_{jt}\right] \\ &\quad -\rho_t^G(\beta)\, p_{j,t}^{GCC} - \rho^E(\beta)\, E\left[p_t^{EL}|z_{jt}\right] k_j \end{aligned} \tag{17}$$

where the capitalization factors $\rho_t^G(\beta)$ and $\rho^E(\beta)$ are defined in (2) and depend on the discount factor β. The optimal instrument for α thus also depends on β for which we use an estimate $\widehat{\beta}$ in a first stage using non-optimal instruments. In contrast with the optimal instrument for γ, it is now also necessary to compute several conditional expectations, namely for the upfront investment cost of a solar panel, the future tax cuts and the electricity price. The predicted gross investment cost $E\left[p_{j,t}^{GROSS}(\beta)\middle|\, z_{jt}\right]$ is obtained from a Poisson regression model with exponential conditional mean (e.g. Silva and Tenreyro (2006). We include logarithmic regressions and fixed effects for each alternative j. We then obtain $E\left[p_{j,t}^{GROSS}(\beta)\middle|\, z_{jt}\right]$. Based on this predicted value we can also calculate the predicted future eligble tax cuts $E\left[taxcut_{j,t+12\tau}|z_{jt}\right]$. The predicted electricity price $E\left[p_t^{EL}|z_{jt}\right]$ is obtained similarly using the oil price as an exogenous regressor. We show the regression results in Tables A2 and A3. Note that any misspecification of these structural assumptions only influences the optimality of our instrument set and not the consistency of the estimates.

Finally, the optimal instrument for the nonlinear parameter β is

$$
\begin{aligned}
E\left[\left.\frac{\partial\widetilde{\xi}_{j,t}(\theta)}{\partial\beta}\right| z_{jt}\right] &= x_{1,t+1}\gamma - E\left[\ln s_{1,t+1}\middle|\, z_{jt}\right] \\
&\quad +\alpha\left(E\left[\left.\frac{\partial p_{j,t}(\beta)}{\partial\beta}\right| z_{jt}\right] - E\left[p_{1,t+1}(\beta)\middle|\, z_{jt}\right] - E\left[\left.\frac{\partial p_{1,t+1}(\beta)}{\partial\beta}\right| z_{jt}\right]\beta\right)
\end{aligned} \tag{18}
$$

In the above expression the expected value of the derivative of price with respect to β is

$$
\begin{aligned}
E\left[\left.\frac{\partial p_{j,t}(\beta)}{\partial\beta}\right| z_{jt}\right] &= -\sum_{\tau=1}^{4} 12\tau\beta^{12\tau-1}E\left[taxcut_{j,t+12\tau}|z_{jt}\right] \\
&\quad -\frac{\partial\rho_t^G(\beta)}{\partial\beta}p_{j,t}^{GCC} - \frac{\partial\rho^E(\beta)}{\partial\beta}E\left[p_t^{EL}|z_{jt}\right]k_j \\
&\quad -E\left[\ln s_{1,t+1}|z_{jt}\right]
\end{aligned} \tag{19}
$$

where the derivatives with respect to the capitalization factors $\rho_t^G(\beta)$ and $\rho^E(\beta)$ are easily computed from (2) and (3). The optimal instrument for β therefore depends on all parameters $\theta=(\alpha,\beta,\gamma)$, for which we obtain a consistent first stage estimate using non-optimal instruments. There is also an additional expectation term for CCP term, i.e. the predicted next period market share of alternative 1, $E\left[\ln s_{1,t+1}|z_{jt}\right]$. We obtain this from a linear regression on several variables, similar to the prediction of the first stage of an IV regression, as shown in Table A4.

To summarize, our final estimation procedure takes the following steps:

- Estimate a 2-step efficient GMM model with instruments $p_{j,t+1}^{MOD}, p_{1,t+1,}^{MOD}p_{j,t}^{GCC}, p_{1,t+1}^{GCC}$ and $x_{j,t}$ to obtain an initial consistent estimate of α, β and γ

- Compute the conditional expectations for the investment price, the electricity price and the CCP term using the regression models
- Estimate the GMM model again, but now using the approximation of optimal instruments, as given by (15), (16) and (18), after substituting (17) and based on the initial consistent estimates of α, β and γ.
- Repeat the last two steps until convergence with the updated parameter estimates.[21]

Table A2: Estimation results for electricity price

Variables	$E\left[p_t^{EL} \mid z_{jt}\right]$
Log of oil price	0.1832***
	(0.0178)
Constant	4.5992***
	(0.0729)
Observations	44

Poisson regression model of exponential conditional mean
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[21] In practice one extra iteration changes some results but afterwards the changes are limited. Therefore we repeat the estimation only 5 times.

Table A3: Estimation results for predicting PV investment cost

Variables	$E\left[p_{j,t}^{GROSS} \mid z_{jt}\right]$
Log of PV module price x kW	0.4986***
	(0.0633)
4kW	0.2018***
	(0.0213)
6kW	0.3103***
	(0.0310)
8kW	0.3999***
	(0.0391)
10kW	0.4679***
	(0.0454)
log of GCC benefits	0.1124*
	(0.0582)
Constant	4.6310***
	(0.3156)
Observations	220

Poisson regression model of exponential conditional mean

Standard errors in parentheses, clustered within time period

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

Table A4: Estimation results for predicting log of CCP

Variables	$E\left[\ln s_{1,t+1} \mid z_{jt}\right]$
PV module price x 4kW in t+1	-0.0017***
	(0.0006)
PV module price x 4kW in t+2	0.0017***
	(0.0005)
GCC benefits of 4kW in t+1	0.1321***
	(0.0166)
GCC benefits of 4kW in t+2	-0.0321*
	(0.0171)
Oil price x 4kW in t+1	-0.0130
	(0.0090)
Oil price x 4kW in t+2	0.0010
	(0.0082)
Spring dummy in t+1	0.2065
	(0.3006)
Summer dummy in t+1	0.0469
	(0.3813)
Fall dummy in t+1	0.3919
	(0.3399)
t+1	0.2624***
	(0.0534)
Spring dummy in t+2	0.1404
	(0.3013)
Summer dummy in t+2	0.4603
	(0.4033)
Fall dummy in t+2	0.0299
	(0.2675)
Constant	-175.0745***
	(32.2514)
Observations	44

OLS regression model of linear conditional mean

Robust standard errors in parentheses

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

A.3 Estimation of model with local market heterogeneity

Section 3.4 specified the model with local market heterogeneity. Our estimation approach for this model can be described in the following three steps.

Step 1. Maximum likelihood estimation including fixed effects $\widetilde{\delta}_{j,t}$
In this step we construct the likelihood function of observing the local market adoption data, and we maximize this likelihood function with respect to the parameters, including a large set of alternative/time fixed effects $\widetilde{\delta}_{j,t}$. We first make use of the Hotz-Miller CCP, $s_{m,1,t+1}$, to obtain an expression for $v_{i,0,t}$ that is parallel to that of (10) above[22]:

$$v_{i,0,t} = \beta\left(v_{i,1,t+1} - \ln s_{m,1,t+1}\right) \tag{20}$$

We then use the expressions for the conditional values $v_{i,j,t}$ and $v_{i,0,t}$, as given by (13) and (20), to write the choice probabilities (14) as:

$$\begin{aligned} s_{m,j,t} &= \frac{\exp(v_{i,j,t} - v_{i,0,t})}{1 + \sum_{j'=1}^{J} \exp(v_{i,j',t} - v_{i,0,t})} \\ &= \frac{\exp(\widetilde{\delta}_{j,t} + \widetilde{w}_{j,t}\lambda_m + \beta \ln s_{m,1,t+1})}{1 + \sum_{j'=1}^{J} \exp(\widetilde{\delta}_{j',t} + \widetilde{w}_{j',t}\lambda_m + \beta \ln s_{m,1,t+1})} \end{aligned} \tag{21}$$

where we define $\widetilde{\delta}_{j,t} \equiv \delta_{j,t} - \beta\delta_{1,t+1}$ and $\widetilde{w}_{j,t} \equiv w_{j,t} - \beta w_{1,t+1}$. We can write (21) more compactly as a function of the parameters to be estimated, $s_{m,j,t}\left(\theta, \widetilde{\delta}\right)$, where $\widetilde{\delta}$ is a vector with the alternative/time fixed effects $\widetilde{\delta}_{j,t}$ and θ is a vector with the remaining parameters (stacking the interaction effects in Λ and the discount factor β).

The maximization problem of the log likelihood function is then

$$\max_{\theta,\widetilde{\delta}} \ln L(\theta, \widetilde{\delta}) = \sum_{m,j,t} q_{m,j,t} \ln s_{m,j,t}(\theta, \widetilde{\delta}),$$

where $q_{m,j,t}$ is the observed number of adopters in local market m of alternative j at period t. Note that this contains a potentially large number of parameters, because of the set of fixed effects $\widetilde{\delta}_{j,t}$ $(J \times T)$.

Step 2. Instrumental variable regression of $\widetilde{\delta}_{j,t}$
The second step is an instrumental variable regression of the estimated fixed effects $\widetilde{\delta}_{j,t} \equiv \delta_{j,t} - \beta\delta_{1,t+1}$ after substituting the expressions of $\delta_{j,t}$ and $\delta_{1,t+1}$ based on (1). This gives the regression

$$\widetilde{\delta}_{j,t} = \left(x_{j,t} - \beta x_{1,t+1}\right)\gamma - \alpha\left(p_{j,t} - \beta p_{1,t+1}\right) + \widetilde{\xi}_{j,t}$$

[22] We follow Scott (2013) and use an inverse distance smoothed version of the local adoption rate of $j = 1$ in the next month. We also experimented with a kernel estimate, smoothing over observables and obtained similar results.

where $\widetilde{\xi}_{j,t}$ was already defined before for the aggregate model as $\widetilde{\xi}_{j,t} \equiv \xi_{j,t} - \beta\xi_{1,t+1}$. Hence, this regression is very similar to the aggregate model. In the disaggregate model the dependent variable consists of the estimated fixed effects $\widetilde{\delta}_{j,t}$ from the first step, while in the aggregate model the dependent variable, including the correction term, was $\ln s_{j,t}/s_{0,t} - \beta \ln s_{1,t+1}$. Price is given by (2), based on the estimate of β in the first step, and the instruments are the same as the ones used before in the aggregate model.

While this two-step approach yields consistent estimates of all parameters, it involves two issues. First, the discount factor β enters in both estimation steps, so that estimating β is not efficient. Second, the fixed effects $\widetilde{\xi}_{j,t}$ that form the dependent variable in the second step are estimates, so that the standard errors need to be corrected. We therefore proceed to a third step that overcomes both problems.

Step 3. Simultaneous GMM

The third step uses the parameter estimates from the first two steps as starting values, and then combines the moment conditions as implied by the first two steps in a simultaneous GMM framework. The first set of moment conditions consists of the score vector, i.e. the vector of the derivatives of log-likelihood function $\ln L(\theta, \widetilde{\delta})$.[23] The second set of moment conditions comes from the orthogality conditions $E\left(z_{j,t}\widetilde{\xi}_{j,t}(\alpha, \beta, \gamma)\right)$, i.e. the instruments interacted with the error term. The stacked vector of sample moment conditions is then

$$g(\theta, \widetilde{\delta}, \alpha, \beta) = \begin{pmatrix} \partial \ln L(\theta, \widetilde{\delta})/\partial(\theta, \widetilde{\delta}) \\ \sum_{j,t} z_{j,t}\widetilde{\xi}_{j,t}(\alpha, \beta, \gamma) \end{pmatrix}$$

The score $\ln L(\theta, \delta)/\partial(\theta, \widetilde{\delta})$ has an intuitive expression for the demographic parameters and the fixed effects:

$$\begin{aligned} \frac{\partial \ln L(\theta, \widetilde{\delta})}{\partial \widetilde{\delta}_{j,t}} &= \sum_m N_{m,t}\left(\frac{q_{m,j,t}}{N_{m,t}} - s_{m,j,t}(\theta, \widetilde{\delta})\right) \\ \frac{\partial \ln L(\theta, \widetilde{\delta})}{\partial \lambda^h} &= \sum_t \sum_m N_{m,t} \sum_j \left(\frac{q_{m,j,t}}{N_{m,t}} - s_{m,j,t}(\theta, \widetilde{\delta})\right) w_{m,j,t} D_m^h \end{aligned}$$

where D_m^h is demographic characteristic h in the vector D_m and λ^h is a $K \times 1$ vector for demographic characteristic h (one of the columns in Λ). These expressions show that the scores serve as micro-moments that are added to the aggregate moments $\sum_{j,t} z_{j,t}\widetilde{\xi}_{j,t}(\alpha, \beta, \gamma)$. This is in the spirit of the static discrete choice literature, as in Petrin (2002) and Berry *et al.* (2004), and applied to local market data in Nurski and Verboven (2016). More

[23] We leave out the derivative to the discount factor here as the macro-moments are our source of identification for this parameter.

specifically, the scores $\partial \ln L(\theta, \widetilde{\delta})/\partial \widetilde{\delta}_{j,t}$ (for each j and t) are essentially conditions that the observed country-level market shares should be equal to the predicted country-level market shares. The scores $\partial \ln L(\theta, \widetilde{\delta})/\partial \lambda^h$ (for each demographic h) are moment conditions that the observed sales-weighted demographic interactions should be equal the model's predictions.

The GMM estimator minimizes $g'Wg$ with respect to the parameters, where W is the weighting matrix. 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.