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Abstract

We study a generous program to promote the adoption of solar photovoltaic (PV) systems through subsidies on future electricity production, rather than through upfront investment subsidies. We develop a tractable dynamic model of new technology adoption, also accounting for local market heterogeneity. We identify the discount factor from demand responses to variation that shifts expected future but not current utilities. Despite the massive adoption, we find that households significantly discounted 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. (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 incentives to adopt a new green technology, and the role played by upfront investment and future 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 generous program for residential solar PV systems, running in Belgium during 2006–2012, and responsible for a particularly high adoption rate compared with other countries.[1] The program relied heavily 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 feed-in tariff system and several other European programs. U.S. programs also involve production subsidies, but tend to rely more heavily relied on upfront investment subsidies.[2] Interestingly, the GCC subsidy program revised its conditions many times at pre-announced dates. These revisions typically consisted of reductions in the future production subsidies, and applied only to new adopting households. The considerable variation in the future subsidies enables us to identify the households' implicit discount factor in a reliable way. Furthermore, because the program mainly consisted of future production subsidies instead of upfront investment subsidies, it potentially enabled the government to shift the financial burden to future electricity consumers. Based on the estimated discount factor, we can assess how costly this was.

[1] Belgium ranked third in the European Union with a total capacity of 240 Watt peak/capita at the end of 2012 (Eurobserv'er 2013).

[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.

To estimate how households discount the future benefits of a new technology, we develop a dynamic discrete choice model, where in each period households face the decision to adopt the new technology or to postpone their investment. We first develop a model to be estimated with aggregate, country-level data. Next, to evaluate the robustness of our findings, we extend the model to account for rich forms of persistent observed and unobserved local market heterogeneity in a tractable way. As discussed further below, our approach does not require specifying an explicit stochastic process for the expected state transitions, which would be particularly difficult for a new technology.

We obtain the following main findings. First, although the program led to a massive adoption of solar PV systems, households significantly discounted the future benefits from the new technology. They use an implicit real interest rate of 15% in evaluating these future benefits, which is much above the real market interest rate of about 3%. Put differently, this implies a considerable undervaluation of the future benefits from electricity production: consumers are willing to pay only approximately 0.5 euro upfront for one euro of discounted future benefits from electricity production. Our finding of considerable time discounting is robust with respect to various assumptions about households' expectations on the value of current and future PV systems. It can either be interpreted as intrinsic consumer myopia or as mistrust in the government's commitment to pay out the future subsidies. This raises specific policy concerns, at least from a budgetary and distributional perspective. Upfront subsidies instead of future production subsidies would have reduced public expenditures by €1.9 billion (or 51% of the amount spent). This is a saving of more than €700 per household, a very large number given that only 8.3% of the households had adopted a PV at the end of the program. We conclude that there was a high public cost in shifting the subsidy burden to future households, as they 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 consumers undervalue future energy cost savings, as this could be responsible for the so-called energy efficiency gap (for overviews, see Allcott and Greenstone (2012) and Gerarden et al. (2017)). After Hausman's (1979) seminal contribution, the recent evidence ranges from moderate undervaluation to correct valuation, see for example Allcott and Wozny (2014) and Busse, Knittel and Zettelmeyer (2013). All this evidence is based on energy-saving investments of existing, mature technologies (such as cars). Furthermore, this previous work has focused only on the decision how much to invest in energy cost savings, and it ignored the timing dimension of adoption. 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 must also decide on the timing of their investment, as it can be beneficial to postpone adoption even if it is already profitable to invest now. Our paper fills this gap and considers consumers' valuation of future payoffs (energy cost savings) when adopting an entirely new technology, which entails both an investment problem and a timing problem (to take advantage of future changes in production subsidies and investment costs). Our evidence suggests that time discounting may be much stronger in this case, with important implications for policy programs.

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 be treated as a static model with discounted benefits. The second is particularly important for new technologies because they are often characterized by increasing quality and decreasing prices. This aspect does require a dynamic model: postponing a beneficial investment can be optimal, and a static model may underestimate the sensitivity to monetary incentives (Gowrisankaran & Rysman 2012). The dynamic discrete choice literature has stressed that the discount factor is nonparametrically unidentified; see Manski (1993), Rust (1994) and Magnac and Thesmar (2002). Magnac and Thesmar (2002) and Abbring and Daljord (2017) show how identification may be obtained through appropriate exclusion restrictions. Intuitively, the discount factor can be identified from demand responses to variation that shifts expected discounted future utilities but not the current utilities.[3] In our setting we obtain identification from variation in the future benefits across products and over time, relative to the investment costs which enter only the current utility of adopting. In particular, we exploit large variation in the future GCC subsidies, which were revised many times on pre-announced dates and implied a guaranteed stream of payoffs for a fixed number of years.

Second, we contribute by proposing a novel method to estimate a dynamic technology adoption model with aggregate data, and we also show how to extend this model to account for local market heterogeneity in a tractable way. The main advantage of our approach is that it is not necessary to specify an explicit stochastic process for the expected state transitions of the future investment costs and benefits. Specifying such a process would be particularly difficult for a new technology, in our setting especially because of the highly idiosyncratic,

[3]Magnac and Thesmar (2002) impose an exclusion restriction on the current value functions. Abbring and Daljord (2017) suggest to directly impose an exclusion restrictions on primitive utilities.

nonstationary nature of the PV subsidy scheme. Our aggregate adoption model amounts to estimating an Euler equation with GMM. We start from Hotz and Miller's (1993) inversion approach, which writes the ex ante value function as the utility of choosing one alternative, plus a correction term. We exploit the fact that technology adoption is a terminating action in our setting (see Arcidiacono and Ellickson (2011) for a particularly clear exposition). Similar to Scott (2013) we write the expected next period ex ante value function as the realized value function plus a prediction error, which is uncorrelated with any variables known by the household at the time of the adoption decision. We then 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 with aggregate data. Conditional on the discount factor, this gives rise to a linear regression equation, where the current adoption rate depends on current and next period 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.

We subsequently suggest a modified approach to account for rich forms of observed and unobserved household heterogeneity at the local market level.[4] In our setting these markets are highly disaggregate (almost 10,000 local markets with on average only 295 households per market). This implies an excessive number of zero (or very low) adoptions, which inhibits us from inverting the demand model and obtaining a regression equation at the local level. We suggest an approach to deal with this within a GMM framework: we combine aggregate, country–level moments (where zero or low adoptions do not occur) with micro-moments at the local market level to account for household heterogeneity.[5] We include demographic variables, interacted with price and capacity size, and a large set of local market fixed effects to control for unobserved heterogeneity that can be identified from variation across markets. Although household heterogeneity is important in explaining adoption behavior, it does not affect our conclusions for the discount factor, and our policy implications.

Third, our work relates to a recent literature using dynamic models to study the adoption of PV systems and the role of government policies. Burr (2016) estimates a dynamic

[4] 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).

[5] Broadly speaking, the static discrete choice literature follows two approaches to deal with zero market shares within a GMM framework. The first approach consists of aggregating and adding micro-moments, as done in Quan and Williams's (2018) nested logit with cross-market random effects, Nurski and Verboven (2016), and our application. An alternative approach, developed by Gandhi et al. (2017), consists of constructing moment inequalities (starting from the Laplace rule of succession to obtain an initial choice probability estimator that does not have zeros).

adoption model of PV systems for California, and also finds that an upfront subsidy program encourages adoption more than future production subsidies. Langer and Lemoine (2018) use the California experience to study optimal dynamic subsidy paths, which may a priori be increasing or decreasing (depending on the distribution of household valuations, time discounting and the rate of technological progress). Finally, Feger et al. (2017) use data on both PV adoption and electricity usage in the Canton of Bern to study optimal tariff design, showing how upfront installation subsidies may be combined with variable and fixed electricity fees to obtain a given solar energy production target. These studies rely on specific assumptions regarding time discounting, and they require a full model of the state space with the stochastic process of expected future state transitions. In contrast, we focus on identifying the discount factor based on rich variation in upfront investment costs and future payoffs. Furthermore, we rely on weak assumptions on the households' expected future investment opportunities and account for endogeneity of investment costs. Finally, we show how to incorporate rich forms of observed and unobserved household heterogeneity.[6]

The rest of the paper is structured as follows. Section 2 describes the datasets and institutional background. 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.

2.1 Datasets

Our main dataset contains information of all installed PVs during 2006-2012 across the region of Flanders, Northern part of Belgium covering about 60% of the total population.

[6]The above papers and our own consider the impact of subsidy policies on the demand side dynamics. Two papers have focused on the supply side dynamics. Bollinger and Gillingham (2014) consider the role of learning by doing in solar panel installation, whereas Gerarden (2017) looks at the incentives to invest in improved technical efficiency of solar panels.

For each installed PV, we observe the time of adoption, the location and the capacity size (but not the brand or other PV characteristics). We will analyze this dataset at the level of five capacity size categories (0–2kW; 2–4kW; ... 8–10kW) at a monthly frequency. We first consider the aggregate level of Flanders (covering about 2.7 million households) and in an extension consider the disaggregate local market level (which divides the entire region in 9,182 statistical sectors, with an average of 295 households per statistical sector).

We combine the information from this main dataset with several additional datasets. First, we collected information on the price quotes of 2,659 PV systems adopted during May 2009 until December 2012. Since we observe only the capacity and time at which PVs were adopted and since the price quotes in any case mainly depend on the PVs' capacity and less on the brand, we aggregate the price information to the median price for each month and each of the five different capacity size categories.[7]

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 from net metering, and tax benefits. Finally, for our extension to the disaggregate local market 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 synchronize 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.

[7] An OLS regression of the price/kW on monthly time dummies and dummy variables for the different capacity size categories results in an R^2 of 72.3%.

Investment price The investment price is the price households have to pay for a PV system, including all additional costs. As discussed above, we construct a price measure per month for each of the five capacity size categories. In 2006 and 2007 households could apply for a 10% investment subsidy for PV installations.[8] 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 € 1,200 in 2006 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%.

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 a legally guaranteed period of 20 years. The program became less favorable to new adopters in 2010, and it was subsequently gradually phased out. By the end of 2012, new PV adopters received a guaranteed price of only €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.[9]

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.

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

[9] 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.

Electricity cost 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 have to pay only 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.[10] 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 92€/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 consumers.

2.3 Evolution of costs, benefits and adoption

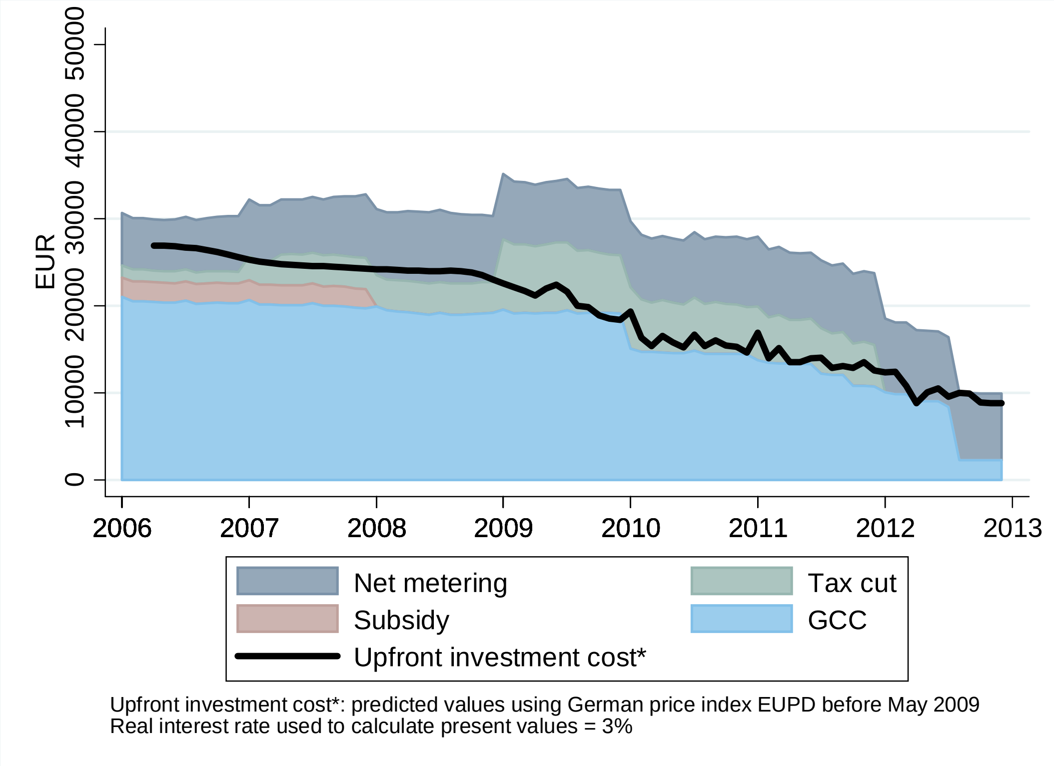
Figure 1 summarizes of the costs and benefits of a PV system of 4kW.We calculate future benefits in present value terms using a real interest rate of 3% and an expected life time of 20 years and we convert all prices to 2013 prices. The gross purchase price (net of any investment tax cuts) dropped from € 21,700 in May 2009 to € 8,800 at the end of 2012.[11] 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. A comparison of the total benefits (shaded area) with total costs (black line) shows that adoption was profitable during the entire period in net present value terms, especially between 2009 and the middle of 2012.

Figure 2 shows the evolution of the monthly number of new adopters between January 2006 and December 2012. Vertical lines indicate drops in the GCC prices, as typically announced a few months in advance. Despite the positive gap between benefits and costs throughout the sample, the number of new adopters remained very low until 2009. This

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

[11] The price data we collected starts in May 2009. We therefore also estimate the model from May 2009 on. For descriptive purposes, we also show a predicted price variable in Figure 1 (based on the German price index).

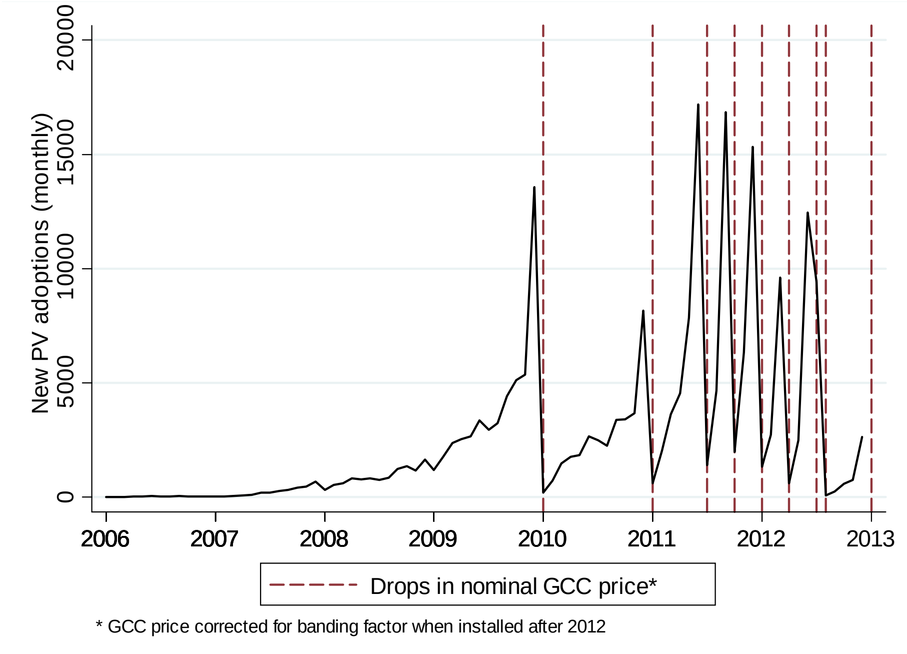
Figure 1: Costs and benefits of 4kW PV in EUR 2013, discounted at market interest rate



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 postpone the adoption of a PV to wait for prices to drop, but they also anticipate the announced drop in the GCC price and thus in the expected benefits of their investment.

Figure 3 shows the cumulative number of adopters over the considered period, broken down into our 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 2: 2006-2012: Time series of new PV adoptions and drops in nominal GCC price



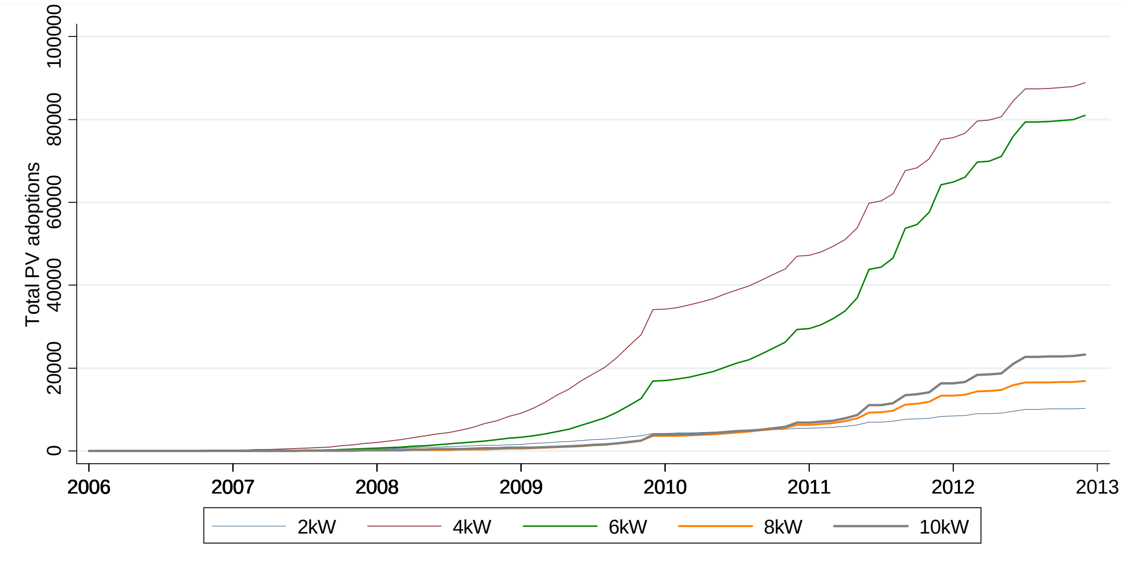
time of new GCC schemes. The 4kW and 6kW systems were the most popular choices for a PV. This is because households benefit from net-metering only for the production that is below their household consumption. In practice, an average household consumes 3.5MWh per year, while a 4kW system produces about 3.4 MWh per year, so that larger PV systems are of value only to households that are sufficiently larger than average. Nevertheless, there is a 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 2012, the cumulative number of adopters had reached $220,464$, amounting to an adoption rate of 8.3% of the households (or 8.4% of the number of buildings). The total capacity of residential PV systems had at that time reached $1,057$MW, or 5% of total electricity capacity in Belgium.[12]

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

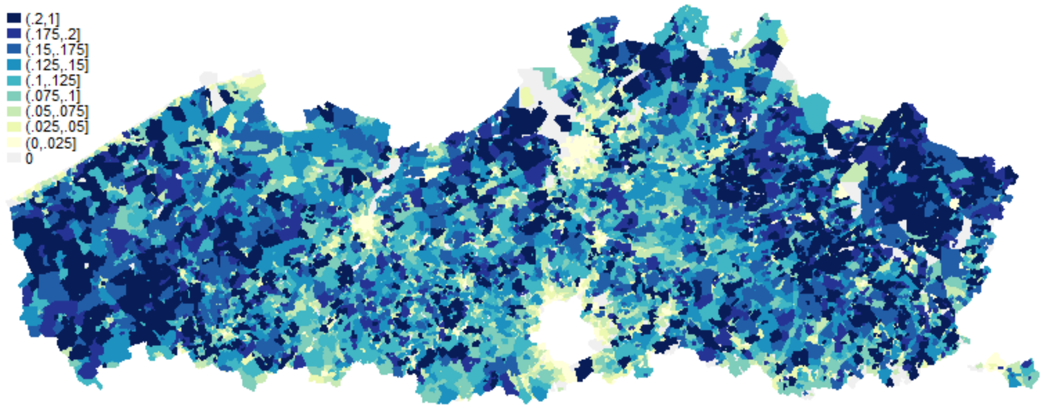
[12] According to the US Energy Information Administration, Belgium had a total installed electrical capacity of 21,000 MW in 2012.

Figure 3: 2006-2012: Time series of total adoption of PVs of different capacity



and income. In an extension of our aggregate demand model, we will take into account the role of these socio-demographic characteristics.

Figure 4: PV adoption rates in Flanders



Adoption data: VREG, household data: ADSEI census 2011

In sum, this overview shows there is considerable variation over time in the adoption of PV systems, and this variation appears to be related to the variation in investment costs and the future benefits, in particular the pre-announced changes in GCC policies.

3 The model of technology adoption

We first specify a dynamic adoption model that can be estimated with aggregate market data and no household heterogeneity (apart from an i.i.d. taste shock): we describe the 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 approach to estimate the model at a highly disaggregate local market level. This makes it possible to account for both observed and unobserved heterogeneity across households (subsection 3.4).

Note that we will not need to specify whether the adoption decision is a finite or infinite horizon problem. Nor will we need to explicitly specify how consumers expect the states to evolve in the future. This is because we can estimate the parameters of the model without having to solve it, using Hotz and Miller's (1993) CCP approach with finite dependence, and because we need to assume only rational expectations on state transitions by modeling the expected ex ante value function as the realized ex ante value function plus a prediction error as in Scott (2013).

3.1 The adoption decision

In a given period t a household i may either choose not to 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 ($j \neq 0$) is a terminating action.[13] Not adopting ($j = 0$) 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 and the next two subsections, we set $\mu_{i,j,t} = 0$, so that $v_{i,j,t} = \delta_{j,t}$. This implies that there is no household heterogeneity except for the extreme value distributed taste shocks $\varepsilon_{i,j,t}$. This leads to a particularly easy to interpret and tractable estimating equation. The downside of this approach is that heterogeneity is then assumed to be uncorrelated over time and over alternatives. In practice, households with a high valuation for adopting now are also likely to have a high valuation for adopting in future periods. Furthermore, households may have

[13] Replacement is not a viable option because households would lose the generous GCC subsidies. In practice, replacement is indeed extremely rare.

correlated preferences for systems with similar capacity sizes. In the final subsection 3.4, we overcome this by allowing for both observed and unobserved heterogeneity at the local market level in $\mu_{i,j,t}$.

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. Since this is a terminating action, we can write it as the expected discounted utility of adoption. We specify $v_{i,j,t} = \delta_{j,t}$ as follows:

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

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 only a set of fixed effects for the alternatives.[14] 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 from net metering ($p_{j,t}^{EL}$):

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

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

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

i.e. the monthly discount factor β adjusted for a 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 tax cuts ($taxcut_{j,t}^{\tau}$) spread over up to

[14] In the Appendix, we also include time effects to assess whether our included variables are sufficient to explain the time variation in adoption.

4 years ($\tau = 1, \ldots, 4$):

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

Before 2009, there was a tax cut only in the first year, capped at an indexed maximum amount. Since 2009 any remaining tax cuts could be shifted to the following three years, so that the last three terms in the summation in (4) become non-zero.[15]

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 ($\frac{0.85}{12} MWh/kW$), following CREG, VEA and 3E (2010).[16] The parameters ρ_t^G and ρ^E are capitalization factors that convert the monthly benefits for R_t^G months of GCCs and R^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 factors β net of any depreciation. The parameter λ captures physical deterioration of electricity production, whereas π is the monthly inflation rate (because GCCs 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 4.3.[17]

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

[15]This possibility only applied to houses older than 5 years. Furthermore, a reduced VAT from 21% to 6% applied to 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).

[16]As pointed out earlier in footnote 10, households are not reimbursed for electricity production that is higher than their annual consumption. The imputed electricity savings $p_{j,t}^{EL}$ may therefore be too large for high capacity options when households are small. As a robustness check, we also estimated a model under the (extreme) assumption that electricity savings are equal to the smallest capacity, and this gave similar results.

[17]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 $R^E = 240$ months (the expected lifetime of a PV, following CREG, 2010), and based on the GCC schemes announced by the government we set $R_t^G = 240$ months for January 2006 - July 2012, $R_t^G = 120$ for August 2012 - December 2012, and $R_t^G = 180$ months for January 2013.

value of waiting. More precisely,

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

where $\overline{V}_{t+1}$ is the ex ante value function, i.e. the continuation value from behaving optimally from period $t+1$ onwards, before the random taste shocks are revealed. 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-known closed-form logsum expression:

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

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

Random utility maximization

With random utility maximization, we obtain the following choice probabilities or predicted market shares for each alternative $j = 0, \ldots, J$ at period t:

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

As in Berry (1994), we can equate the predicted market shares $s_{j,t}(\delta_t)$ to the observed market shares $S_{j,t}$ because of the inclusion of unobserved qualities $\xi_{j,t}$ for every product and period. The aggregate market share of alternative $j \neq 0$ 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 terminal action, the potential number of adopters is the total number of households N minus the number of households that adopted in the past, i.e. $N_t = N - \sum_{\tau=1}^{t-1} \sum_{j=1}^{J} q_{j,\tau}$. The aggregate market share of not adopting is $S_{0,t} = 1 - \sum_{j=1}^{J} S_{j,t}$

3.2 Estimating equation

The aggregate market share equation (7) involves two complications. First, the conditional value for not adopting $\delta_{0,t}$, as given by (5), involves the expected future value term $E_t\overline{V}_{t+1}$, which is recursively defined by (6). Second, the conditional value for adopting, $\delta_{j,t}$, contains the unobservable product quality term $\xi_{j,t}$, which enters nonlinearly. We now show how to solve both complications, by obtaining an analytic expression for the future value term $E_t\overline{V}_{t+1}$ and by inverting the market share equation.

Expected ex ante value function

The expectation operator before $\overline{V}_{t+1}$ in (5) integrates over uncertainty about the next period state variables, i.e. the vector $\omega_t = (u_{0,t+1}, \delta_{1,t+1}, ..., \delta_{J,t+1})$. The usual approach specifies an explicit stochastic process of the state transitions.[18] Following Scott (2013), we instead decompose $E_t\overline{V}_{t+1}$ into the realized ex ante value function $\overline{V}_{t+1}$ and a short run prediction error $\eta_t \equiv \overline{V}_{t+1} - E_t\overline{V}_{t+1}$. We assume that households' expectations are on average correct, such that η_t is mean zero. We can then write (5) as

$$\delta_{0,t} = u_{0,t} + \beta(\overline{V}_{t+1} - \eta_t). \tag{8}$$

Specifying a flexible prediction error, avoids having to make arbitrary assumptions on how households expect the future states to evolve. This is particularly important in this application because the GCC subsidies were revised many times and it is unclear how this influenced households' expectations.[19]

The ex ante value function $\overline{V}_{t+1}$, as given by the logsum formula (6), recursively depends on future value functions (through the term $\delta_{0,t+1}$). Hotz and Miller (1993) show how to write $\overline{V}_{t+1}$ in terms of the conditional choice probabilities (CCPs). This is particularly convenient when the decision problem has a terminal action, as is the case in our set-up for any adoption decision $j = 1, \ldots, J$.[20] We can then take the next period CCP for any arbitrary terminating choice, so we take the CCP of alternative $j = 1$, as given by $s_{1,t+1}(\delta_{t+1}) \equiv \exp(\delta_{1,t+1}) / \sum_{j=0}^{J} \exp(\delta_{j,t+1})$. After rewriting and taking logs, this gives:

$$\ln \sum_{j=0}^{J} \exp(\delta_{j,t+1}) = \delta_{1,t+1} - \ln s_{1,t+1}(\delta_{t+1}),$$

which can be substituted in (6) to obtain the following expression for the ex ante value function at $t+1$:

$$\overline{V}_{t+1} = 0.577 + \delta_{1,t+1} - \ln s_{1,t+1}(\delta_{t+1}). \tag{9}$$

As discussed in Arcidiacono and Ellickson (2011), expression (9) has an intuitive interpretation. The ex ante value function (at $t+1$) is essentially equal to the utility of choosing option $j = 1$ plus the mean of the Type I extreme value distribution (0.577) plus the CCP correction term $-\ln s_{1,t+1}(\delta_{t+1}) \geq 0$. The CCP correction term adjusts for the fact that

[18] For example, if the states follow a Markov process with density $f(\omega_{t+1}|\omega_t)$, we have $E_t\overline{V}_{t+1} = \int \overline{V}_{t+1}(\omega_{t+1}) f(\omega_{t+1}|\omega_t)\, d\omega_{t+1}$.

[19] Burr (2016), Feger et al. (2017) and Langer and Lemoine (2018) also model PV adoption with a dynamic model. As in Rust (1987), they solve the model during estimation, which requires assumptions on how households expect the state variables to transition over time.

[20] This is a particular example of a simplification that occurs because of finite dependence (Arcidiacono & Miller 2011). An alternative action that qualifies for finite dependence is the renewal action, as in Scott (2013).

$j = 1$ may not be optimal, so that the expected utility is on average higher than that of adopting $j = 1$ (unless $s_{1,t+1}(\delta_{t+1}) = 1$).

We can now substitute (9) in the mean utility from not adopting (8) to obtain:

$$\begin{aligned} \delta_{0,t} &= u_{0,t} + \beta\left(0.577 + \delta_{1,t+1} - \ln s_{1,t+1}(\delta_{t+1}) - \eta_t\right) \\ &= \beta\left(\delta_{1,t+1} - \ln S_{1,t+1} - \eta_t\right) \end{aligned} \tag{10}$$

where the second equality follows from normalizing $u_{0,t} + \beta 0.577 = 0$ and from the fact that the CCP at the realized mean utilities is equal to the observed market share ($S_{1,t+1} = s_{1,t+1}(\delta_{t+1})$). Note that this differs from other applications that use the Hotz and Miller (1993) inversion as this usually requires predicting the CCP in a first stage. Here we apply the Hotz and Miller (1993) inversion on aggregate data with the realized ex ante value function. This implies that the CCP is simply the observed market share of $j = 1$ in the next period.[21]

Market share inversion

To invert the market share equation, we follow the approach of Berry (1994) for estimating static discrete choice models with aggregate market share data. Using the market share expressions (7), 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:

$$\ln S_{j,t}/S_{0,t} = \left(x_{j,t} - \beta x_{1,t+1}\right)\gamma - \alpha\left(p_{j,t} - \beta p_{1,t+1}\right) + \beta \ln S_{1,t+1} + e_{j,t}, \tag{12}$$

where

$$e_{j,t} \equiv \xi_{j,t} - \beta(\xi_{1,t+1} - \eta_t) \tag{13}$$

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:

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

[21] As discussed further in subsection 3.4 below, in the model that accounts for local market heterogeneity we will need to predict the CCPs in a separate first stage, because the number of adopters can be very small at the local level.

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 next period price drop is large. As pointed out by Scott (2013), one may think of the estimating equation (12) as analogous to an equilibrium Euler equation in continuous decision problems (reflecting indifference between adopting now and tomorrow in probability terms).[22]

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 $e_{j,t}$. 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 some of the variables may be correlated with the error term $e_{j,t}$. Notice first that the estimating equation (12) is non-linear in β because of the way it enters the price term (2), so a non-linear estimator is necessary. More importantly, several variables in equation (12) give rise to endogeneity concerns. Recall that, according to (13), the error term $e_{j,t}$ consists of the households' prediction error η_t and the demand shocks $\xi_{j,t}$ and $\xi_{1,t+1}$. As discussed in Scott (2013), the prediction error η_t is by construction uncorrelated with any variables known by the households at time t, so it does not give rise to endogeneity concerns. In contrast, the demand shocks give rise to endogeneity issues that are similar to those in static discrete choice demand models. First, $p_{j,t}$ contains the investment price variable $p_{j,t}^{INV}$, which may be correlated with the error term if firms charge higher prices when demand is high. Second, $p_{j,t}$ also contains the electricity price variable $p_{j,t}^{EL}$. This may also be correlated with the error term to the extent that the GCC subsidies were financed through higher electricity prices. Third, the next period adoption rate $\ln S_{1,t+1}$ may be correlated with the error term, since it contains the next period demand shock $\xi_{1,t+1}$.

To account for these problems we construct an instrument vector $z_{j,t}$ that is uncorre-

[22] Gandal *et al.* (2000) obtain a related equation in a model with different distributional assumptions about heterogenous consumers, who decide when to adopt new hardware-software.

lated with the error term, and estimate the model using GMM with the following moment conditions:

$$E\left(z_{j,t}e_{j,t}\right)=0 \tag{14}$$

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 variable $p_{j,t}^{INV}$, and as a cost shifter it is reasonable to assume it does not directly influence demand. The price index of Chinese PV modules thus provides a strong and valid instrument to identify the price coefficient α. Second, we include the contractually fixed future benefits from the GCC subsidies $p_{j,t}^{GCC}$ as an instrument. As discussed in section 2, 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 drops in several months. The variable $p_{j,t}^{GCC}$ thus provides a strong instrument to identify the discount factor β, i.e. how households trade off upfront investment costs with future benefits. After also adding the exogenous $x_{j,t}$ to the set of instruments, the model is identified. However, to improve efficiency, in a second stage we use an approximation to optimal instruments (Chamberlain 1987), 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 nonparametrically unidentified (Manski (1993) and Rust (1994)), but identification can be obtained with appropriate exclusion restrictions (Magnac & Thesmar (2002) and Abbring and Daljord (2017)). More precisely, the discount factor can be identified if there are two or more states that affect expected future utilities but not current utility. In our setting, the upfront investment costs affect only current utility, whereas the GCC subsidies, electricity bill savings and tax credits affect the future benefits. A first concrete source of identification comes from the variation in the generosity of the GCC subsidies to new adopters over our sample period (as documented in Figure 1). Note that "static" models of intertemporal choice, which abstract from the timing decision and focus only on the investment decision, implicitly use a similar identification strategy. For example, after Hausman's (1979) contribution, 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). This work also relies on variation in expected future energy costs, relative to upfront car prices.[23] In dynamic choice models, Lee (2013) uses a related identification approach in

[23]This work mainly relies on cross-sectional variation between cars of different fuel efficiency, whereas we

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 upfront costs versus future benefits.[24]

A second possible source of identification comes from the dynamics of the model. In Figure 2 we see large increases in adoptions just before a change in GCC subsidies, even though this change is irrelevant for the utility of adopting a PV in that month. This is because subsidies for new adoptions change at well-known pre-announced dates. These future changes do not directly impact the utility of adopting today but they do change the option value if households choose not to adopt. In the sensitivity analysis we attempt to estimate a separate discount factor relating to this option value to evaluate which source of variation is mainly responsible in identifying the discount factor.

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. To evaluate the robustness of our findings, in this subsection we show how to extend the empirical analysis to account for observed and unobserved heterogeneity at the very disaggregate level of $M = 9182$ local markets, where each market m consists of on average 295 households.[25] 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 to interact with the price and capacity size in the utility specification. We also include local market fixed effects to control for unobserved heterogeneity. As such, we relax the assumption that valuations of solar systems are i.i.d. across alternatives and over time. We allow households in different markets to have persistent differences in their valuation for adopting versus not adopting, and to have correlated preferences for systems with similar capacity sizes.

One approach to incorporate this heterogeneity would be to specify (12) at the local market level. The dependent variable would become $\ln S_{m,j,t}/S_{m,0,t}$, the error term would become $e_{m,j,t}$ and the regression would include local market demographics and interactions with product characteristics. However, at a highly disaggregate level the number of new adopters is often zero, so that the log market share terms are not defined (both the dependent variable $\ln S_{m,j,t}/S_{m,0,t}$ and the next period CCP term $\ln S_{m,1,t+1}$). Scott (2013) addresses

rely mainly on variation over time.

[24]Related approaches to identify the discount factor in dynamic choice models are (Dube *et al.* 2012), (Bollinger 2015) and (Yao *et al.* 2012).

[25]Within these disaggregate local markets, we continue to assume consumers are homogeneous.

this issue using a smoothing procedure for all market share terms (in a dynamic model with replacement instead of terminating actions). We instead take an alternative approach, which combines the moment conditions from the aggregate model (involving aggregate shares $\ln S_{j,t}/S_{0,t}$) with a set of micro-moments at the local level, that arise from the likelihood of observing new adoption levels in local markets. This is similar to the static discrete choice literature, for example Berry et al. (2004) and Quan and Williams's (2018) (although we continue to rely on first-stage predictions for the next period CCP term as is common in the dynamic discrete choice literature (Arcidiacono and Ellickson (2011)).

Our specification incorporates unobserved heterogeneity in the decision whether to adopt through a rich set of local market fixed effects (in addition to observed heterogeneity for the decision which alternative to adopt through demographic interactions with product characteristics). Alternative approaches to account for unobserved heterogeneity would be to estimate random coefficients, similar to Gowrisankaran and Rysman (2012), or a finite mixture of unobserved types in the population as in Scott (2013), based on the EM algorithm of Arcidiacono and Miller (2011). While a random coefficients model gives more flexibility in modeling heterogeneity for the valuation of product characteristics, it requires an explicit specification of the state transitions, and it does not make efficient use of the rich local market heterogeneity we observe. A mixture of unobserved types would be difficult to identify in our context, since households do not make repeat purchases so that we cannot infer their types from correlations in their decisions over time.

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).

As in the aggregate model, the conditional value of adoption $v_{i,j,t}$ ($j = 1, \ldots, J$) is still the expected discounted utility, because adoption is a terminal action. The difference with the aggregate model is that $v_{i,j,t}$ no longer consists of only a mean utility term $\delta_{j,t}$ (given by (1) and including an unobserved quality term $\xi_{j,t}$ as before). It now also includes an individual-specific component $\mu_{i,j,t} = \mu_{m,j,t}$, which depends on demographics of the local market m (but households are identical within these disaggregate local markets). More precisely, we have:

$$\begin{aligned} v_{i,j,t} &= \delta_{j,t} + \mu_{m,j,t} \\ &= x_{j,t}\gamma - \alpha p_{j,t} + \xi_{j,t} + w_{j,t}\lambda_m, \quad j = 1, \ldots, J \end{aligned} \tag{15}$$

where $\mu_{m,j,t} \equiv w_{j,t}\lambda_m$ 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 relative 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 dummy variables for each local market m, but also 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. We interact the constant with local market dummy variables, and price and capacity with a selection of the household demographics. In a sensitivity analysis we also consider heterogeneity in the discount factor. We explain this approach in Appendix A.4.2.

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

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

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

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

Assume that $\eta_t \equiv \overline{V}_{m,t+1} - E_t \overline{V}_{m,t+1}$, i.e. the expectational error is common across local markets, so there is only aggregate uncertainty. As shown in Appendix A.3, the logit choice probabilities in market m are then given by:

$$\begin{aligned} s_{m,j,t} &= \frac{\exp(v_{i,j,t})}{\sum_{j'=0}^{J} \exp(v_{i,j',t})} \\ &= \frac{\exp(v_{i,j,t} - v_{i,0,t})}{1 + \sum_{j'=1}^{J} \exp(v_{i,j',t} - v_{i,0,t})} \\ &= \frac{\exp(\widetilde{\delta}_{j,t} + \widetilde{w}_{j,t}\lambda_m + \beta \ln s_{m,1,t+1})}{1 + \sum_{j'=1}^{J} \exp(\widetilde{\delta}_{j',t} + \widetilde{w}_{j',t}\lambda_m + \beta \ln s_{m,1,t+1})} \end{aligned} \tag{16}$$

where we define $\widetilde{\delta}_{j,t} \equiv \delta_{j,t} - \beta(\delta_{1,t+1} - \eta_t)$ and $\widetilde{w}_{j,t} \equiv w_{j,t} - \beta w_{1,t+1}$.

We explain estimation of the model in Appendix A.3. In short, we combine moments at the aggregate level with micro-moments at the local market level in one GMM estimator. These micro-moments are the scores from the likelihood function of the model, using (16). The scores relating to the demographic variables can be interpreted as moment conditions that match the observed covariances between the demographic variables and product characteristics to the model's predictions. The scores relating to the local market (m) fixed effects can be interpreted as matching the total number of adopters in each market at the end of the sample to the predicted number. Finally, instead of using Berry's market share inversion to match the monthly adoption rates at the aggregate level, we estimate product-time (j, t)

fixed effects.[26] The aggregate moment is similar to the one in the aggregate model (14, 13, 12), with the difference that (j, t) fixed effects replace the inversion of aggregate market shares, which will not coincide unless local market heterogeneity is fully absent). Note that the model therefore still allows for unobserved quality and prediction errors at the aggregate level.

4 Empirical results

We first discuss our main findings with a focus on the estimated discount factor (subsection 4.1). We then perform a sensitivity analysis with respect to several specification choices (subsection 4.2). Next, we assess the sources of time discounting by estimating the model under alternative assumptions about how future payoffs enter utility (subsection 4.3). Finally, we use the parameter estimates to consider the budgetary impact of an alternative policy to promote PV adoption with upfront investment instead of future production subsidies (subsection 4.4).

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 9182 local markets, resulting in more than 2 million observations. The average number of adopters per capacity level is 901 at the country level, and it has always been positive for every capacity and month. At the local market level, the average number of monthly 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

[26] This differs from Quan and Williams (2018). They have a very large set of local interactions (markets m times alternatives j), which induces them to develop a random effects approach. We instead have additive fixed effects for each of the local markets m and each alternative-time combination (j, t).

variables that do not enter the model directly but are correlated with the endogenous investment cost and electricity price. Finally, the fourth panel of Table 1 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	$q_{j,t}$	901.1	1309.58	4	311.5	7226	220
Local market 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	4.82	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	$taxcut_{j,t}^{1}$	2.63	1.62	0	3.69	3.69	220
Tax cut year 2	$taxcut_{j,t}^{2}$	1.83	1.57	0	2.44	3.36	220
Tax cut year 3	$taxcut_{j,t}^{3}$	1.20	1.50	0	0	3.36	220
Tax cut year 4	$taxcut_{j,t}^{4}$	0.55	1.11	0	0	3.36	220
Excluded instruments							
Module price (10^3 EUR)	$p_{j,t}^{MOD}$	7.81	5.01	1.06	6.56	23.27	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
Average house age (decades)		5.19	1.49	0.37	5.07	11.3	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, following the regression equation (12). Both specifications include fixed effects for each capacity size using the most popular 4kW system as the base. As a point of comparison, specification (1) is the static version of the model (often estimated in other contexts), i.e. we set $\beta = 0$ in equation (12) so that the next period terms drop out, and at the same time keep β in the price variable, as given by (2) and (3). Specification (2) is the full dynamic version of (12), where we set the terminating action $j = 1$ to the base capacity level of 4kW.

The investment price coefficient is negative and statistically significant, meaning that consumers responded positively to the decline in investment prices of PV systems. The magnitude of the investment price coefficient is smaller in absolute value in the static specification than in the dynamic specification (-0.318 versus -0.470). This appears to be consistent with Gowrisankaran and Rysman's (2012, p. 1176) interpretation: "a static estimation applied to a durable good purchase decision with falling prices will then result in mismeasurement that may tend to bias the price coefficient toward zero." The difference in the price coefficient between the static and dynamic specification is however less pronounced in our application, because the falling investment prices are occasionally interrupted by sharp drops in subsidy benefits.

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, and differs significantly from 1. It is more informative to convert the monthly discount factor into an annual implicit interest rate. The results show that the real implicit interest rate is 14.82% in the first specification (standard error of 2.28%), and a similar 15.09% in the second specification (standard error of 3.43%). These estimates are much higher than market interest rates on risk-free or moderate risk investments (even though our estimates are in real terms, while the market rates are in nominal terms). For example, the interest rate on mortgages ranged between 3.6% and 5.3% in the period 2006-2012.[27] Moreover, between 2009 and 2011, the government subsidized loans for environmentally friendly investments, so that the effective interest rates at which households could borrow would be even lower.[28]

This then suggests that consumers discount the future benefits of new technologies such as PV installations much more than has been observed in recent work on mature technologies such as the car industry. The high implicit interest rate implies that consumers are willing to pay only 0.5 euro upfront for one euro of total discounted future benefits from electricity

[27] Source: National Bank of Belgium (http://stat.nbb.be). Monthly averages of fixed rates on new contracts for durations over 10 years.

[28] https://financien.belgium.be/nl/particulieren/belastingvoordelen/groene_fiscaliteit/groene_leningen

production.[29] 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 subsection 4.3, we will investigate the sources of these high implicit interest rates.

Before turning to this, we discuss the results of specification (3), which is estimated with local market data and accounts for rich patterns of household heterogeneity. The investment price coefficient changes somewhat (from -0.470 to -0.604), 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 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 15.00% (compared with 15.09% in the model without heterogeneity). So also in the richer model there is evidence of considerable time discounting in adopting the new PV technology.

Finally, the coefficients for the household characteristics interacted with the capacity of a PV usually have an intuitive interpretation. As expected, large households, households living in large houses or in areas with a low population density especially value a large capacity. High income households, highly educated people and home owners tend to adopt smaller PVs. Foreigners and households living in older houses tend to invest in larger PVs.[30]

[29]One (real) euro of production benefits is valued at $A(\beta) = \frac{1-((1-\lambda)\beta)^{R^E}}{1-(1-\lambda)\beta}$. We obtain the cited number as the ratio of the benefits at the estimated household discount factor over the benefits at the market discount factor, i.e. $A(0.9884)/A(0.9975) = 0.5$, where $0.9975 = 1.03^{-1/12}$ at the market interest rate of 3%.

[30]In De Groote *et al.* (2016), we estimate descriptive models with a more elaborate set of demographic variables.

Table 2: Empirical results

	(1) Static		(2) Dynamic		(3) + micro-moments	
Price sensitivity in 10^3 EUR ($-\alpha$)	-0.318***	(0.074)	-0.470***	(0.098)	-0.604***	(0.100)
Monthly discount factor (β)	0.9886***	(0.0016)	0.9884***	(0.0025)	0.9884***	(0.0024)
Annual interest rate ($r \equiv \beta^{-12} - 1$)	14.82%***	(2.28%)	15.09%***	(3.43%)	15.00%***	(3.42%)
Control variables (γ)						
Alternative-specific constant						
Common constant	-8.169***	(0.483)	-1.422	(16.374)	3.633	(16.880)
2kW	-1.909***	(0.231)	-1.828***	(0.562)	-1.214*	(0.724)
6kW	-0.388	(0.241)	-0.512	(0.595)	-1.225	(0.753)
8kW	-2.248***	(0.459)	-2.452**	(1.158)	-3.926***	(1.473)
10kW	-2.356***	(0.670)	-2.602	(1.683)	-4.878**	(2.159)
Local market variables (Λ)						
Interactions with constant					Local market fixed effects included	
Interactions with capacity difference						
Pop. density (10^4 inhab / m^2)					-0.689***	(0.029)
Average house size					0.057***	(0.009)
Average household size					0.124***	(0.016)
Average house age (decades)					0.011***	(0.002)
Median income (10^4 EUR)					-0.066**	(0.030)
% home owners					-0.075**	(0.038)
% higher education					-0.128***	(0.041)
% foreign					0.383***	(0.040)
Interaction with price						
Median income (10^4 EUR)					0.049***	(0.007)
Obs. macro moments (JxT)	220		220		220	
Obs. micro moments (MxJxT)	0		0		935,440	

Notes: For all models, standard errors are clustered across alternatives within 44 time periods. In the third model, for the micro moments at the local market level we additionally cluster across time periods within each of the 4252 local markets. Instruments are approximations of optimal instruments (Chamberlain, 1987). Standard errors of r and common constant obtained via delta method. *** p<0.01, ** p<0.05, * p<0.1

4.2 Sensitivity analysis

We now perform a sensitivity analysis with respect to several modeling choices. For simplicity, we mainly focus on the aggregate adoption model, because the estimates of the implicit interest rate were very close to the disaggregate model with household heterogeneity.

Specification choices We first consider the sensitivity of our results with respect to the terminating action, $j = 1$, in the implementation of the CCP approach. In the above analysis we set $j = 1$ to the capacity level of 4kW, which is the most popular capacity level. In principle, one can do a sensitivity analysis by taking each of the five possible capacity choices as the terminating action. To explore this more formally, we create a GMM estimator with moments for each of the five possible terminal actions. As shown in the first column of Table 3, this results in a comparable estimate of the implicit interest rate (16.62%) and a reduced standard error of 1.03%. Since this approach yields five times as many moments than parameters, it is possible to perform a test of overidentification restrictions. Hansen's J is 31.7 with a P-value of 0.2858, so we cannot reject the hypothesis that the model is correctly specified. Table A5 in Appendix shows the empirical results when we take each of the five possible capacity choices as the terminating action. The empirical results are very similar across the five different models, with estimated implicit interest rates varying between 11.94% and 16.99%.[31]

We also considered a specification with a different assumption of the potential market size. Our base specification assumed that the potential market is equal to the total number of households, but many households might not be able to install a solar panel because of a bad roof orientation, too much shadow or because they live in an apartment building. We therefore consider an alternative specification where the potential market size is only 10% of the total number of households (only slightly above the adoption rate of 8.3% observed at the end of the subsidy period). Table 3 shows that the estimated discount factor remains very similar.

Next, we considered a specification with a time trend and seasonal dummy variables. According to Table 3, the coefficients of these variables are insignificant and only slightly affect the estimated implicit interest rate (change from 15.09% to 13.52%). This confirms that the main variables in our structural dynamic model (investment cost and future benefits) explain the variation over time rather well.

[31] We also considered a specification where we take a varying capacity choice j as the terminating action (rather than keeping it fixed as in standard approaches). This essentially becomes a "first-differences" model, and it results in imprecisely estimated parameters. This is because this differences specification eliminates most long-term variation, and the main remaining variation comes at infrequent occasions of policy changes.

Table 3: Robustness: specification choices

	All terminal choices		10 % potential market		Time controls	
Price sensitivity in 10^3 EUR ($-\alpha$)	-0.422***	(0.046)	-0.471***	(0.098)	-0.439***	(0.117)
Monthly discount factor (β)	0.9873***	(0.0007)	0.9883***	(0.0025)	0.9895***	(0.0016)
Annual interest rate ($r \equiv \beta^{-12} - 1$)	16.63%***	(1.03%)	15.13%***	(3.44%)	13.52%***	(2.17%)
			Control variables (γ)			
Alternative-specific constant						
Common constant	-10.152	(11.278)	1.557	(16.345)	-610.0	(1,017.3)
2kW	-2.045***	(0.129)	-1.834***	(0.562)	-1.614***	(0.421)
6kW	-0.282**	(0.136)	-0.507	(0.595)	-0.721	(0.460)
8kW	-2.021***	(0.262)	-2.442**	(1.158)	-2.879***	(0.881)
10kW	-1.989***	(0.399)	-2.587	(1.683)	-3.250***	(1.260)
Time controls						
Linear trend					1.172	(1.985)
Spring					-0.177	(0.470)
Summer					-0.047	(0.493)
Fall					-0.021	(0.358)
Hansen's J (p-value)	31.736 (p= 0.2854)		Exactly identified		Exactly identified	
Obs. macro moments	220		220		220	

Notes: Standard errors clustered within 44 time periods. Instruments are approximations of optimal instruments (Chamberlain, 1987). Standard errors of r obtained via delta method. *** p<0.01, ** p<0.05, * p<0.1

Finally, we re-estimated the model under alternative assumptions regarding the evolution of expected future electricity prices. Our base specification assumed a constant annual growth in electricity prices of 3.4% ($\vartheta = 0.0028148$). Alternative assumptions such as zero growth or a growth of 6.8% had a negligible impact on the results.

Separate discount factors for different utility components To shed light on the sources of variation behind the identification of the discount factor β, we relax some of the parametric restrictions in our structural dynamic model. On the one hand, β directly enters the regression equation (12), capturing the valuation for the option value of postponing adoption. On the other hand, β also enters (12) indirectly through the present value term $p_{j,t}(\beta)$, as given by (2), capturing the valuation of the future GCC benefits and other benefits (electricity cost savings and future tax credits). Table 4 shows two specifications where we attempt to empirically distinguish between different discount factors for separate components.[32]

The first column of Table 4 estimates a separate discount factor for the valuation of all future financial benefits (entering $p_{j,t}(\beta)$) and for the option value of postponing adoption (entering (12) directly). The first discount factor is close to the estimate from our base model. The second discount factor is considerably lower, but is also estimated very imprecisely, and a Wald test does not reject the hypothesis that both discount factors are equal. This indicates that, in our application, the discount factor is mainly identified from variation in the future benefits relative to the upfront investment costs, instead of from variation in the option value. The second column of Table 4 estimates a separate discount factor for benefits that do not come from GCC subsidies. The discount factor relating to the GCC benefits is larger than the one relating to other benefits. But the former is estimated more precisely than the latter, and a Wald test does not reject that both discount factors are equal. In sum, both specifications show that identification of the discount factor mainly comes from variation in the GCC benefits, and that it is difficult to separately distinguish between various components.[33]

Heterogeneity in the discount factor The model with local market heterogeneity allowed for heterogeneity in the valuation of price and capacity, but not in the discount factor β. A homogenous discount factor allows for a transparent interpretation and counterfactual simulation. Accounting for heterogeneity in the discount factor is more complex than accounting for heterogeneity in the valuation of price or capacity, because it involves interacting the unobserved expectational errors (η_t) with local market demographics. In Appendix A.4.2 we explain a procedure to solve this problem, and show the empirical results for a flexible specification in which a rich set of demographics influences the valuation of price, capacity and the discount factor. Figure 5 plots the distribution of the implicit interest rate, implied by our estimates. This shows that there is some heterogeneity, but the interest rate of 90% of households falls within a narrow range of 13.34% to 16.87%.

[32] To estimate the additional parameters, we update the approximation of optimal instruments and add additional instruments in the first stage. The first column adds the next month value of the cost instrument and the GCC benefits, and the second column adds the cost instrument multiplied with the tax cut rate, and the oil price multiplied with the capacity.

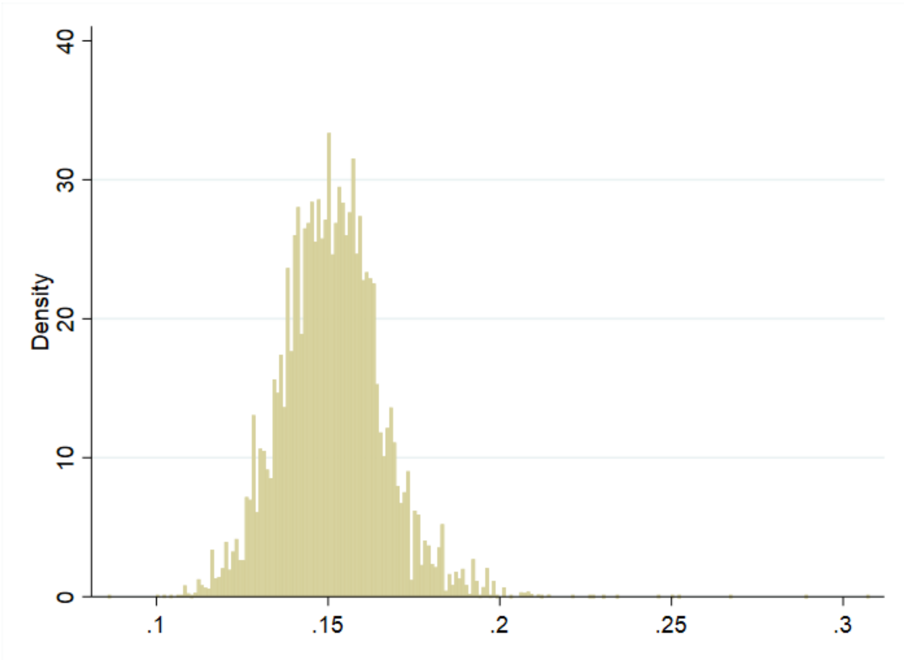
[33] We also considered a specification with a separate parameter for electricity savings (hence also controlling for possible measurement error in this variable). This gives imprecise estimates, while the estimated discount factor for the GCC benefits remains robust. This confirms that identification of the discount factor mainly comes from variation in the GCC benefits.

Table 4: Robustness: separate discount factors for different utility components

	Option value and benefits		GCC and other	
Price sensitivity in 10^3 EUR ($-\alpha$)	-0.279***	(0.108)	-0.771***	(0.145)
Monthly discount factor on GCC benefits	0.9870***	(0.0033)	0.9933***	(0.0011)
Monthly discount factor on non-GCC benefits	0.9870***	(0.0033)	0.9031***	(0.0476)
Monthly discount factor on option value	0.4328	(0.3451)	0.9933***	(0.0011)
Control variables (γ)				
Alternative-specific constant				
Common constant	-4.365	(2.862)	0.056	(0.191)
2kW	-2.120***	(0.375)	-3.602***	(0.575)
6kW	-0.164	(0.387)	1.088**	(0.498)
8kW	-1.809**	(0.751)	0.723	(0.957)
10kW	-1.717	(1.096)	1.915	(1.375)
Wald test discount factors different (p-value)	2.56 (p= 0.1095)		3.58 (p= 0.0584)	
Obs. macro moments	220		220	

Notes: Standard errors clustered within 44 time periods. Instruments are approximations of optimal instruments (Chamberlain, 1987). The first regression assumes that the discount factor in the valuation of investment benefits is the same for all components but the valuation of option value can be different. The second regression allows for a different valuation of non-GCC benefits. *** p<0.01, ** p<0.05, * p<0.1

Figure 5: Heterogeneous interest rate



Implicit real interest rate, resulting from the estimated distribution of the discount factor, as explained in the Appendix section A.4.2. Discount factor estimated at the local market level and weighted by number of potential adopters at start of the sample period.

4.3 Sources of time discounting

Before turning to the implications for the government's GCC policy, we consider various possible sources of the considerable time discounting we have estimated. 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. 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 is possible.

We distinguish between three alternative explanations for the high estimate of the implicit interest rate: the durability of the PV technology, consumer expectations about the government's commitment, and intrinsic consumer undervaluation or 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 6 shows how the estimated implicit interest rate varies as we change the assumptions on the durability of the PV technology: the life expectancy R and the yearly deterioration rate λ. The vertical lines denote the assumptions made in the base model.

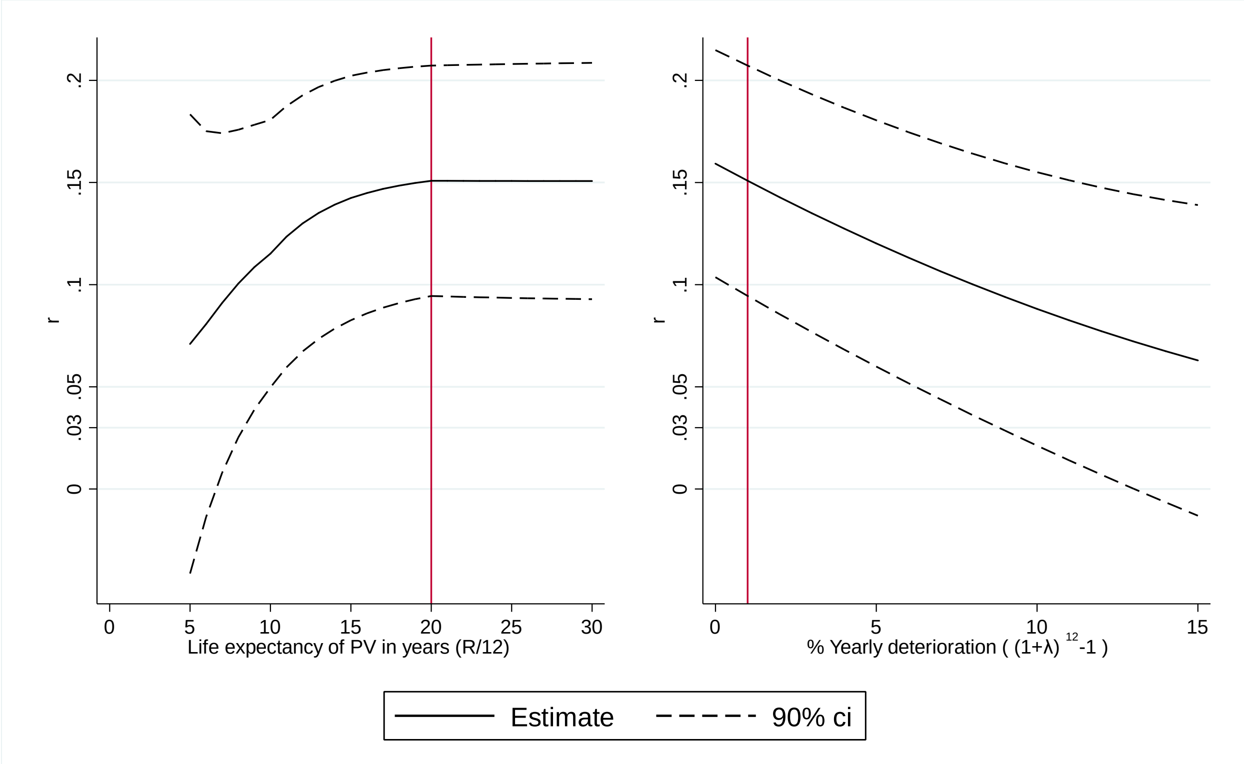
The left part of Figure 6 shows that the estimated implicit interest rate remains robust if we increase the PV's life expectancy R above the assumed value of 20 years or if we reduce it by several years. We estimate a low, market-oriented implicit interest rate only under unrealistically low values for the life expectancy, say 5 years or shorter. Such low levels may be relevant if the value of a PV is not sufficiently capitalized in house prices. However, Dastrup et al. (2012) show that this is not the case based on evidence for California.

According to the right part of Figure 6, 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 deterioration rate of 5% annually does not bring market interest rate within the confidence interval of our estimates.

We conclude that the estimated implicit interest rate would become close to market interest rates only under unrealistic assumptions regarding the durability of the PV technology.

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 commitments to the 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 (10 to 20 years, depending on

Figure 6: Estimated implicit interest rate under different investment assumptions



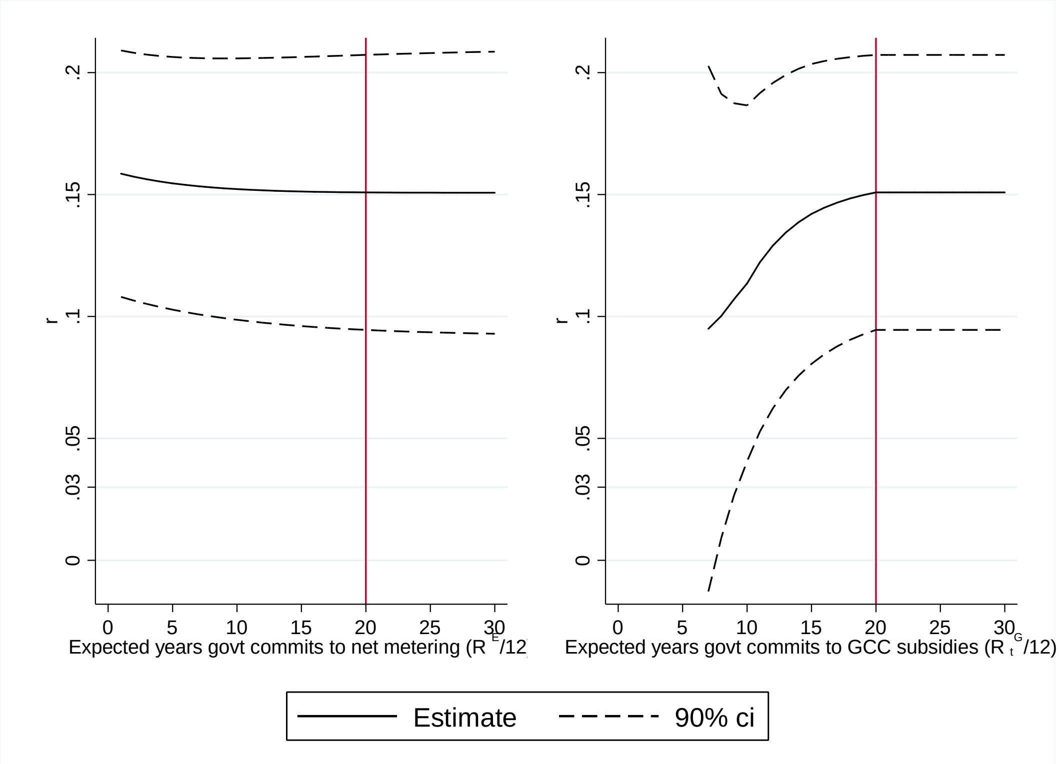
Note: vertical line indicates assumption used in the baseline model

the date of installation). Figure 7 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 R^E or R_t^G in (2).[34]

Changes in expectations about the duration of net metering do not affect the estimated implicit interest rate. In contrast, a change in expectations about the duration of the 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 in principle 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 would have legal consequences and has in fact not actually occurred.

[34] A breach in both contracts is equivalent to the change in the lifetime of a PV, which we considered earlier in Figure 6.

Figure 7: Estimated implicit interest rate under different beliefs for the duration of goverment's commitments

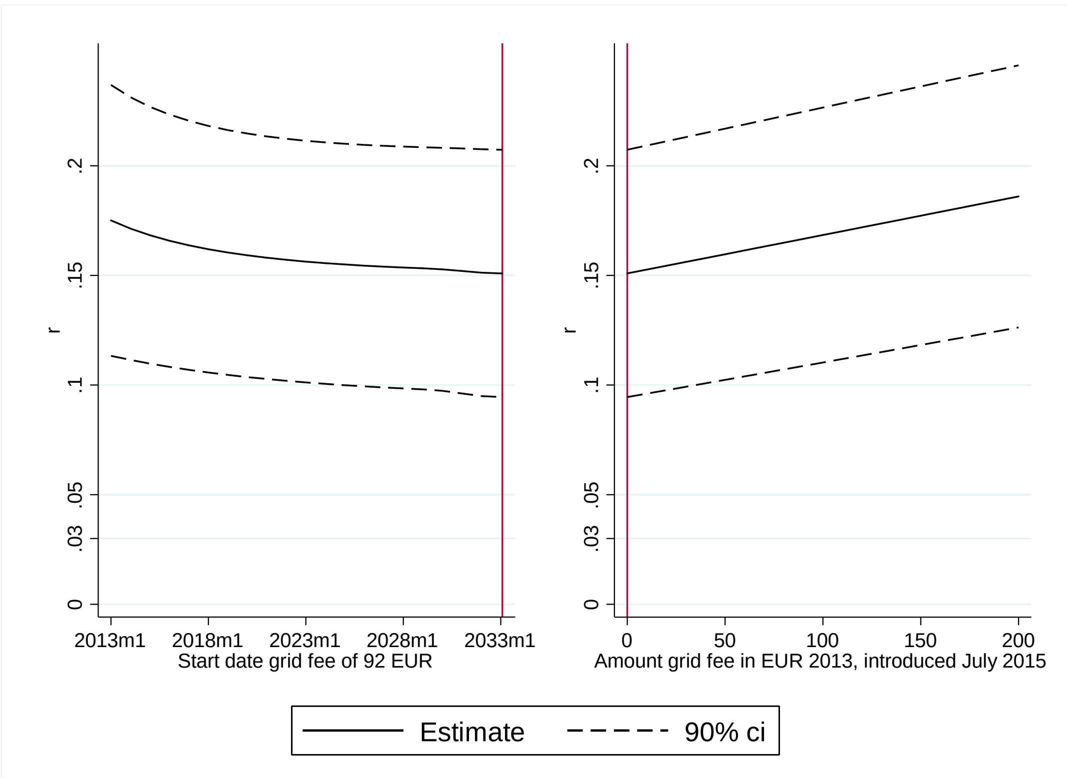


Note: vertical line indicates assumption used in the baseline model

A more realistic scenario to account for consumers' concerns about the lack of government commitment is the introduction of a grid fee, i.e. an access fee to transfer the generated electricity to the network. In July 2015, the government in fact introduced such a fee, after an earlier failed attempt in 2013 (declared illegal by a Brussels Court of Appeal). The annual fee amounted to about €92 per kW of capacity (hence an annual fee of €368 for a household with the most common capacity of 4kW). In principle, the government could have introduced an even higher grid fee, but the incentive to do so is limited as it would discourage new adopters who would also have to pay the grid fee (and do not benefit from any subsidy program in contrast to old adopters).

Since the grid fee was introduced well after the last month of our sample (December 2012), our base specification assumed households did not anticipate such a fee. However, rumors (and failed government attempts) may have influenced consumer expectations. Note that the expectation of a grid fee does not affect the estimated discount factor if the expected level and time frame of introduction remain constant over time (as alternative assumptions on the level or time frame would then be absorbed in the choice-specific fixed effects). We therefore assess how the estimated discount factor changes when the expected time frame or level of the grid fee changes. The left part of Figure 8 shows the estimated interest rate, assuming that consumers expect the grid fee of €92 per kW to be introduced in different months since January 2013 (the first month after the end of our sample). This shows that the estimated interest rate slightly increases as the expected introduction of the grid fee moves closer to January 2013. The right part of Figure 8 shows the estimated interest rate, assuming consumers expect a grid fee in July 2015 (when it actually happened) for various possible levels of this grid fee. We see that for larger values of this expected grid fee, the estimated interest rate increases. Intuitively, accounting for consumer expectations of an earlier and/or higher grid fee results in higher estimates for the interest rate, because with such expectations forward-looking consumers would have adopted earlier to take advantage of the months without a grid fee.

Figure 8: Estimated implicit interest rate under different beliefs about grid fee



Note: vertical line indicates assumption used in the baseline model

Uncertainty or intrinsic undervaluation ("myopia") In the above we assessed whether uncertainty about future payoffs (e.g. because of uncertainty about government's commitment) could be responsible for the high implicit interest rates.[35] A remaining explanation for the high implicit interest rate would be that this is evidence for intrinsic undervaluation or consumer myopia. It is then still interesting to ask where such myopia might come from. A first possibility is that consumers take into account only the future GCC subsidies but fail to take into account the tax cuts. Another possibility is that consumers correctly value the benefits only up to the pay-back period, and undervalue the benefits after that. The pay-back period is that time when all collected benefits are equal to the investment costs. This number is often quoted in advertising or media coverage, so it may be an important source of information for households who cannot do a net present value calculation. Figure 9 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.

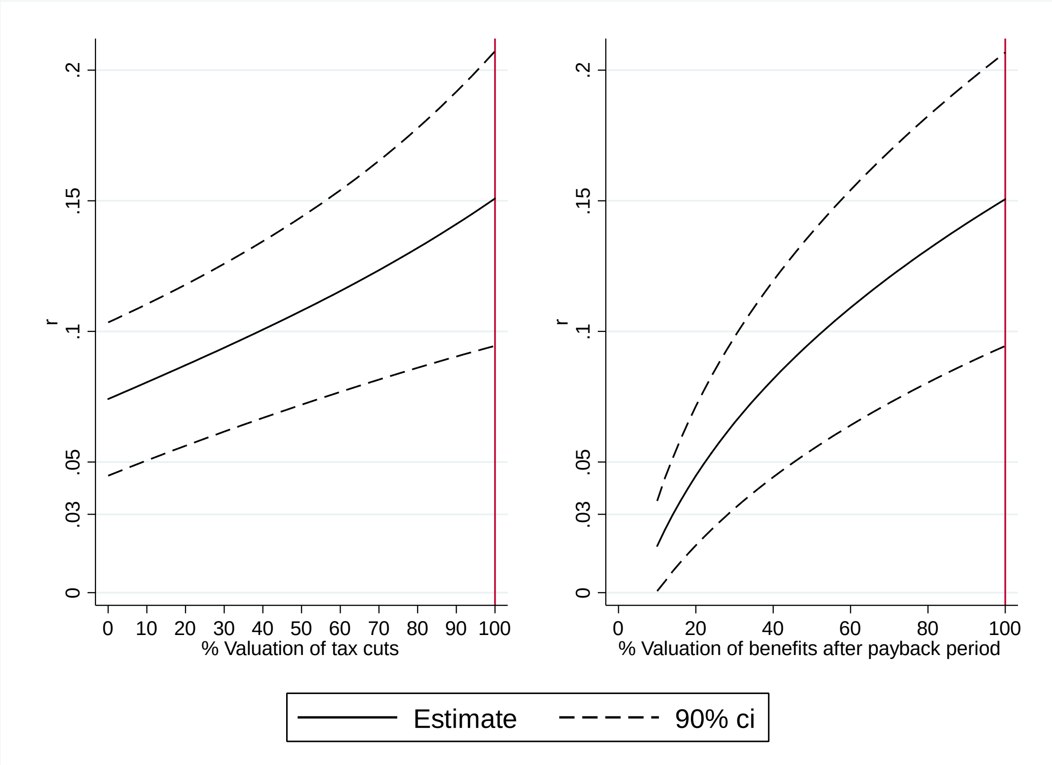
To assess the role of an incorrect valuation of the tax cuts, we multiply the tax cut benefits by a parameter between 0 and 100%. The estimated implicit interest rate remains high even for quite severe undervaluation of the tax cuts. Hence, a failure to take into account the tax cuts may partly explain household myopia, but the high interest rate is also due to the 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 only for strong undervaluation after the payback period (less than 20% 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 substantial time discounting 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.

[35] Another source of uncertainty may be the expected amount of electricity production, which may vary from year to year. However, annual statistics show that the 95% confidence interval bounds for the total number of hours of sunshine are only 4.6% higher or lower than the average, implying uncertainty is limited over a 15- or 20-year period.

Figure 9: Estimated implicit interest rate under consumer myopia



Note: vertical line indicates assumption used in the baseline model

4.4 Upfront investment subsidies instead of future production subsidies

Our finding that consumers use a real implicit interest rate of 15% 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 at a lower budgetary cost by removing the future GCC subsidy program and instead paying an equivalent upfront subsidy. It could then borrow the required amount to finance the upfront subsidy 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 R_t^G months of

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

where the estimated monthly discount factor $\beta = 0.9884$ corresponds to an implicit annual interest rate of $r = \beta^{-12} - 1 = 15.00\%$. The government could thus have paid out the households' perceived amount $NPV_{j,t}^{PERC}$ as an upfront subsidy program and obtained the same adoption rate. Because the government instead spread the subsidies over the next R_t^G months, the net present value at the government bond interest rate $r_{gov} = \beta_{gov}^{-12} - 1 = 3\%$ amounted to

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

Hence, the government could have reached an identical number of adopters with an upfront subsidy $NPV_{j,t}^{PERC}$ and saved the amount $NPV_{j,t}^{ACTUAL} - NPV_{j,t}^{PERC}$ for a household that adopts PV system j at time t. Summing this over all adopters and all PV systems, we find that the cost of the actual subsidy program was € 3.79 billion in net present value terms, while the cost of an upfront subsidy program would have been only € 1.87 billion (actualized to 2013). Hence, the government could have achieved the same adoption rates at only 49% of the current subsidy costs, amounting to a saving of € 1.92 billion (with a 90% confidence interval of [€ 1.48– € 2.22] billion[36]). This is a saving of more than € 700 per Flemish household, which is a very large number given that only 8.3% of the households had adopted a PV by December 2012. Note that savings might have been even larger if the government would also have abandoned the net metering principle (future benefits through electricity cost savings $p_{j,t}^{EL}$) in favour of an even larger upfront subsidy. However, such a policy may create incentive problems, since households may be induced to invest in PVs even if they do not have good investment conditions (such as a good roof orientation).[37]

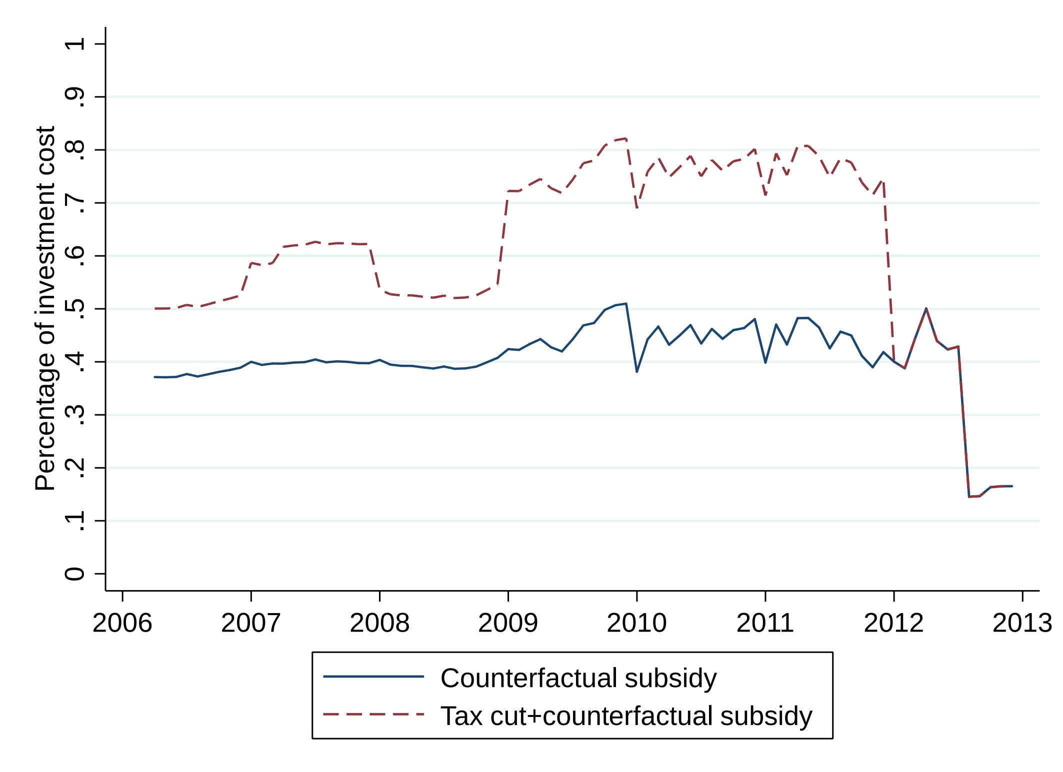
How large should the upfront subsidy be to obtain these budgetary savings? The answer to this question depends on the specific point in time, because the generosity of the GCC subsidy program fluctuated over time. The blue line on Figure 10 plots the evolution of the required upfront investment subsidy to avoid the expensive GCC system, as a percentage of the investment price of an average sized PV of 4kW in each month.[38] This shows that the required investment subsidy varies between 37% and 51% over the period 2006-2011, but drops to 15% at the end of the program. The red line shows the total required upfront

[36] To calculate the confidence interval, we take 1000 draws of β which, as a GMM estimate, is normally distributed with mean of 0.9884 and standard error of 0.0024. We calculate the government loss for each draw of β to obtain a distribution of this loss.

[37] Savings may also have been larger if the government would also have followed an upfront subsidy policy for the equally important commercial users (capacity size higher than 10kW). This would however require further investigation, since it is possible that commercial users have a lower implicit interest rate.

[38] The required percentage subsidy is slightly larger for larger PVs and slightly smaller for smaller ones. This is because GCC subsidies are proportional to the capacity of a PV, while investment costs exhibit small returns to scale.

Figure 10: Counterfactual investment subsidy



Note: investment cost extrapolated before May 2009 using predicted values from price index EUPD

subsidy, i.e. including the tax credit which the government already applied.[39] The total upfront subsidy required to avoid the expensive GCC system varied around 55% in the first half of the period. It then increased to around 80% until the end of 2011. Afterwards, it coincides with the other line as the tax cuts were abolished. In sum, large upfront investment subsidies (of up to 82%) are required to obtain the large budgetary savings from removing the GCC subsidy program. While this might seem paradoxical, it simply illustrates how generous the GCC system was.

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

[39] In 2006 and 2007, the Flemish government also applied a small investment subsidy. We included this in the tax cut component of this graph.

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 51% or € 1.9 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. Recent evidence points to moderate undervaluation to correct valuation for energy saving investments of existing, mature technogies (such as cars). Our findings indicate that consumers may discount the future benefits more when adopting an entirely new green technology.

We adopted a tractable dynamic model of technology adoption, and several directions of future work are possible. First, in our sensitivity analysis we found little heterogeneity in discounting across consumers. If such heterogeneity is more important, subsidization policies would have additional distributional effects, and may need targeting to consumers with a low discount factor. 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 commercial PV adopters discount future benefits in the same way. It would also be interesting to apply our framework to other countries or regions, or to other renewable technologies, such as wind power, to analyze how different subsidy schemes may influence the outcomes.

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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 prices, GCCs and socio-demographic data at the local market 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 295 households. 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 quotes; 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 proceeded 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 time 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 reported 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 website of the government agency VEA before and after this publication.[40] Information on spreading tax cuts or splitting bills over multiple years comes from newspaper articles[41] and the Economic Recovery Plan of the Federal Government (March 2009). Details about the abolishment of the tax cut were found on the official website of the finance department of the federal government.[42] Information on the VAT rules also can be found on this website.[43]

We combine this information with the price data to compute the net investment price, as described more formally in section 3.1.

Net metering 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 cubic spline interpolation. We multiply the electricity prices with the expected electricity production to compute the expected electricity cost savings from net metering, as described more formally in section 3.1.

[40] 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).

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

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

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

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.[44] 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 expiration 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 (and the first months of 2013). Figure 1 in the text makes use of this information to express the various subsidies in present value terms.

[44] 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).

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 used population data for each statistical sector in 2011 to create the following variables: population density, average house size (number of rooms), average household size, average house age, median income, % of home owners, % with a higher education degree and % foreign (people who do not have the Belgian nationality). 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.1.5 Exogenous instruments

Two variables we use do not directly influence the adoption decision of households, but we use them as instruments for endogenous variable that do affect the decision. The first exogenous instrument is the price index for Chinese Crystalline PV modules of "pvxchange" that is available on their website. The prices are per kW so we multiply them by the kW of each category to create $p_{j,t}^{MOD}$. In the discussion on optimal instruments, we also added the oil price as an additional exogenous instrument. The price of crude oil was obtained from Thomson Reuters Datastream. As with other price variables in the model, we correct for inflation by using the HICP.

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 . In this section we discuss the optimal instruments in the model that uses only macro data, i.e. ignoring local market heterogeneity. In the next section, which provides details on how we estimate the model when local market data are added, we discuss how we adapt optimal instruments in this case.

Defining the parameter vector $\theta = (\alpha, \beta, \gamma)$, the conditional moment conditions are

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

where

$$e_{j,t}(\theta) = \ln S_{j,t}/S_{0,t} - \left(x_{j,t} - \beta x_{1,t+1}\right)\gamma + \alpha\left(p_{j,t}(\beta) - \beta p_{1,t+1}(\beta)\right) - \beta \ln S_{1,t+1} \tag{17}$$

The optimal instrument matrix of Chamberlain (1987) for a single-equation GMM estimator is:

$$\begin{aligned}
g_{jt}(z_{jt}) &= D_{jt}(z_{jt})'\Omega_{jt}^{-1} \\
\text{with } \Omega_{jt} &= E[(e_{j,t})^2|z_{jt}] \\
D_{jt}(z_{jt}) &= \left(E\left[\frac{\partial e_{j,t}(\theta)}{\partial \theta'} \middle| z_{jt} \right] \right) \\
&= \left(E\left[\frac{\partial e_{j,t}(\theta)}{\partial \alpha} \middle| z_{jt} \right] \quad E\left[\frac{\partial e_{j,t}(\theta)}{\partial \beta} \middle| z_{jt} \right] \quad E\left[\frac{\partial e_{j,t}(\theta)}{\partial \gamma'} \middle| z_{jt} \right] \right)
\end{aligned}$$

In our approximation, we follow Newey (1990) and set $\Omega_{jt} = \Omega$, i.e. we ignore potential heteroscedasticity. Moreover, since Ω is a scalar in the single-equation GMM estimator, we can also replace it by the identity matrix.

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

$$E\left[\left.\frac{\partial e_{j,t}(\theta)}{\partial \gamma'}\right| z_{jt}\right] = -E\left[x_{j,t} - \beta x_{1,t+1}|z_{jt}\right] = -\left(x_{j,t} - \beta x_{1,t+1}\right). \tag{18}$$

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

$$E\left[\left.\frac{\partial e_{j,t}(\theta)}{\partial \alpha}\right| z_{jt}\right] = E\left[p_{j,t}(\beta) - \beta p_{1,t+1}(\beta)|z_{jt}\right] = E\left[p_{j,t}(\beta)|z_{jt}\right] - \beta E\left[p_{1,t+1}(\beta)|z_{jt}\right]. \tag{19}$$

In this expression the conditional expectation of price is

$$\begin{aligned} E\left[p_{j,t}(\beta)|z_{jt}\right] &= E\left[p_{j,t}^{INV}(\beta)|z_{jt}\right] - \rho_t^G(\beta) E\left[p_{j,t}^{GCC}|z_{jt}\right] - \rho^E(\beta) E\left[p_{j,t}^{EL}|z_{jt}\right] \\ &= E\left[p_{j,t}^{GROSS}|z_{jt}\right] - \sum_{\tau=1}^{4} \beta^{12\tau} E\left[taxcut_{j,t}^{\tau}|z_{jt}\right] \\ &\quad -\rho_t^G(\beta) p_{j,t}^{GCC} - \rho^E(\beta) E\left[p_t^{EL}|z_{jt}\right] k_j' \end{aligned} \tag{20}$$

where the capitalization factors $\rho_t^G(\beta)$ and $\rho^E(\beta)$ are defined in (2) and depend on the discount factor β. $p_{j,t}^{EL}$ is the electricity price per MWh, multiplied by k_j', the monthly electricity production of a PV with capacity k_j. 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 $E\left[p_{j,t}^{GROSS}(\beta)\right| z_{jt}\right]$ is obtained from a constant elasticity model, using a Poisson regression and logarithmic regressors (see Silva and Tenreyro (2006)). Based on this predicted value we can also calculate the predicted future eligible tax cuts $E\left[taxcut_{j,t}^{\tau}|z_{jt}\right]$. The predicted electricity price $E\left[p_t^{EL}|z_{jt}\right]$ is similarly obtained using the oil price as an exogenous regressor. We show the regression results in Tables A2 and A3. Note that any misspecification influences only the optimality of our instrument set and not the consistency of the structural estimates of our model.

Finally, the optimal instrument for the nonlinear parameter β is

$$\begin{aligned} E\left[\left.\frac{\partial e_{j,t}(\theta)}{\partial \beta}\right| z_{jt}\right] &= x_{1,t+1}\gamma - E\left[\ln S_{1,t+1}\right| z_{jt}\right] \\ &\quad +\alpha\left(E\left[\left.\frac{\partial p_{j,t}(\beta)}{\partial \beta}\right| z_{jt}\right] - E\left[p_{1,t+1}(\beta)\right| z_{jt}\right] - E\left[\left.\frac{\partial p_{1,t+1}(\beta)}{\partial \beta}\right| z_{jt}\right]\beta\right) \end{aligned} \tag{21}$$

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

$$E\left[\left.\frac{\partial p_{j,t}(\beta)}{\partial\beta}\right|z_{jt}\right] = -\sum_{\tau=1}^{4}12\tau\beta^{12\tau-1}E\left[taxcut^{\tau}_{j,t}|z_{jt}\right] -\frac{\partial\rho^{G}_{t}(\beta)}{\partial\beta}p^{GCC}_{j,t}-\frac{\partial\rho^{E}(\beta)}{\partial\beta}E\left[p^{EL}_{t}|z_{jt}\right]k'_{j}$$

where the derivatives with respect to the capitalization factors $\rho^{G}_{t}(\beta)$ 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 the CCP term, i.e. the log of the predicted next period market share of alternative 1, $E[\ln S_{1,t+1}|z_{jt}]$. 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. Note that by using future values of exogenous instruments, we assume that these variables are not correlated with the demand shock or prediction error at time t. Therefore, they must be known at time t. Since we are using only one and two month leads, we believe this is a reasonable assumption as new policies were announced several months ahead (see section A.1).

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

- Estimate a GMM model with instruments $p^{MOD}_{j,t}, p^{GCC}_{j,t}$ 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 (18), (19) and (21), after substituting (20) and the initial consistent estimates of α, β and γ.

Table A2: Estimation results for electricity price

Variables	$E\left[p_t^{EL} \mid z_{jt}\right]$
Log of oil price	0.183***
	(0.018)
Constant	4.599***
	(0.073)
Observations	44

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 A3: Estimation results for PV investment price

Variables	$E\left[p_{j,t}^{GROSS} \mid z_{jt}\right]$
Log of PV module price x kW	0.499***
	(0.063)
4kW	0.202***
	(0.021)
6kW	0.310***
	(0.031)
8kW	0.400***
	(0.039)
10kW	0.468***
	(0.045)
Log of GCC benefits	0.112*
	(0.058)
Constant	4.631***
	(0.316)
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 CCP correction term

Variables	$E\left[\ln s_{1,t+1} \mid z_{jt}\right]$
PV module price x 4kW in t+1	-0.001**
	(0.001)
PV module price x 4kW in t+2	0.001
	(0.001)
GCC benefits of 4kW in t+1	0.116***
	(0.019)
GCC benefits of 4kW in t+2	-0.054***
	(0.019)
Oil price x 4 kW in t+1	0.006
	(0.009)
Oil price x 4 kW in t+2	0.003
	(0.008)
Constant	-12.995***
	(2.485)
Observations	44

OLS regression model of linear conditional mean

Standard errors in parentheses, clustered within time period

*** 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. We estimate this model using a GMM estimator that combines macro and micro-moments at the local market level. 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).

First, we explain how one could proceed when the discount factor β is known, i.e. does not need to be estimated. In this case it is possible to estimate the impact of local market heterogeneity and of the mean utility determinants in two separate steps. Second, we explain how to proceed if the discount factor β is not known, i.e. needs to be estimated. This also includes a discussion of how we implement optimal instruments and some final estimation details.

A.3.1 Estimation when the discount factor β is known

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 $\widetilde{\delta}_{j,t}$, defined below. We first make use of the Hotz-Miller inversion to obtain an expression for $v_{i,0,t}$ that is parallel to that of (10) above:

$$v_{i,0,t} = \beta \left(v_{i,1,t+1} - \ln s_{m,1,t+1} - \eta_t \right). \tag{22}$$

Note that this assumes that a household's prediction error is common across local markets, i.e. $\eta_t \equiv \overline{V}_{m,t+1} - E_t \overline{V}_{m,t+1}$. We then use the expressions for the conditional values $v_{i,j,t}$ and $v_{i,0,t}$, as given by (15) and (22), to write the choice probabilities as:

$$\begin{aligned} s_{m,j,t}\left(\widetilde{\delta}, \Lambda\right) &= \frac{\exp(v_{i,j,t})}{\sum_{j'=0}^{J} \exp(v_{i,j',t} - v_{i,0,t})} \\ &= \frac{\exp(v_{i,j,t} - v_{i,0,t})}{1 + \sum_{j'=1}^{J} \exp(v_{i,j',t} - v_{i,0,t})} \\ &= \frac{\exp(\widetilde{\delta}_{j,t} + \widetilde{w}_{j,t}\lambda_m + \beta \ln s_{m,1,t+1})}{1 + \sum_{j'=1}^{J} \exp(\widetilde{\delta}_{j',t} + \widetilde{w}_{j',t}\lambda_m + \beta \ln s_{m,1,t+1})} \end{aligned} \tag{23}$$

where we define $\widetilde{\delta}_{j,t} \equiv \delta_{j,t} - \beta(\delta_{1,t+1} - \eta_t)$ and $\widetilde{w}_{j,t} \equiv w_{j,t} - \beta w_{1,t+1}$. The choice probabilities $s_{m,j,t}\left(\widetilde{\delta}, \Lambda\right)$ are thus a function of the alternative/time fixed effects $\widetilde{\delta}_{j,t}$ (collected in the vector $\widetilde{\delta}$) and of the local market interaction effects λ_m (collected in the parameter matrix Λ).

Note that the right hand side of (23) depends on the next period probabilities $s_{m,1,t+1}$, which are treated as data from a first-stage prediction. In contrast to the model with only aggregate data, we no longer accurately observe the CCP correction term $\ln s_{m,1,t+1}$ directly due to the small number of households in each statistical sector m. In many local markets adoption rates are zero, so that the CCP correction term would be undefined. We therefore use a first-stage prediction of the CCP correction term, $\widehat{s}_{m,1,t+1}$, based on a flexible logit. We include local market fixed effects, capacity fixed effects for each time period, capacity-specific effects for each demographic, and capacity-time-specific effects for the demographics that enter the price parameter. We then use the parameters of this model to calculate the predicted market shares for $j = 1$ in every time period and use the predictions in $t + 1$ in the conditional value functions at time t.

The maximization problem of the log likelihood function is then

$$\max_{\widetilde{\delta},\Lambda} \ln L(\widetilde{\delta}, \Lambda) = \sum_{t=1}^{T} \sum_{m=1}^{M} \sum_{j=0}^{J} q_{m,j,t} \ln s_{m,j,t}(\widetilde{\delta}, \Lambda)$$

where $q_{m,j,t}$ is the observed number of households in local market m that adopt $(j = 1, ...J)$ or choose not to adopt $(j = 0)$ at period t. This is similar to a maximum likelihood estimator that sums over individual data but since $\ln s_{m,j,t}(\widetilde{\delta}, \Lambda)$ is identical for each household in market m, we can multiply it by the number of households that make each choice. Note that this contains a potentially large number of parameters, because of the set of alternative/time fixed effects $\widetilde{\delta}_{j,t}$ $(J \times T)$, but also a large number of parameters in Λ due to the inclusion of local market fixed effects.

Step 2. Instrumental variables regression of $\widetilde{\delta}_{j,t}$

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

$$\widetilde{\delta}_{j,t} = (x_{j,t} - \beta x_{1,t+1})\,\gamma - \alpha\,(p_{j,t} - \beta p_{1,t+1}) + e_{j,t} \text{ for } j = 1, ...J \tag{24}$$

where $e_{j,t}$ was already defined before for the aggregate model as $e_{j,t} \equiv \xi_{j,t} - \beta(\xi_{1,t+1} - \eta_t)$. The IV regression then imposes the following moment conditions

$$E\,(z_{j,t} e_{j,t}) = 0$$

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 imposed value of β, and the instruments are the same as the ones used before in the aggregate model (though one can reduce the number of instruments, since the discount factor is treated as known).

Simultaneous GMM

Given the known discount factor β, this two-step approach yields consistent estimates of all parameters, but in the second step standard errors need to be corrected because the $\widetilde{\delta}_{j,t}$ are estimated values. Alternatively, this model can be estimated at once using a GMM estimator that combines the scores of the likelihood function of the first step (micro-moments), with the moment condition that is imposed by the IV regression of the second step (macro-moment). The stacked vector of sample moment conditions is then

$$g(\widetilde{\delta}, \Lambda, \alpha, \gamma) = \begin{pmatrix} \partial \ln L(\widetilde{\delta}, \Lambda)/\partial(\widetilde{\delta}, \Lambda) \\ \sum_{t=1}^{T} \sum_{j=1}^{J} z_{j,t} e_{j,t} \left(\widetilde{\delta}, \alpha, \gamma\right) \end{pmatrix}$$

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

$$\begin{aligned} \frac{\partial \ln L(\widetilde{\delta}, \Lambda)}{\partial \widetilde{\delta}_{j,t}} &= \sum_{m=1}^{M} N_{m,t} \left(\frac{q_{m,j,t}}{N_{m,t}} - s_{m,j,t}(\widetilde{\delta}, \Lambda) \right) \\ \frac{\partial \ln L(\widetilde{\delta}, \Lambda)}{\partial \lambda^h} &= \sum_{t=1}^{T} \sum_{m=1}^{M} N_{m,t} \sum_{j=1}^{J} \left(\frac{q_{m,j,t}}{N_{m,t}} - s_{m,j,t}(\widetilde{\delta}, \Lambda) \right) \widetilde{w}_{j,t} D_m^h \end{aligned}$$

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). The scores $\partial \ln L(\widetilde{\delta}, \Lambda)/\partial \widetilde{\delta}_{j,t}$ (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 $\partial \ln L(\widetilde{\delta}, \Lambda)/\partial \lambda^h$ (for each demographic h) are moment conditions that the observed sales-weighted demographic interactions should be equal the model's predictions. Since we include dummy variables for each local market in the flow utility of a PV, it essentially also introduces a moment condition that matches the total number of adoptions at the end of the sample predicted by the model with that observed in the data. The GMM estimator minimizes $g'Wg$ with respect to the parameters, where W is the weighting matrix.

A.3.2 Estimating the discount factor β

When β is known, a two-step procedure is possible because no parameter estimated in the second step, enters the estimation in the first step. If β also has to be estimated, this is no longer the case. The discount factor enters the local market shares directly as the coefficient in front of the CCP term (see (23)), but also implicitly in the interaction effects of demographic variables with the price variable. We therefore proceed with joint estimation. The stacked vector of sample moment conditions then also depends on the discount factor

$$g(\widetilde{\delta}, \Lambda, \alpha, \beta, \gamma) = \begin{pmatrix} \partial \ln L(\widetilde{\delta}, \Lambda, \beta)/\partial(\widetilde{\delta}, \Lambda) \\ \sum_{j,t} z_{j,t} e_{j,t} \left(\widetilde{\delta}, \alpha, \beta, \gamma\right) \end{pmatrix}$$

Similar to the aggregate model, we now also need an extra instrument in $z_{j,t}$ to identify the discount factor.

Optimal instruments

We again make use of the approximation to optimal instruments we discussed in section A.2. However, due to the variation of the CCP correction term across local markets, the error term, and therefore also the optimal set of instruments, is different. From (24) it follows that the error term is now

$$e_{j,t}(\widetilde{\delta}, \alpha, \beta, \gamma) = \widetilde{\delta}_{j,t} - (x_{j,t} - \beta x_{1,t+1}) \gamma + \alpha \left(p_{j,t}(\beta) - \beta p_{1,t+1}(\beta)\right) \tag{25}$$

Notice the difference with (17): $\widetilde{\delta}_{j,t}$ has replaced $\ln S_{j,t}/S_{0,t} - \beta \ln S_{1,t+1}$.Therefore the derivative of the discount factor no longer depends on the CCP so that (26) replaces (21) in the construction of the optimal instrument vector:

$$\begin{aligned} E\left[\left.\frac{\partial e_{j,t}(\widetilde{\delta}, \alpha, \beta, \gamma)}{\partial \beta}\right| z_{jt}\right] &= x_{1,t+1}\gamma \\ &+\alpha \left(E\left[\left.\frac{\partial p_{j,t}(\beta)}{\partial \beta}\right| z_{jt}\right] - E\left[\left. p_{1,t+1}(\beta)\right| z_{jt}\right] - E\left[\left.\frac{\partial p_{1,t+1}(\beta)}{\partial \beta}\right| z_{jt}\right]\beta \right). \end{aligned} \tag{26}$$

Estimation details

Our main specification includes a full set of local market fixed effects in Λ. We then exclude the local markets where adoption never occurred, because with the local market fixed effects these markets do not add any information to the likelihood function which we use to construct the micro-moments of the model. To reduce the number of fixed effects and speed up the estimation procedure, we use a random sample of 50%. We also estimated an alternative specification with all local markets, but with a reduced number of 308 fixed effects at the municipality level and with household characteristics interacted with the constant. This gave similar results to the specification with a full set of local market fixed effects.

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.

A.4 Additional results for robustness checks

A.4.1 Alternative terminal actions for CCP approach

Table A5: Robustness: terminal action

	Terminal action: 2kW		Terminal action: 4kW (used in paper)		Terminal action: 6kW	
Price sensitivity in 10^3 EUR ($-\alpha$)	-0.351***	(0.113)	-0.470***	(0.098)	-0.513***	(0.102)
Monthly discount factor (β)	0.9870***	(0.0032)	0.9884***	(0.0025)	0.9906***	(0.0016)
Annual interest rate ($r \equiv \beta^{-12} - 1$)	16.99%***	(4.68%)	15.09%***	(3.43%)	11.94%***	(2.10%)
	Control variables (γ)					
Alternative-specific constant						
Common constant	-0.983	(15.425)	-1.423	(16.38)	-4.575	(19.325)
2kW	-2.111***	(0.457)	-1.828***	(0.562)	-1.199**	(0.531)
6kW	-0.193	(0.484)	-0.513	(0.595)	-1.162**	(0.565)
8kW	-1.847**	(0.942)	-2.453**	(1.158)	-3.742***	(1.097)
10kW	-1.747	(1.372)	-2.605	(1.684)	-4.507***	(1.592)
Hansen's J (p-value for endogeneity)	Exactly identified		Exactly identified		Exactly identified	
Obs. macro moments (JxTx terminal choices)	220 x 1		220 x 1		220 x 1	
Obs. micro moments (MxJxT)	0		0		0	

	Terminal action: 8kW		Terminal action: 10kW		Terminal action: All (joint estimation)	
Price sensitivity in 10^3 EUR ($-\alpha$)	-0.542***	(0.112)	-0.505***	(0.111)	-0.422***	(0.046)
Monthly discount factor (β)	0.9885***	(0.0018)	0.9882***	(0.0020)	0.9873***	(0.0007)
Annual interest rate ($r \equiv \beta^{-12} - 1$)	14.85%***	(2.46%)	15.27%***	(2.81%)	16.62%***	(1.03%)
	Control variables (γ)					
Alternative-specific constant						
Common constant	-2.599	(16.429)	-1.270	(18.673)	-10.158	(11.278)
2kW	-1.734***	(0.416)	-1.832***	(0.429)	-2.044***	(0.129)
6kW	-0.628	(0.432)	-0.518	(0.448)	-0.282**	(0.136)
8kW	-2.663***	(0.849)	-2.453***	(0.879)	-2.022***	(0.262)
10kW	-2.890**	(1.246)	-2.591**	(1.288)	-1.990***	(0.399)
Hansen's J (p-value for incorrect specification)	Exactly identified		Exactly identified		31.726 (p= 0.2858)	
Obs. macro moments (JxTx terminal choices)	220 x 1		220 x 1		220 x 5	
Obs. micro moments (MxJxT)	0		0		0	

Notes: Standard errors clustered within 44 time periods. Instruments are approximations of optimal instruments (Chamberlain, 1987). Standard errors of r obtained via delta method. *** p<0.01, ** p<0.05, * p<0.1

A.4.2 Heterogeneous discount factor

This section first explains how we extend our model of local market heterogeneity to incorporate heterogeneity in the discount factor. Next, we present the empirical results.

Approach With a local market-specific discount factor β_m, the predicted local market shares are given by the following generalization of (23):

$$s_{m,j,t} = \frac{\exp(\widetilde{\delta}_{m,j,t} + \widetilde{w}_{j,t}\lambda_m + \beta_m \ln s_{m,1,t+1})}{1 + \sum_{j'=1}^{J} \exp(\widetilde{\delta}_{m,j',t} + \widetilde{w}_{j',t}\lambda_m + \beta_m \ln s_{m,1,t+1})} \tag{27}$$

where

$$\widetilde{\delta}_{m,j,t} = (x_{j,t} - \beta_m x_{1,t+1})\gamma - \alpha_m(p_{j,t}(\beta_m) - \beta_m p_{1,t+1}(\beta_m)) + \xi_{j,t} \underbrace{-\beta_m\left(\xi_{1,t+1} - \eta_t\right)}_{\widetilde{\tau}_{m,t}}. \tag{28}$$

Note that we explicitly write a local market specific price coefficient α_m, therefore $\widetilde{w}_{j,t}$ no longer contains interactions with the price variable. Suppose the discount factor is the following function of $H \times 1$ vector of household characteristics D_m:

$$\begin{aligned} \beta_m &= g\left(\beta_0 + \kappa_\beta D_m\right) \\ &= \frac{\exp(\beta_0 + \kappa_\beta D_m)}{1 + \exp(\beta_0 + \kappa_\beta D_m)}, \end{aligned}$$

where κ_β are parameters measuring how the discount factor varies with household characteristics. This allows for a very flexible specification of β_m and ensures that $\beta_m \in (0,1)$, even with continuous variables in D_m.

Apart from the non-linearity through which β_m enters (also through the term $p_{j,t}(\beta_m)$), the key issue relates to the term $\widetilde{\tau}_{m,t}$ entering (28). This term contains interactions between the market-specific discount factor β_m and the expectational error η_t. One approach would be to discretize the vector of household characteristics D_m to D possible realizations or "demographic groups", $d = 1, \ldots, D$. One can then absorb the $\widetilde{\tau}_{m,t}$ with fixed effects by period t and group d, allowing us to also control for expectational errors $\eta_t(d)$ by period t and group d.

To make better use of the rich and continuous variables in D_m we also follow an alternative approach. Let the term $\widetilde{\tau}_{m,t}$ be given by the following function of household characteristics

$$\widetilde{\tau}_t\left(D_m\right) \equiv -g\left(\beta_0 + \kappa_\beta D_m\right)\left(\xi_{1,t+1} - \eta_t\left(D_m\right)\right)$$

where $\eta_t(D_m)$ is a differentiable function of D_m, reflecting an expectational error that may vary across markets by demographics. We approximate $\widetilde{\tau}_t(D_m)$ using the following first-order Taylor expansion for $\widetilde{\tau}_t(D_m)$ around the mean of D_m, which we normalize to 0:

$$\widetilde{\tau}_t(D_m) \approx -g(\beta_0)\left(\xi_{1,t+1} - \eta_t(0)\right) + \nabla\widetilde{\tau}_t(0) D_m,$$

where $\nabla\widetilde{\tau}_t(0)$ is the $1 \times H$ gradient for each t at $D_m = 0$. A typical element of $\nabla\widetilde{\tau}_t(0)$ is $\nabla\widetilde{\tau}_t^h$, yielding t-specific parameters to be estimated as interactions with each of the demographics D_m^h. The main benefit of this Taylor expansion is that $\widetilde{\tau}_t(D_m)$ now depends linearly on D_m in each time period.

We add the following scores as micro-moments to identify the discount factor parameters κ_β^h (elements of κ_β) and the parameters $\nabla\widetilde{\tau}_t^h$:

$$\begin{aligned}
\frac{\partial \ln L}{\partial \kappa_\beta^h} &= \sum_{t=1}^{T}\sum_{m=1}^{M} N_{m,t} \sum_{j=1}^{J} \left(\frac{q_{m,j,t}}{N_{m,t}} - s_{m,j,t}(\widetilde{\delta}, \Lambda) \right) \frac{\partial \Upsilon_{m,j,t}}{\partial \beta_m} g'\left(\beta_0 + \kappa_\beta D_m\right) D_m^h \\
\frac{\partial \ln L}{\partial \nabla\widetilde{\tau}_t^h} &= \sum_{m=1}^{M} N_{m,t} \sum_{j=1}^{J} \left(\frac{q_{m,j,t}}{N_{m,t}} - s_{m,j,t}(\widetilde{\delta}, \Lambda) \right) D_m^h,
\end{aligned}$$

where $\Upsilon_{m,j,t}\left(\beta_m\right)$ is the differenced value function that enters the choice probabilities (27).

Findings Table A6 shows the empirical results. We allow for a very flexible specification in which the valuation of price, capacity and the discount factor depends on all demographics.[45] This flexible specification mainly aims to document the role of heterogeneity in the discount factor, as summarized in Figure 5 and the corresponding discussion in the main text. The coefficients themselves are difficult to interpret on a stand-alone basis, because we include a large set of demographics in all valuation terms, which show multicollinearity and may also capture other location characteristics. For example, home owners tend to have a higher discount factor. Households with a higher income tend to have a lower discount factor, perhaps because they have better investment opportunities or because the home ownership variable also captures the impact of wealth.

[45] We also considered a specification where we do not rely on the Taylor approximation but instead discretize the vector of household characteristics into eight groups according to below/above average income, percentage foreigners and population density. The resulting distribution of the implicit interest rate is discrete but otherwise comparable to our more flexible approach, with most mass at 14.7% and 90% of households has a rate between 12.8% and 15.2%.

Table A6: Empirical results with heterogeneous discount factor

	Interactions with capacity difference		Price sensitivity in 10^3 EUR ($-\alpha$)		Index of monthly discount factor (κ_β)	
Effect at mean of demographics			-0.487***	(0.105)	4.468***	(0.223)
Pop. density (10^4 inhab / m^2)	-0.738***	(0.076)	-0.077***	(0.030)	0.010	(0.052)
Average house size	0.108***	(0.033)	-0.034*	(0.018)	-0.058*	(0.033)
Average household size	-0.157*	(0.094)	-0.118***	(0.028)	0.157**	(0.066)
Average house age (decades)	-0.014	(0.013)	-0.004	(0.006)	0.016	(0.011)
Median income (10^4 EUR)	0.187**	(0.085)	0.097***	(0.024)	-0.173***	(0.064)
% home owners	-0.973***	(0.224)	-0.178***	(0.062)	0.632***	(0.185)
% higher education	-0.027	(0.175)	0.020	(0.085)	-0.038	(0.146)
% foreign	-0.126	(0.153)	0.172	(0.107)	0.456**	(0.193)
Alternative-specific constants			YES			
Local market fixed effects			YES			
Local market expectational errors			YES			
Obs. macro moments (JxT)			220			
Obs. micro moments (MxJxT)			935,440			

Notes: Demographic variables demeaned. Standard errors are clustered accross alternatives within 44 time periods. For the micro moments at the local market level we additionally cluster across time periods within each of the 4252 local markets. Instruments are approximations of optimal instruments (Chamberlain, 1987).
*** p<0.01, ** p<0.05, * p<0.1