Who Pays, Who Adopts?
Efficiency and Equity of Residential Solar Policy

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October 29, 2025

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Abstract

This paper studies the equilibrium outcomes of diverse residential solar subsidies within a nested discrete choice framework, introducing endogenous capacity choice and heterogeneous household preferences. I find solar subsidies have intensive effects and would motivate different sizes of solar panel installation. Furthermore, households respond heterogeneously to subsidies: switching from a subsidy based on future production to one that reduces upfront investment costs shifts solar photovoltaics adoption toward lower-income households. There is no single dominant policy in both cost-efficiency and equity. I propose a novel policy screening that is the most cost-efficient, but at the expense of equity. The method of raising subsidies also shapes distributional outcomes. These findings highlight the importance of subsidy policy design.

Keywords: Photovoltaics, Renewable subsidy, Distributional effects, Policy design, Structural estimation. **JEL:** D12, D31, D63, Q52, Q58

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1 Introduction

Residential solar photovoltaic (PV) has been promoted through a range of subsidy instruments. While all aim to encourage adoption, the choice of instruments affects which households adopt and how much capacity is installed. These endogenous consequences are related to two critiques of solar subsidies. First, subsidies may lead to inefficient adoption of residential solar PV. Second, subsidies may disproportionately benefit higher-income households, resulting in regressive effects. This raises a key question for policymakers: can better residential solar subsidy design address these unintended outcomes while keeping the goals of the energy transition?

I develop a nested logit framework to describe households' adoption decisions, which are based on the installation cost of solar panels, the expectations about future revenues of adopting solar PV, the electricity consumption, rooftop area constraints, and, importantly, the structure of the subsidy instrument. Households have heterogeneous preferences for the PV installation costs and the future revenue. The model is estimated using Dutch administrative data from 2019 to 2022, which include detailed information on household solar PV adoption decisions, installed capacity, and socio-demographic characteristics.

The first finding is that, given the adoption rate, the subsidy structure has a remarkable intensive effect on households' PV capacity decisions. I consider four types of subsidy instruments: lump-sum transfers, (proportional) investment subsidies, feed-in tariffs, and net metering. Lump-sum transfers pay households once they adopt, regardless of the size of solar panels. Investment subsidies provide a one-time payment to reimburse partial installation costs and are independent of future electricity production from solar panels. Feed-in tariffs reimburse each kilowatt-hour (kWh) of electricity fed into the grid (henceforth: electricity feed-in) at a fixed price, while net metering offsets household electricity consumption from the public grid (henceforth: grid consumption) with electricity feed-in at the current electricity retail price. In the rest of the paper, the lump-sum transfer and proportional investment subsidy are referred to as *investment-based* subsidy, and the feed-in tariff and net metering are referred to as *production-based* subsidy.

Specifically, the results show that investment subsidies, feed-in tariffs, and net metering all change the marginal value of solar capacity and distort installed capacity upwards. The investment subsidies distort the least. Net metering creates a kink in incentives and bunches capacity at the level of household consumption. Feed-in tariffs reward additional capacity with a high and constant price and hence result in a capacity that is usually restricted by the rooftop area. These intensive effects matter in two ways. First, they determine installation costs through economies of scale, and grid costs through the amount of feed-in. A small installed capacity has a higher average installation cost while lowering the grid burden through higher self-consumption, meaning less electricity is exported to the public grid. The countervailing cost effects make the total social cost associated with different policies modest.

However, the intensive effect has important implications for the fiscal budget. In particular, investment-based subsidies tend to induce smaller PV installations, requiring the government to raise the subsidy level and achieve the same capacity target as production-based subsidies through higher adoption rates. The increase in the extensive margin makes investment-based subsidies very costly when discounting is not considered. This finding complements De Groote and Verboven (2019), who argue that investment-based subsidies are more cost-efficient due to the high discounting of future benefits under production-based subsidies. Using the same discount factor of 0.85, I find that an investment subsidy can save approximately €70 million in fiscal expenditure per gigawatt (GW) of PV capacity. However, this difference is considerably smaller than that reported by De Groote and Verboven (2019), who do not account for the intensive effect, and the cost difference would vanish when the discount factor increases slightly to 0.87.

The second main finding is that households respond heterogeneously to different subsidies, depending on whether future electricity production or current installation costs are reimbursed. Specifically, low-income households are much more sensitive to immediate cost reduction than future benefits, while richer households are relatively indifferent between the two ways of subsidy. Hence, given an adoption target, switching from a production-based subsidy to an investment-based subsidy shifts adoption from high-income to low-income households.

Then, I use the estimated heterogeneous preferences to examine the distributional effects of residential solar subsidies across households in different income quintiles. Low-income households are more price sensitive and therefore benefit proportionally more from subsidies. For example, the yearly conditional adoption rate, defined as the number of new adoptions out of the potential adoption market, of the first twenty percent income quintile rises from 1.5% when subsidy is not available to 2.7% when net metering is used, an increase of around 80%. In absolute terms, however, the subsidies favor high-income households such that for the top twenty percent households, the conditional adoption rate increases from 6.8% to 10.5%, since they are more likely to cross the adoption threshold and install solar panels once subsidies are available. This effect persists across all subsidies, but consistent with the second finding, changing to an investment-based subsidy, such as a lump-sum transfer, can make the additional adoption relatively equal, which is 2.3% for the bottom twenty percent households and 2.7% for the top quintile.

The distributional effect also depends on the method of raising the subsidy. By studying the intersection between subsidy design and the taxation mechanism used to finance subsidies, I show that lump-sum taxes are regressive across all subsidy instruments. Surcharges on electricity consumption are less regressive at the early stage of solar adoption. However, when the adoption rate reaches 32%, net metering combined with a surcharge becomes even more regressive than when the subsidy is financed through a lump-sum tax, whereas other instruments under a surcharge still outperform the lump-sum tax. An income tax is progressive, no matter which subsidy is used.

The results change when households are grouped in different ways. For instance, when comparing welfare redistribution between households that adopt solar panels (henceforth, PV adopters) and those that do not (henceforth, non-adopters), PV adopters obtain substantial welfare gains under all types of subsidies and financing schemes. Among the financing methods, the surcharge on electricity consumption is the most regressive, as PV adopters pay less taxes through self-consumption. To the contrary, the lump-sum tax is the least regressive, as all households pay the same amount of tax regardless of solar PV adoption. However, when considering home ownership or dwelling type, the lump-sum tax becomes most regressive again. Therefore, no policy can achieve fairness across all dimensions, and the policy choice depends on the specific distributional objective.

Finally, the finding of heterogeneous household preferences suggests the potential for policy screening. While a combination of policies cannot outperform a single policy in any single objective such as cost efficiency or equity, a menu of instruments can. Specifically, designing a policy menu that includes both a feed-in tariff and an investment subsidy, and allowing households to self-select the option that best fits their preferences, can reduce total fiscal expenditure by about 18% relative to the optimal single policy. However, this policy screening is more regressive than an investment-based subsidy.

This paper comprehensively discusses residential solar policies within a unified structural framework of household decision-making by twisting the endogenous capacity choice and heterogeneous household preferences together. The closest paper by Bollinger et al. (2025) calibrates heterogeneous discount factors for low-income and high-income households, and also suggests reimbursing upfront costs to reduce regressivity. My paper differs by allowing households to choose installation capacity within the structural model, and explicitly capturing the intensive effects and associated welfare changes under diverse policy designs, which provide the countervailing effects that, to my best knowledge, have not been identified in previous studies.

There is a bunch of literature discussing the role of subsidies on solar PV installation. For instance, Burr (2016) uses a quasi-experiment in California and shows that the investment subsidy encourages more adoption, while the production subsidy is more efficient as it encourages adoption in optimal locations for solar electricity production. There are some other papers estimating the price elasticity of investment subsidies (Hughes and Podolefsky 2015; Gillingham and Tsvetanov 2019; Crago and Chernyakhovskiy 2017). On the other hand, Aldy et al. (2023) study wind farm subsidies and give the opposite result. Comello and Reichelstein (2017) predict PV adoption in three cities in the US when a lower-than-retail overage tariff is paid to solar adopters and find that the adoption will not be affected as long as this tariff is above the levelized cost of electricity. With an input-output model, Eid et al. (2014) calculate the bills in different scenarios and net-metering designs, providing insights into the effect of net-metering policy on cost recovery and inequality. Londo et al. (2020) use the cash-flow model and investigate the effects of alternative policies on pay-back period, government cost, and amount of PV uptake by exogenously given parameters. Masciandaro et al. (2025) show how net metering affects adopters and non-adopters across different regions in the Netherlands. Böning et al. (2025) assess the effects of different incentive schemes with a reduced form estimation using regional data in Belgium.

This paper also contributes to the growing literature on the welfare effects of residential solar PV adoption, with a particular focus on its subsidy policies. Closely enough, Feger et al. (2022) take research on optimal tariff design to incentivize residential solar PV adoption and avoid an enormous grid cost burden on non-adopters in Switzerland. They argue that consumption-based grid cost is less regressive than fixed grid cost because adopters are more affluent and less price sensitive to electricity price increases. Wolak (2018) uses distribution network price and installation from the three largest utilities in California and finds that residential solar capacity contributed two-thirds of increasing network prices from 2003 to 2016. Dauwalter and Harris (2023) further show that residential solar capacity has unequal environmental benefits, and there is no trade-off between efficiency and equity. Rather than documenting the unequal outcomes, this paper contributes by identifying the underlying mechanisms of inequalities and proposing a subsidy design that would improve this issue.

Last, this paper enriches the discussion on the inequity of environmental policies. For instance, Holland et al. (2019) examine the distributional effects of local air pollution from electric vehicle adoption in the US. Ito et al. (2023) demonstrate that price-elastic consumers are more likely to benefit from dynamic pricing. Känzig (2023) shows that the poor are more exposed to carbon pricing because they have a higher energy share and face a larger fall in income. This paper shows that residential solar subsidies have regressive effects similar to those of other environmental policies.

The rest of the paper is organized as follows. Section 2 describes the policy discussed in this paper. Section 3 describes the datasets and sample construction. Section 4 specifies the structural model for residential solar PV adoption decisions. Section 5 discusses the empirical results. Section 6 performs counterfactual analyses. Section 7 discusses the policy implications and conducts robustness checks. Section 8 concludes.

2 Residential Solar Benefits and Policies

In this section, I describe the economic benefits faced by households when deciding whether to adopt solar PV and how much capacity to install. I start with a situation without government intervention, after which I introduce the four policy instruments analyzed in this paper.

2.1 *Laissez-faire* case

Without any subsidy, households that adopt solar PV benefit in two ways. First, they save on their electricity bills by directly consuming part of their own electricity generation, referred to as *self-consumption*. Each kilowatt-hour consumed in this way offsets the need to purchase electricity from the grid and is therefore valued at the current electricity retail price. Second, households can sell any surplus electricity back to the grid, but only at the electricity wholesale market price, which is typically well below the retail price. The gap between retail and wholesale prices reflects the profit margin of energy companies as well as taxes and levies imposed by the government and system operators. See Appendix A for a brief background of Dutch electricity markets. Consequently, without subsidy, solar PV adoption is attractive when households consume a significant share of their own production, while exporting surplus to the grid is far less profitable.

2.2 Policy instruments

Household electricity consumption is inelastic, and electricity storage is limited, so solar PV adoption progress was slow. Subsidies are used to correct these market frictions. This paper focuses on four policy instruments: lump-sum transfers, investment subsidies, feed-in tariffs, and net metering. Each instrument increases the value of solar adoption, but they do so in different ways and with different implications for household capacity choices. See Figure 1.

2.2.1 Lump-sum transfer

The first policy instrument is a lump-sum transfer, paid once a household adopts solar PV, regardless of the capacity of the PV system. This policy makes adoption itself more attractive because the household receives a reward upon installing solar PV. However, since the transfer does not depend on capacity, it does not distort how many panels households choose once they adopt. Its main role is to stimulate adoption at the extensive margin.

2.2.2 Investment subsidy

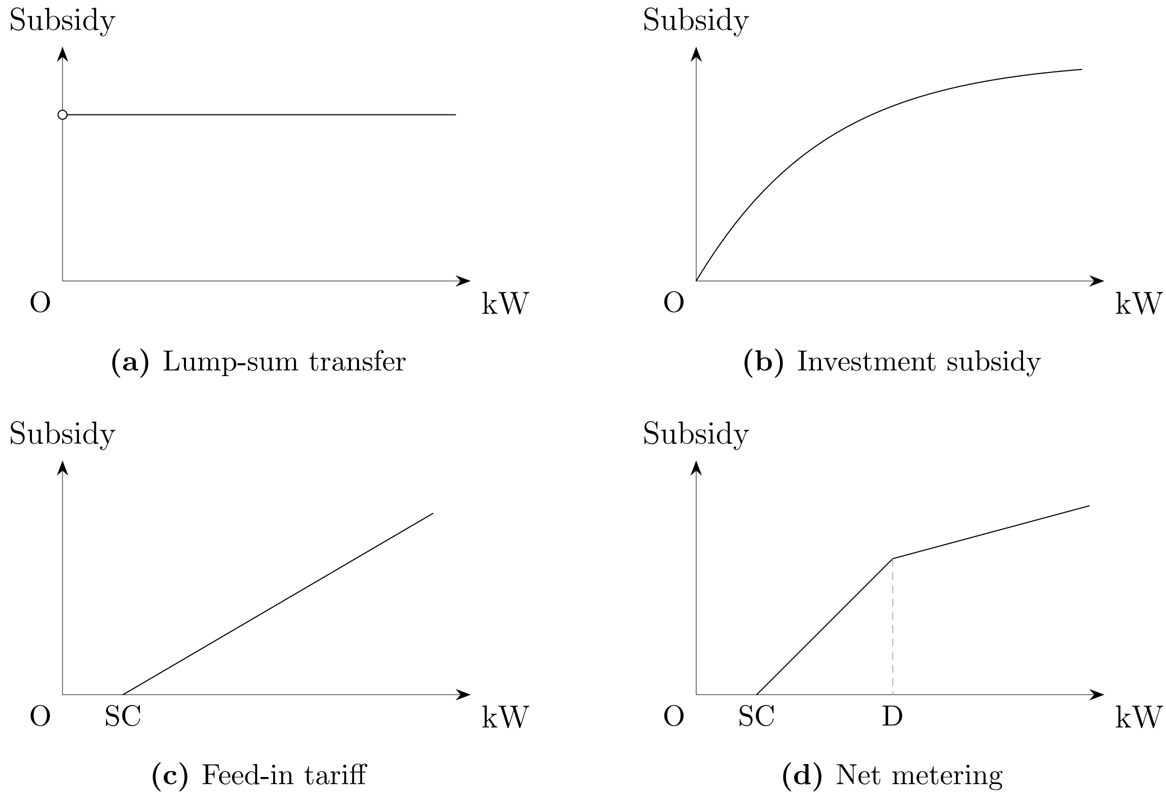
The second instrument is an investment subsidy. Here, the government reimburses a share of the upfront installation cost. There are some variations of this investment subsidy, such as a tax credit spread over the next few years or a zero-interest loan. By lowering the installation cost, this policy reduces the marginal cost of each kilowatt (kW) of capacity. Households that would otherwise find solar panels too costly can now adopt, and those that would have adopted anyway are encouraged to install larger systems, especially when the solar PV installation exhibits economies of scale, which will be discussed in Section 3. In short, investment subsidies stimulate both the decision to adopt and the size of the installation.

2.2.3 Feed-in tariff

The third instrument is a feed-in tariff, where households are paid a guaranteed price far above electricity wholesale prices for each kWh of electricity they feed into the grid. This tariff provides a stable and proportional incentive to expand solar system size: every additional panel generates additional revenue at the fixed tariff. Therefore, it strongly affects the intensive margin, leading to larger capacity choices. This often results in a corner solution, where households install as many panels as their rooftop can accommodate.

2.2.4 Net metering

The fourth instrument is net metering, with which households can offset their electricity consumption with their own solar generation, receiving the retail price for kWh of electricity produced, up to a certain amount. Any surplus beyond that threshold is



(a) Lump-sum transfer

(b) Investment subsidy

(c) Feed-in tariff

(d) Net metering

Figure 1: Subsidy Structure

Notes: The figure illustrates the subsidy as a function of capacity: (a) Under a lump-sum transfer, the subsidy is independent of capacity. (b) Under an investment subsidy, the curve is concave because the marginal investment cost decreases with capacity. (c) Under a feed-in tariff, the curve starts with self-consumption and after that, increases linearly with capacity. (d) Under net metering, the curve increases steeply up to the level of household demand, beyond which additional capacity yields much smaller returns. SC refers to self-consumption. D refers to electricity consumption.

typically reimbursed at a lower price. This creates a kink in incentives: installing capacity up to the given amount is very attractive, but additional expansion beyond this point yields much less benefit. Thus, capacity choice would bunch at the threshold. An intuitive threshold is the level of household electricity demand.

3 Data

I quantify the effects of different residential solar subsidy instruments in the context of the Dutch residential solar PV market. In the Netherlands, the official and default subsidy is net metering, which was formally introduced in 2004.[1] Under this scheme, households with solar panels can offset their grid electricity consumption with electricity feed-in. They thereby save on the retail energy price and avoid paying energy tax and value-added taxes (VAT) on electricity. Grid costs, however, are fixed and unaffected by net metering. Initially, households could net a maximum of 3000 kWh per year, which was increased to 5000 kWh in 2011. Since 2013, the upper limit has been abolished, and households can offset up to 100% of their annual electricity consumption from grid.[2]

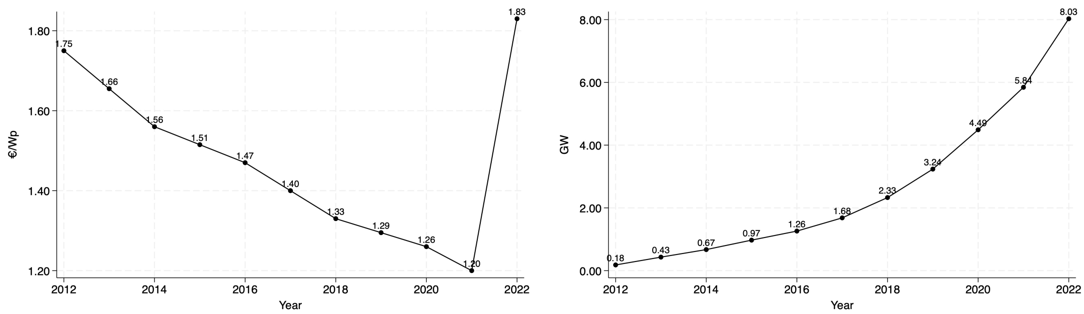
Several datasets are used for this research. First, I collected Dutch electricity day-ahead hourly wholesale electricity prices from 2015 to 2022. The day-ahead prices are publicly available from SMARD. Second, I obtained the average household grid consumption and feed-in profile from 2020 to 2022 at a 15-minute frequency from MFFBAS. I also have information on solar installation costs and retail electricity prices. Finally, I obtained detailed household data from the Centraal Bureau voor de Statistiek of the Netherlands (henceforth: CBS). These data include household yearly electricity consumption from the grid and electricity feed-in to the grid, as well as solar PV adoption status and adopted capacity if adopted from 2019 to 2022. They also offer socio-demographic attributes such as household wealth and income, and dwelling characteristics such as residence type and surface areas.

PV costs and adoption Residential solar PV installation costs consist of solar PV module costs, inverter costs, labor costs, and other material and operating costs. Until 2023, households paid VAT of 21% when purchasing solar panels, but this tax could be fully reclaimed. Since 2023, there has been no VAT on solar panels unless someone gets roof-integrated PV panels when buying a newly built house. In this case, solar panels are considered part of the roof and need to be paid VAT. The PV installation costs vary according to the type of PV modules and the roof. For

[1]Before 2004, there was also "unofficial" net metering because the discs on traditional meters would spin backward when electricity was fed into the grid. Between 2008 and 2010, residential solar PV also benefited from feed-in premiums on top of net metering. After 2011, net metering became the sole incentive policy. In addition, low-interest loans under the program "National Heat Fund" (Warmtefonds) are available for low-income households, but their conditions have changed over time. Since these loans are not a default subsidy and applications are unobservable, they are not included in the analysis.

[2]As of June 2024, energy companies are allowed to charge a feed-in fee to PV households for returning electricity to the grid. Furthermore, the Dutch government has announced the complete phase-out of the net metering policy, effective January 1, 2027. From that date, PV adopters will no longer be able to offset their grid consumption with feed-in. Instead, they will pay retail prices for grid consumption and receive a "reasonable compensation" price for electricity fed into the grid.

instance, Monocrystalline cells have higher efficiency and are 20-30% more expensive than standard polycrystalline cells. Installing solar panels on a sloping roof is more costly than on a flatter one. Furthermore, as module costs have dramatically decreased in the past few years, labor costs take a larger share in the breakdown of installation costs. Since labor costs and operating costs do not linearly increase with PV capacity, residential solar PV installation benefits from economies of scale, meaning a decreasing marginal cost. Figure 2a depicts the simple average price per watt-peak (Wp) from 2012-2022.[3] There was a price spike in 2022 because soaring electricity prices led to a substantial surge in installations, while supply was low due to the COVID-19 pandemic.[4] The Netherlands has witnessed a steady growth in residential solar PV adoption. See Figure 2b. Until 2022, the number of residential solar PV adoption was 2129616, accounting for 26.23% of the total Dutch households.



(a) Installation cost (€/Wp) **(b)** Accumulated capacity

Figure 2: Residential solar PV in the Netherlands.

Notes: Panel (a) shows the average price (VAT excluded) of residential solar installation per watt-peak, sourced from Milieu Centraal. Panel (b) shows the total installed residential solar capacity, accumulated at the end of each year, published by CBS.

Grid consumption and feed-in profiles The grid consumption profile measures how much electricity a household draws from the grid over time, and the feed-in profile refers to how much surplus electricity from residential solar is fed back into the grid. I focus on the electricity grid consumption and feed-in profiles provided by

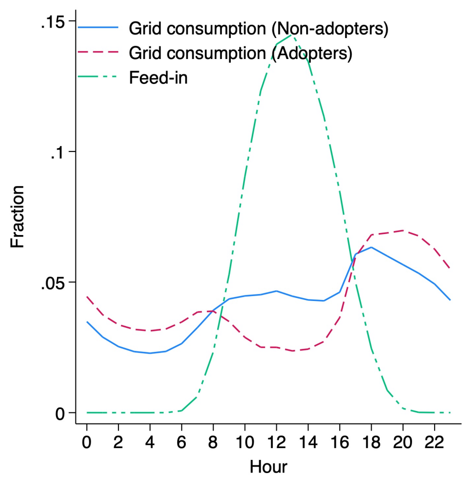
[3]Watt-peak measures the maximum power of a solar panel. For instance, one kWp can generate 1 kWh on an ideally sunny hour. However, depending on local weather conditions and solar panel deterioration, one kWp generates less than 1 kWh in one hour.

[4]Milieu Centraal did the market research once every two years and made a linear regression based on all the data collected in the previous years. After consulting with Milieu Centraal, the mean price between survey years is a good approximation of skipped years. The prices in the years 2013, 2015, 2017, and 2019 are estimated data.

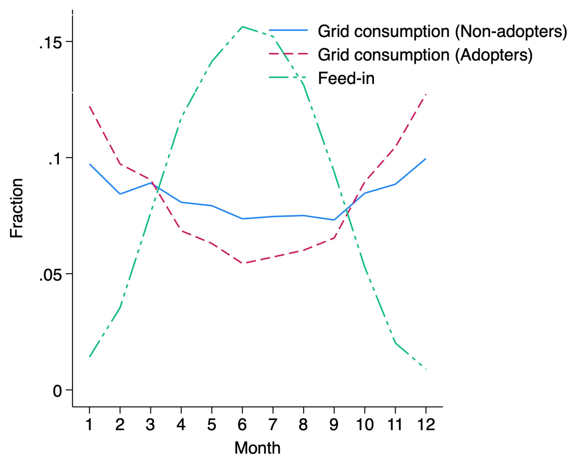
MFFBAS for small-scale consumers who have a connection of 3x25 Ampère or lower.[5] The profiles represent 15-minute intervals over an entire year, and separate profiles are available for households with and without solar panels.

MFFBAS collects power flow data every fifteen minutes, so there are 35040 or 35136 samples each year. Then, MFFBAS sums the flow data and publishes the fraction of the total for each quarter hour. Hence, the fraction for each profile sums up to one. Figure 3 aggregates the profiles into hourly and monthly levels. For instance, the feed-in fraction from 1 to 2 p.m. is 0.145, meaning this one hour contributes to 14.5% of the total feed-in. Similarly, the feed-in fraction in June is 0.156, meaning this month accounts for 15.6% of the total feed-in.

The feed-in profile exhibits evident daily and seasonal patterns, peaking in the afternoon and summer. On the other hand, grid consumption is higher in the evening and winter. A typical daily consumption profile has two peaks. One is around 8:00 AM, when people wake up and start to work, while solar electricity takes a small share of total production. The other one is at 7:00 PM. After sunset, the demand for lighting increases. Furthermore, grid consumption profiles differ between PV adopters and non-adopters, because PV adopters can directly use part of the electricity produced by solar panels, resulting in a smaller share during the afternoon and summer.



(a) Hourly Profile



(b) Monthly Profile

Figure 3: Grid Consumption and Feed-in Profile

Notes: This figure shows the average electricity grid consumption and feed-in profiles for Dutch households from 2020 to 2022. Quarter-hourly data are collected from MFFBAS and summed up at monthly and hourly levels.

[5] 99.42% of residential consumers are in this group.

Household data A full sample of over 32 million household data is available from 2019 to 2022. It is expressed as unbalanced panel data. To accurately merge the household demographic attributes and energy data, I made several sample restrictions. First, I dropped the households that moved within a year. Second, I dropped the households with unverified electricity consumption. Furthermore, households with PV capacity larger than 10kW were removed to rule out commercial PV systems. Finally, I dropped the households that shared the same dwelling since assigning dwelling-based electricity grid consumption and feed-in to each household was impossible. 21638637 observations remain.

With growing residential solar, the average electricity grid consumption and feed-in have changed over time. Table 1 gives descriptive statistics for the snapshot from 2022. In total, there are 5444262 households in the sample, and 1491062 have adopted solar panels. We can observe the difference between PV adopters and non-adopters. All households are classified into five income quintiles: the first quintile represents the bottom 20% of households (poorest), while the fifth quintile represents the top 20% (richest). PV adoption varies significantly across different income quintiles. The average adoption rate is 27%,[6] from 12% for the poorest households and 44% for the richest ones. There are several potential reasons to explain the distinct adoption rates. First, high-income households have fewer financial constraints and can bear high installation costs. Second, homeowners are more likely to install residential solar than tenants. 93% of the richest households are homeowners, while only 9% of households of the first wealth quintile live in their own house. We also observe that poorer households tend to reside in apartments and do not have their own independent roofs. Finally, there are clear capacity differences among households that have adopted solar panels, and the installed capacity is close to electricity consumption.[7]

Sample construction Starting with 21638637 household-year observations, the final sample used for adoption estimation is constructed as follows. First, I only keep households that did not move from 2019 to 2022. I impose this restriction because PV adoption entails a long-term future production and income stream, and residing in the same dwelling helps with predictability. Second, I assume the potential PV adopters are only those without solar systems and who own a dwelling. Although some rental houses are also equipped with solar panels, it is difficult to argue whether

[6]The adoption rate across the Netherlands is 26.23%. Hence, the sample used in this paper is representative.

[7]One may notice that PV capacity is larger than grid consumption. This is because part of the electricity demand is met directly by solar generation (self-consumption), which is not recorded by the meter. This is referred to as behind-the-meter consumption.

the decision is made by agencies, landlords, or tenants. Third, since solar PV adoption is a terminal action, the households installed in year t are removed from the potential market in year $t+1$. Finally, identifying PV adoption in 2019 is impossible, as I cannot distinguish whether an adopter installed a solar system in 2019 or before 2019. Therefore, only data from 2020 to 2022 are used for estimation. In total, there are 4245808 observations left.

Table 1: Summary Statistics

Panel A: PV adopters vs non-adopters			
	Non-adopter	Adopter	p-value of difference
Age	57.47	56.37	0.000
HH size	2.01	2.57	0.000
Ownership	0.55	0.79	0.000
House	0.59	0.94	0.000
Wealth percentile	50.00	62.41	0.000
Income percentile	47.50	63.63	0.000
House size (m^2)	108.82	140.88	0.000
Grid consumption (kWh)	2547.37	2821.91	0.000
# of Obs	3955200	1491062	5446262

Panel B: attributes by income quintile							
	# of Obs	All	< 20%	20–40%	40–60%	60–80%	> 80%
Dispo-income (€)	5444262	50859	19364	29607	42152	60110	100591
Grid consumption (kWh)	5444262	2623	1694	2048	2455	3032	3778
Feed-in (kWh)	5444262	523	152	237	458	730	994
House size (m^2)	5444262	118	83	99	116	130	156
Ownership (%)	5444262	62	9	40	72	84	93
House (%)	5444262	68	37	56	71	83	89
Adoption (%)	5444262	27	12	16	26	36	44
PV Capacity (kW)	1491062	3.62	2.40	2.77	3.33	3.79	4.27
Feed-in (kWh)	1491062	1910	1229	1469	1788	2005	2239

Notes: Panel A compares household characteristics between PV adopters and non-adopters in 2022. Panel B describes the average PV adoption rate, adopted capacity, disposable income, house ownership, electricity grid consumption, and feed-in for five income quintiles of Dutch households in 2022.

4 Model

I propose a static nested discrete choice model (McFadden, 1977) for residential solar PV adoption.[8] In each year t, a household denoted by i either chooses to install one of the nested solar panel capacities $j = 1, ..., 5$ or not adopt $j = 0$. Each j only differs in capacity sizes, and there are five types. $j = 1$ refers to capacity less than 2kW, $j = 2$ includes the capacity between 2 to 4kW, and for every subsequent category, each represents a 2kW increment. Each household is subject to a physical rooftop constraint, such that the installed capacity cannot exceed the maximum that the roof can accommodate. Hence, not all alternatives j are available for some households.[9] I follow Feger et al. (2022) and assume that each square meter of house surface can accommodate 0.08 kW of capacity. All solar panel types are classified into *adoption* group, denoted by g, with nesting parameter σ capturing the correlation of utilities that consumers experience among different types in the group. As $\sigma \to 0$, the correlation between solar panel types disappears and the nested model reduces to a standard multinomial model. The nested structure relaxes the restriction of substitution between capacities to be the same as the substitution between adoption and non-adoption, which also reduces bias from unobserved correlations. Intuitively, PV adoption can be seen as a sequential decision process. Households first decide whether to adopt based on physical and financial feasibility. If they choose to adopt, they then determine a PV capacity considering the rooftop surface and electricity consumption. See Figure 4.

Each household receives an idiosyncratic taste for adoption ζ_{igt}, and a random taste shock ε_{ijt}. ζ_{igt} follows the unique distribution proposed by Cardell (1997) such that $\zeta_{igt} + (1 - \sigma)\varepsilon_{ijt}$ is type I extreme value random variable.

PV cost and revenue Denote C_{ijt} as the solar panel installation costs.

$$C_{ijt} = K_j p_{It}. \tag{1}$$

[8] De Groote and Verboven (2019) and Feger et al. (2022) use a dynamic model because solar modules were quite expensive before the 2010s and have declined over the years. Hence, the waiting value for households was high, even though some households could install solar panels in the current period rather than non-adoption, and a dynamic model was useful to capture this waiting incentive. However, this paper uses the data from 2019 to 2022, when module prices have significantly declined and stabilized, and the waiting value is relatively low. Furthermore, De Groote and Verboven (2019) find that the main estimates, such as the discount factor and the price sensitivity, do not change much in a static and dynamic setting.

[9] For notational simplicity, I do not introduce extra terms to define the choice set of each household i, but note that this is modeled in the estimation.

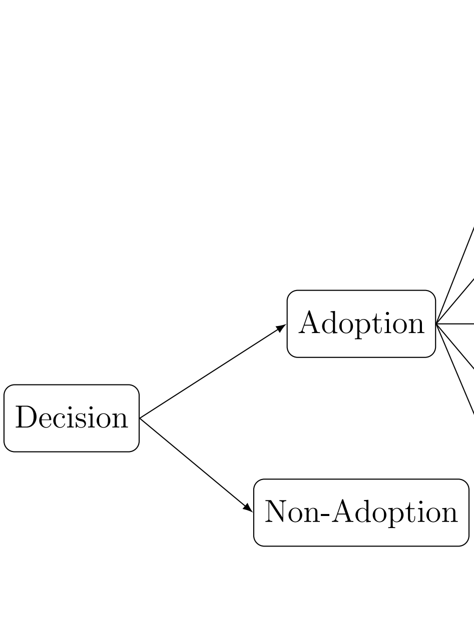


Figure 4: Nested Model Tree Diagram

K_j is the capacity level taken by the household, and in the case of discrete choice, I use the median capacity level of each type j. p_{It} is the panel installation cost per kW. Solar panel installation benefits from economies of scale. I calibrate that, compared to the smallest capacity size, the capacity 2-4 kW offers a 40% reduction in unit price, to increase capacity to 4-6 kW offers a 12% reduction in unit price, and the further upgrade of one capacity type leads to a 5% reduction in unit price.[10]

Before presenting the PV revenue, I first define the following variables and parameters. Denote D_i as the electricity consumption of household i. R is the yearly average retail price. p_s is the wholesale price. Y_j is the yearly electricity production from solar panels with capacity j. The life span of solar panels is set at 25 years. I follow De Groote and Verboven (2019) and set the yearly discount factor $\rho = 0.85$. $\pi = 3\%$ is the inflation rate borrowed from a wide range of literature and close to the actual average inflation rate in the Netherlands.[11] α is the self-consumption rate,

[10]The installation costs differ among installation companies, the location, and the specific installation time, while the data are not available. Retail electricity prices also depend on the energy company and the month when the energy contract is signed. However, as the solar panel market and the electricity retail market are competitive, the cross-sectional price difference should not raise a big issue.

[11]The average yearly inflation rate in the Netherlands from 2012 to 2022 is 2.47%. The yearly inflation rates from 2019 to 2022 are 2.67%, 1.11%, 2.82% and 11.62% respectively. The low inflation in 2020 caused by COVID-19 and the exceptionally high inflation in 2022 driven by the energy crisis are unsustainable and unrepresentative.

defined as self-consumption over total solar electricity production. The calibration in Appendix B gives $\alpha = 0.33$ under the current net metering policy, suggesting that households, on average, directly use 33% of electricity produced by residential solar systems.[12] ι is solar efficiency that measures how effectively the panel converts solar energy into electricity, expressed as a percentage of the actual power production to its capacity, kWh/W. The calibration in Appendix B yields $\iota = 0.91$. Hence, in the Netherlands, 1kW of PV capacity can, on average, produce 910kWh per year. λ is the solar panel's depreciation factor, which is set to be 3% in the first year and 0.7% afterward, according to Feger et al. (2022). [13] See Table 2 for the summary of parameters.

In the *laissez-faire* scenario without government subsidies, PV adopters can save on retail price through self-consumption, and they sell surplus electricity at wholesale prices. The discounted *laissez-faire* revenue is given by

$$\begin{aligned}\mathcal{R}_{ijt}^{lf} = &\underbrace{\sum_{k=t}^{t+24} \rho^{k-t}(1-\pi)^{k-t}\mathbb{E}_t^k[R]\min\{\mathbb{E}_t^k[D_i], \mathbb{E}_t^k[Y_j]\}}_{\text{self-consumption}} \\ &+ \underbrace{\sum_{k=t}^{t+24} \mathbb{E}_t^k[p_s]\rho^{k-t}(1-\pi)^{k-t}\max\{\mathbb{E}_t^k[Y_j] - \mathbb{E}_t^k[D_i], (1-\alpha)\mathbb{E}_t^k[Y_j]\}}_{\text{revenue from wholesale market}}.\end{aligned} \tag{2}$$

As discussed in Section 2, government subsidies can take four forms. The first is a lump-sum transfer that is conditional on adoption but independent of the specific installed capacity, which is denoted as T. The second is an investment subsidy proportional to the PV investment cost, the reimbursement ratio is denoted as κ. The third is a feed-in tariff that pays a fixed price p_c per kWh for electricity fed back into the grid.[14] The fourth subsidy is the net metering policy described earlier. The government sets the proportion of surplus electricity eligible for net metering, denoted by η, meaning that only an η share of surplus electricity can be used to offset consumption from the grid.[15] The discounted total government subsidy is

[12] I further obtain that the amount of self-consumption accounts for 31% of the household's total electricity consumption. This means that under the current net metering policy, households install capacity that is very close to their actual electricity consumption.

[13] The solar efficiency typically ranges from 0.85 to 0.95, depending on weather conditions and module efficiency.

[14] When self-consumption is not possible, the fixed price is paid for all electricity produced by the solar panels.

[15] Alternatively, the government can also set a threshold $\bar{D}$ for the surplus electricity that can be used to offset consumption. So the revenue from net metering becomes to $\sum_{k=t}^{t+24}(\mathbb{E}_t^k[R] - \mathbb{E}_t^k[p_s])\rho^{k-t}(1-\pi)^{k-t}\min\{\mathbb{E}_t^k[D_i] - \alpha\mathbb{E}_t^k[Y_j], \bar{D}, (1-\alpha)\mathbb{E}_t^k[Y_j]\}$.

$$
\begin{aligned}
\mathcal{R}^{gs}_{ijt} = & \underbrace{T}_{\text{lump-sum}} \cdot \mathbf{1}\{K_j > 0\} + \underbrace{\kappa C_{ijt}}_{\text{investment subsidy}} \\
& + \underbrace{\sum_{k=t}^{t+24} (p_c - \mathbb{E}^k_t[p_s])\rho^{k-t}(1-\pi)^{k-t} \max\{\mathbb{E}^k_t[Y_j] - \mathbb{E}^k_t[D_i], (1-\alpha)\mathbb{E}^k_t[Y_j]\}}_{\text{feed-in tariff}} \\
& + \underbrace{\sum_{k=t}^{t+24} (\mathbb{E}^k_t[R] - \mathbb{E}^k_t[p_s])\rho^{k-t}(1-\pi)^{k-t} \min\{\mathbb{E}^k_t[D_i] - \alpha\mathbb{E}^k_t[Y_j], (1-\alpha)\eta\mathbb{E}^k_t[Y_j]\}}_{\text{net metering}} .
\end{aligned}
\tag{3}
$$

The total discounted revenue is the sum of *laissez-faire* revenue and government subsidy,

$$
\mathcal{R}_{ijt} = \mathcal{R}^{lf}_{ijt} + \mathcal{R}^{gs}_{ijt}. \tag{4}
$$

I assume that households form a naive expectation of future electricity prices and their electricity consumption. Specifically, households make adoption decision based on one-year lagged electricity consumption, which is assumed to remain relatively stable over time. Hence, $E^k_t[D_i] = D_{i,t-1}$.[16] Also, retail and wholesale prices are fixed at the levels in the year of adoption and remain constant over the lifetime of the solar panels. $\mathbb{E}^k_t[R] = R_t$ and $\mathbb{E}^k_t[p_s] = p_{st}$. Electricity production expection follows the function: $\mathbb{E}^k_t[Y_j] = (1-\lambda)^{k-t}\iota K_j$.

The *status quo* policy is a net metering policy that reimburses all surplus solar electricity up to the level of electricity consumption from the public grid. Hence, $\eta = 1, \kappa = 0, T = 0, p_c = p_s$. The total discounted *status quo* revenue is:

$$
\mathcal{R}^{sq}_{ijt} = \sum_{k=t}^{t+24} \rho^{k-t}(1-\pi)^{k-t} \left(R_t \min\{D_{i,t-1}, (1-\lambda)^{k-t}\iota K_j\} + p_{st} \max\{(1-\lambda)^{k-t}\iota K_j - D_{i,t-1}, 0\} \right) . \tag{5}
$$

[16] Note that only electricity consumption from the grid and electricity fed back into the grid are recorded, while self-consumption is unobserved. Once a household installs solar panels during the year, its total electricity consumption can no longer be directly observed. Therefore, I use one-year lagged consumption as a proxy. This assumption is also supported by the data: regressing residential solar capacity on lagged electricity consumption gives a coefficient not significantly different from one. While energy efficiency improvements have gained attention in recent years and could affect household electricity usage, modeling this dynamic is beyond the scope of this paper. This assumption also implies that households' electricity consumption remains unchanged regardless of solar PV adoption.

Table 2: Summary of Parameters

Parameter	Definition	Value	Source
ι	Solar efficiency	0.91	This paper
α	Self-consumption rate	0.33	This paper
ρ	Discount factor	0.85	De Groote and Verboven (2019)
λ	Depreciation factor	0.03, 0.007	Feger et al. (2022)
π	Inflation rate	0.03	Literature

Value of adoption The utility function of adoption is:

$$u_{ijt} = \delta_{ijt} + \zeta_{igt} + (1-\sigma)\epsilon_{ijt}, \tag{6}$$

where δ_{ijt} is the conditional value of household i adopting capacity type $j \in \{1,2,3,4,5\}$:

$$\delta_{ijt} = \beta^R_{q_i}\mathcal{R}^{sq}_{ijt} - \beta^C_{q_i}C_{ijt} + \mathbf{\Phi}_j\mathbf{w}_i + \boldsymbol{x_{ijt}\gamma}. \tag{7}$$

$\beta^C_{q_i}$ measures the price sensitivity to the upfront installation cost, while $\beta^R_{q_i}$ captures the sensitivity to the discounted future revenue. I assume that household income is divided into five quintiles, $q_i \in \{1,2,3,4,5\}$, and price sensitivity is allowed to differ across these quintiles. $\mathbf{w}_i$ is a K-dimensional vector of household characteristics, consisting of housing type, year of construction, age of the household's reference person, household wealth and income, as well as house size and household size (measured by the number of members). $\mathbf{\Phi}_j$ is a $K \times 1$ vector of parameters. For house size and household size, I assume that $\phi_j = \phi \cdot j$, while for the remaining household characteristics, I assume that ϕ_j is constant across all $j \neq 0$. $\boldsymbol{x_{ijt}}$ denotes a vector of control variables, including alternative-location fixed effects, and year fixed effects. The parameters of interest are $\Theta = \{\boldsymbol{\beta^C_i}, \boldsymbol{\beta^R_i}, \sigma, \boldsymbol{\gamma}, \Phi_j\}$.

Value of non-adoption The utility function of non-adoption is:

$$u_{i0t} = \delta_{i0t} + \epsilon_{i0t}. \tag{8}$$

Without loss of generality, δ_{i0t} is normalized to be 0.

Estimating strategy I maximize the sum of the log likelihood of the adoption decision of all households. The probability of choosing each type $j = 0, 1, ..., 5$ takes a well-known closed-form expression,

$$s_{ijt} = \frac{1}{1+\exp(I_{igt})}, \quad j = 0, \tag{9}$$

$$s_{ijt} = \underbrace{\frac{\exp\left(\frac{\delta_{ijt}}{1-\sigma}\right)}{\sum_{l=1}^{5}\exp\left(\frac{\delta_{ilt}}{1-\sigma}\right)}}_{s_{j|g,t}} \cdot \underbrace{\frac{\exp(I_{igt})}{1+\exp(I_{igt})}}_{s_{gt}}, \quad j = 1, \ldots, 5, \tag{10}$$

where I_{igt} is the inclusive value of adopting solar panels:

$$I_{igt} = (1-\sigma) \cdot \log\left(\sum_{l=1}^{5} \exp\left(\frac{\delta_{ilt}}{1-\sigma}\right)\right). \tag{11}$$

Let $y_{ijt} = 1$ if j is chosen by household i in year t, and otherwise $y_{ijt} = 0$. The sum of log likelihood is calculated as:

$$\mathcal{L}(\Theta) = \sum_{t}\sum_{i=1}^{N}\sum_{j=0}^{5} y_{ijy} \log s_{ijt}(\Theta). \tag{12}$$

Hence, the parameters can be estimated by maximizing the log-likelihood function.

$$\hat{\Theta} = \arg\max_{\Theta} \mathcal{L}(\Theta). \tag{13}$$

5 Results

The estimation is conducted on a 10% random subsample of the data. Each household has up to six alternatives, and the resulting estimation sample comprises 2314295 observations.

The estimates show a large and robust alternative correlation parameter (σ) across all specifications, validating the nesting structure of the model. As expected, installation costs negatively affect adoption decisions, while future revenue has a positive impact. The sensitivity to future revenue is higher than that of the installation cost.[17] The terms $\Delta\beta$ capture the interaction of income quintiles with installation costs or future revenue. The results show that poorer households are more sensitive to installation costs. For future revenue, when heterogeneity is allowed only across the future revenue, the results indicate that richer households are more responsive to subsidies and benefits. However, when both revenue and costs are controlled for, the results reverse: poorer households remain more sensitive to future revenue than

[17] The estimate of β^R changes with the assumption of discounting factor ρ. I will discuss this in Section 7.

richer ones, and they are more responsive to costs than to future revenue. Specifically, $\Delta\beta^C_{q_1} - \Delta\beta^R_{q_1} > \Delta\beta^C_{q_2} - \Delta\beta^R_{q_2} > ... > \Delta\beta^C_{q_4} - \Delta\beta^R_{q_4} > 0$. Hence, reallocating an equivalent subsidy from future revenue to cost reduction yields a larger utility improvement for poorer households. Moreover, note that the sensitivity ratio β^C/β^R changes with income quintile monotonically, implying the feasibility of tailoring policy instruments to different income groups. I will discuss this in more detail in Section 7.

Table 3: Estimation Results

	(1)	(2)	(3)	(4)
β^R (€10^3)	0.407*** (0.022)	0.400*** (0.015)	0.481*** (0.017)	0.204*** (0.014)
$-\beta^C$ (€10^3)	-0.274*** (0.017)	-0.246*** (0.012)	-0.305*** (0.013)	-0.179*** (0.011)
$\Delta\beta^R_{q_1}$			-0.130*** (0.015)	0.219*** (0.043)
$\Delta\beta^R_{q_2}$			-0.157*** (0.009)	0.217*** (0.020)
$\Delta\beta^R_{q_3}$			-0.050*** (0.004)	0.112*** (0.011)
$\Delta\beta^R_{q_4}$			-0.013*** (0.003)	0.042*** (0.008)
$-\Delta\beta^C_{q_1}$		-0.126*** (0.015)		-0.298*** (0.037)
$-\Delta\beta^C_{q_2}$		-0.129*** (0.005)		-0.297*** (0.016)
$-\Delta\beta^C_{q_3}$		-0.054** (0.030)		-0.145*** (0.009)
$-\Delta\beta^C_{q_4}$		-0.016*** (0.002)		-0.053*** (0.008)
Apartment	-2.443*** (0.048)	-2.400*** (0.048)	-2.399*** (0.048)	-2.396*** (0.047)
HH age	-0.006*** (0.001)	-0.004*** (0.001)	-0.004*** (0.001)	-0.003*** (0.001)
House age	0.094*** (0.003)	0.089*** (0.003)	0.086*** (0.003)	0.089*** (0.003)
Wealth (€10^5)	-0.013*** (0.001)	-0.013*** (0.001)	-0.013*** (0.001)	-0.013*** (0.001)
Income (€10^4)	0.026*** (0.002)	0.007*** (0.002)	0.011*** (0.002)	0.008*** (0.002)
House size ($100m^2$)	0.064*** (0.003)	0.060*** (0.003)	0.059*** (0.003)	0.061*** (0.003)
HH size	0.023*** (0.002)	0.005*** (0.002)	0.007*** (0.002)	0.008*** (0.002)
Year 2022	0.706*** (0.022)	0.733*** (0.022)	0.730*** (0.024)	0.737*** (0.020)
σ	0.733*** (0.015)	0.727*** (0.010)	0.687*** (0.011)	0.764*** (0.009)
# of Obs	2,314,295	2,314,295	2,314,295	2,314,295

Notes: This table reports estimation results for PV adoption from 2020 to 2022, in four specifications. Standard errors in parentheses are clustered at the household level. Fixed effects are included in the estimation but not reported. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The estimates on other household characteristics are intuitive. For example, households living in apartments face a large fixed cost when installing solar panels, which can be interpreted as an information friction or an installation obstacle in the absence of an independent roof. The cost of this friction is substantial. For example, in specification (4), the coefficient of -2.396 on apartment friction corresponds to an additional cost of €5023 for households in the first income quintile and €13385 for those in the highest quintile. When the household head is older, adoption is less likely, although this effect is very small. Moreover, newly built dwellings are more likely to install solar panels. Higher-income households are also more inclined to adopt, but this pattern does not exist across wealth quintiles.[18] With respect to solar PV size, households living in larger dwellings or with larger household sizes tend to install larger PV systems. Finally, the year 2022, with exceptionally high electricity prices, is associated with a surge in solar PV installations.

6 Counterfactual

This section performs a counterfactual analysis based on the estimation results. I first examine how different subsidy instruments influence households' solar adoption decisions. I then explore the heterogeneous responses across households. Finally, I assess the welfare effects of alternative subsidy policy designs.

6.1 Intensive effect of policy

To begin, it is crucial to realize that the government not only decides which subsidy to use, but also the level of subsidy. To make meaningful comparisons, it is necessary to establish a benchmark that fixes the subsidy level. I do so by calculating the subsidy rate under each policy to achieve the same conditional adoption rate, defined as the share of adopting households among all households in the sample.[19] This approach allows me to study the intensive margin of adoption conditional on the same extensive margin.

Table 4 reports the predicted outcomes. A lump-sum transfer affects the adoption decision but not the adopted panel size. Households increase their capacity only when self-consumption is high or when wholesale electricity prices are elevated. An investment subsidy effectively lowers the marginal installation cost and increases the optimal installed capacity. Nevertheless, the difference relative to the lump-sum transfer remains small, because for most households, the marginal revenue from wholesale electricity sales does not offset the additional investment cost. Distortions become

[18]Table 1 shows that PV adopters hold both more wealth and income. However, once home ownership is controlled, wealth differences vanish, while income differences remain.

[19]This is to distinguish from the unconditional adoption rate, which is defined as the adoption over the total population.

more pronounced under net metering, where the marginal benefit of capacity remains at the value of retail price up to the level of a household's consumption, which is why adoption bunches at that threshold. Under a feed-in tariff, adoption almost reaches a corner solution, since the marginal benefit is fixed at a relatively high level while marginal installation costs fall with economies of scale. In this case, the corner solution is constrained by the physical limit of rooftop surface area.

Table 4: Equilibrium Outcomes of Alternative Policies

	Net metering (*status quo*)	**Feed-in tariff**	**Investment subsidy**	**Lump-sum**
Avg. capacity (kW)	4.23	5.05	3.97	3.50
Avg. self-consumption rate	0.28	0.25	0.31	0.35
Avg. installation cost (10^3€/kW)	1.41	1.40	1.49	1.53
Avg. grid cost (10^3€/kW)	1.02	1.06	0.98	0.92

Notes: This table gives the average adopted capacity, average self-consumption rate, average installation and grid costs, and average subsidy under alternative subsidy policies: net metering, feed-in tariff, investment subsidy proportional to investment costs, and a lump-sum transfer conditional on adoption. The comparison between the four policies is subject to the same adoption rate.

The intensive effects across alternative policies have crucial implications for the cost efficiency of residential solar adoption. First, due to economies of scale, the average installation cost is highest under the lump-sum transfer (€1.53/W) and lowest under the feed-in tariff (€1.40/W). Second, the installed capacity of the solar PV has an impact on the grid burden. I calculate the counterfactual self-consumption rate by assuming that households' consumption behavior is independent of solar adoption and the subsidy instrument implemented. Therefore, when a larger capacity is installed, the self-consumption rate is lower, and more electricity is fed back into the grid. As a proxy, I use feed-in volume to calculate the grid cost difference between different policy instruments. Compared to the net metering policy (*status quo*), the feed-in tariff demands 24.36% more grid investment, while it requires 10.06% less under the investment subsidy, and 25.3% less under the lump-sum transfer. According to Tennet, 2.3 billion euros must be invested to accommodate 1GW of offshore wind capacity. Assuming the power injection from offshore wind has the same grid requirement as solar panels, 1 Watt of residential solar under net metering requires a grid investment of €1.02. Lump-sum subsidies reduce this cost to €0.92, whereas feed-in tariff increases it to €1.06. As a result, the high grid costs dominate the low installation costs associated with the feed-in tariff, making it the most expensive total cost related to residential solar installation.

6.2 Adoption distribution

While residential solar adoption is important at the aggregate level, understanding how adoption is distributed across households is equally crucial. If certain households are excluded, the energy transition may become regressive and politically fragile. Moreover, if incentives are designed inefficiently, the transition will be slower and incur a higher cost.

Panel A of Table 5 reports the conditional adoption rate across the five income quintiles under different policy instruments. As a baseline, I also calculate the conditional adoption rates in the absence of a subsidy. There are two patterns. First, the conditional adoption rates differ substantially across income quintiles, and high-income households adopt more. Second, in proportional terms, subsidies incentivize low-income households more strongly than high-income households. For example, under the *status quo* of net metering, the conditional adoption rate of first-quintile households more than doubles compared to the no policy baseline. However, in absolute numbers, subsidies result in more adoption among high-income households. The reason is that poorer households are more sensitive to installation costs. When all households receive the same subsidy, the amount is often insufficient to shift low-income households into adoption, but large enough to tip high-income households.

The results that subsidies raise adoption rates proportionally more among low-income households but encourage more high-income adopters in absolute numbers are robust across alternative policy instruments. The specific adoption distribution across income quintiles, however, is different. As shown in Table 3, low-income households are more sensitive to upfront installation costs than to future revenue, and this cost–income sensitivity difference is larger than that of high-income households. Hence, policies that directly reduce costs increase adoption in this group. In contrast, high-income households are disadvantaged by policy change from future revenue to immediate reimbursement, conditional on the same overall adoption rate being achieved. This finding has important implications for the traditional efficiency–equity trade-off. As low-income households respond more strongly to immediate subsidies, policies that reduce upfront installation costs improve both efficiency and equity.

Panel B reports adopted capacity across income quintiles. This complements the findings in Table 4, which focus on aggregate adoption. The panel shows that policies not only shift adoption across income groups but also interact with heterogeneous capacity choices. Thus, even though adopted capacity patterns across policies look similar to those in Table 4, Panel B of Table 5 reveals that policies favor low-income households—such as investment subsidies and lump-sum transfers—amplify intensive effects, leading to lower installed capacity compared to a scenario where households' capacity preferences are homogeneous.

Table 5: Adoption Distribution of Alternative Policies

	< 20%	20–40%	40–60%	60–80%	> 80%
Panel A: conditional adoption rate (%)					
No policy (baseline)	1.49	1.57	2.94	4.98	6.78
Net metering (*status quo*)	2.68	2.89	5.06	8.12	10.53
Feed-in tariff	3.26	3.48	5.37	7.92	9.89
Investment subsidy	3.63	3.89	5.47	7.75	9.56
Lump-sum	3.80	4.04	5.51	7.72	9.44
Panel B: adopted capacity (kW)					
No policy (baseline)	3.36	3.18	3.41	3.41	3.69
Net metering (*status quo*)	3.73	3.46	3.75	4.19	4.65
Feed-in tariff	5.21	4.89	5.03	5.05	5.16
Investment subsidy	3.86	3.86	3.84	3.87	4.08
Lump-sum	3.42	3.23	3.45	3.37	3.60

Notes: Panel A reports the conditional adoption rate across five income quintiles under the baseline (no subsidy) and alternative solar support policies. Panel B reports the corresponding average adopted capacity (kW) among PV adopters.

6.3 Welfare distribution

To study the welfare effects of residential solar policy instruments, I compare the equilibrium outcomes under the four different policies with a baseline equilibrium in which subsidies are not available. I compute the equivalent variation (EV_i^{gs}), expressed in euros, which represents the monetary amount required to make a household indifferent between the subsidy and the no-subsidy scenario. In addition, I calculate the total subsidy expenditure borne by the government and assume that this expenditure is financed by all households, which I refer to as the "subsidy tax". The net welfare effect, dW_i^{gs} for household i is then given by the equivalent variation minus the subsidy tax contributed by this household.

$$dW_i^{gs} = EV_i^{gs} - \text{Subsidy tax}_i^{gs}, \tag{14}$$

and $EV_i^{gs} = \frac{1}{\bar{\beta}_i}\{\log[1 + exp(I_{igt}^{gs})] - \log[1 + exp(I_{igt}^{base})]\}$, where $\bar{\beta}_i$ is the average price sensitivity of household i.

Note that the estimation sample excludes tenants, as it is difficult to justify their decision on solar PV adoption. Therefore, tenant responses to residential solar subsidies remain unclear. In the welfare analysis, I assume that tenants cannot adopt solar panels, implying a zero adoption rate. Nonetheless, all households, regardless of home ownership, contribute to financing the subsidies. To assess the robustness of this assumption, Table 10 in Appendix D reports results under the alternative assumption that tenants adopt in the same way as homeowners. Moreover, income quintiles are defined using the original data, where the number of households in each quintile is equal, while in the cleaned sample, the quintile sizes are slightly different. I assume that the data cleaning process is random within each quintile, so it represents the population.

Welfare change by income quintiles Table 6 summarizes the results across five income quintiles. Panel A reports EV_i^{gs} of households in each quintile under alternative policies, which are consistent with the adoption pattern shown in Table 5. The regressive effect is stronger across all households under the assumption that tenants cannot adopt solar panels, since most low-income households do not own property and cannot benefit from the subsidy.

To gain deeper insight into the welfare effects of subsidies, it is necessary to examine the net welfare impact, which depends on how the subsidy is financed. I consider three cases. First, a lump-sum tax that is the same for all households. Second, a surcharge on each kilowatt-hour of net electricity consumption, which acts as a marginal tax so that households consuming more electricity pay more.[20] Third, financing the subsidy through higher income taxes, with the revenue raised as part of the general budget rather than an energy-specific charge.

Panel B gives the net welfare change when a lump-sum tax is charged. The total net welfare is negative because the subsidy is just a redistribution among all households, while solar installation incurs costs. Note that the analysis is conducted in partial equilibrium, as it does not account for the redistribution of solar installation costs, in particular how labor costs translate into labor income.[21] In addition, environmental benefits and the effect of residential solar capacity on the wholesale

[20] Net electricity consumption is defined differently across subsidy instruments. Under net metering, it is measured as the difference between grid consumption and electricity fed into the grid. Under the other three policies, net consumption is equal to grid consumption because electricity is purchased and sold separately.

[21] The labor market effects of energy policy are an interesting and important topic, but they are beyond the scope of this paper.

electricity prices are not included.[22] We observe a large negative number for net metering and feed-in tariff because we assume households heavily discount future benefits. A lump-sum tax does not mitigate the regressive effect of residential solar support policies, since the subsidy costs are distributed equally across all households, while high-income households receive a larger share of the benefits.

Table 6: Welfare Change of Alternative Policies (€, per HH)

	< 20%	20–40%	40–60%	60–80%	> 80%
Panel A.1: equivalent variation of homeowners					
Net metering (*status quo*)	+26.23	+27.56	+60.99	+118.89	+177.27
Feed-in tariff	+38.57	+40.25	+70.59	+111.44	+145.13
Investment subsidy	+46.07	+48.39	+72.69	+104.09	+129.76
Lump-sum	+49.12	+50.87	+73.18	+101.79	+122.35
Panel A.2: equivalent variation of all households					
Net metering (*status quo*)	+2.49	+11.63	+45.89	+102.86	+166.90
Feed-in tariff	+3.66	+16.98	+53.10	+96.42	+136.63
Investment subsidy	+4.37	+20.42	+54.68	+90.06	+122.17
Lump-sum	+4.66	+21.46	+55.05	+88.07	+115.19
Panel B: welfare change with lump-sum tax					
Net metering (*status quo*)	-229.41	-220.27	-186.01	-129.04	-65.00
Feed-in tariff	-166.53	-153.21	-117.09	-73.78	-33.56
Investment subsidy	-83.99	-67.94	-33.68	+1.69	+33.81
Lump-sum	-75.69	-58.89	-25.30	+7.72	+34.84
Panel C: welfare change with surcharge					
Net metering (*status quo*)	-154.93	-179.81	-182.75	-178.36	-167.21
Feed-in tariff	-108.05	-119.91	-113.97	-114.47	-119.99
Investment subsidy	-53.61	-50.62	-32.03	-19.45	-11.15
Lump-sum	-48.06	-43.12	-23.79	-11.51	-6.07
Panel D: welfare change with income tax					
Net metering (*status quo*)	-81.65	-119.44	-155.13	-200.74	-396.24
Feed-in tariff	-58.09	-79.22	-94.43	-126.40	-276.66
Investment subsidy	-27.69	-29.53	-21.91	-25.63	-92.41
Lump-sum	-24.49	-23.95	-14.60	-17.13	-79.93

Notes: This table gives the welfare changes relative to the baseline across five income quintiles of alternative solar support policies and alternative ways to finance subsidy.

[22] Masciandaro et al. (2025) estimate the merit order effect of solar PV and find it is very small. Hence, I do not expect it to overturn the main result.

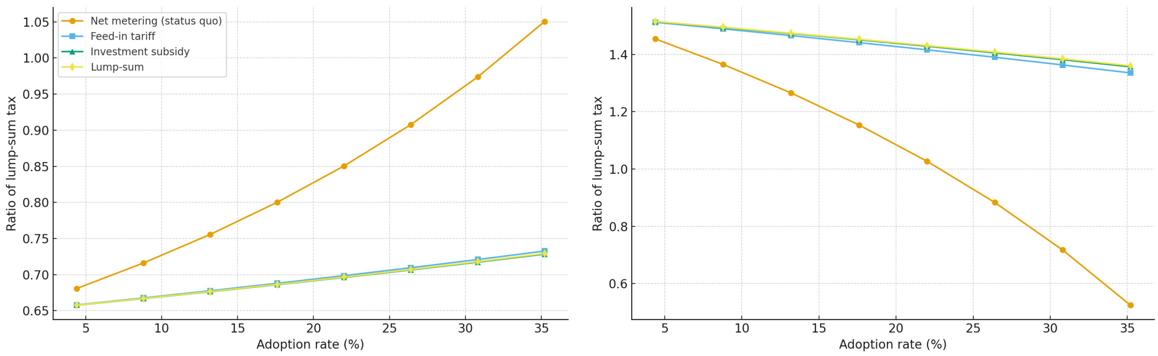
When the subsidy is financed through a surcharge, higher-income households bear a larger share of the cost than in the case when a lump-sum tax is used. This is because high-income households consume more electricity: in our sample, households in the first quintile consume, on average, 1742 kWh per year, while those in the fifth income quintile consume 4119 kWh. At the early stage of residential solar adoption, the surcharge makes the net effect of the policy much less regressive than when the subsidy is financed through a lump-sum tax, as richer households contribute more to financing residential solar adoption.[23]

However, this result does not necessarily hold over time. Our data begins with a sample where adoption is zero. As adoption increases and the adoption rates of low- and high-income households rise at the constant pace in Table 5, the surcharge under the net metering policy becomes increasingly regressive. Specifically, once the overall adoption rate reaches around 26%, the first-quintile-income households end up paying a larger cost than households in the fifth quintile, and when the adoption rate reaches 32.3%, the households in the first quintile contribute more than in the case when an identical lump-sum tax is charged. While this pattern is less obvious under other policies. See figure 5.

Finally, the regressive effect can be largely mitigated if the subsidy is financed through income taxation. In this case, high-income households contribute more subsidies than they receive, while paying for their own installation costs, making them the main contributors to residential solar adoption.

Welfare change by adoption status Welfare distribution is also heterogeneous within each income quintile, depending on whether a household adopts solar panels. As shown in Table 7, adopters receive substantial welfare gains under all scenarios. When comparing welfare change between PV adopters and non-adopters, financing the subsidy through a surcharge or income tax hurts non-adopters more than a lump-sum tax. This is because PV adopters can reduce their surcharge payments through self-consumption, and under net metering, this effect is most significant since they avoid paying the surcharge at all. In the case of the income tax, high-income non-adopters bear most of the subsidy burden. A lump-sum tax distributes the cost most equally, because the payment is independent of adoption status. See Table 11 and 12 from Appendix D for the welfare change of PV adopters and non-adopters across five income quintiles.

[23] Although high-income households still receive more subsidies than they pay in taxes, they invest a lot in solar panel installations.



(a) First income quintile

(b) Fifth income quintile

Figure 5: Surcharge Contribution of Households

Notes: This figure plots the change in the surcharge, expressed as a ratio of the lump-sum tax, against the total adoption rate. The subfigures show the change for households in the first income quintile and those in the fifth income quintile.

Welfare change by home ownership Because I assume that only homeowners can adopt solar panels, it is not surprising to see that homeowners have a larger net benefit than tenants when the subsidy contribution is raised through a lump-sum tax. Because high-income households are much more likely to own a dwelling and they consume more electricity, the welfare implications between homeowners and tenants are similar to those between high and low-income households.

Welfare change by dwelling type Households living in apartments find it very costly to adopt solar panels. Hence, a lump-sum tax would negatively affect apartment dwellers more, who rarely benefit from the subsidy. Since high-income households are more likely to live in detached houses with independent rooftops, an income tax shifts the subsidy burden to this group. Under a surcharge scheme, two opposing effects emerge. On the one hand, households living in houses consume more electricity and thus contribute more to financing the subsidy. On the other hand, these households are also more likely to adopt solar panels, reducing their reliance on the public grid and resulting in a lower surcharge payment. Table 7 shows that apartment dwellers pay slightly more than households living in detached houses. It can be expected that, when the share of solar PV adoption increases, apartment dwellers will pay more, widening the welfare gap between them and households living in detached houses.

Table 7: Welfare Change by Groups (€, per HH)

	Adoption		Ownership		Dwelling type	
	PV adopters	Non-adopters	Homeowners	Tenants	Houses	Apartments
Panel A: Lump-sum tax						
Net metering (*status quo*)	+1252.22	-231.9	-135.37	-231.9	-144.68	-230.06
Feed-in tariff	+1228.55	-170.19	-77.68	-170.19	-86.99	-168.09
Investment subsidy	+1280.52	-88.36	+0.90	-88.36	-8.25	-86.24
Lump-sum	+1236.87	-80.35	+7.25	-80.35	-1.83	-78.15
Panel B: Surcharge						
Net metering (*status quo*)	+1484.12	-249.66	-165.92	-184.17	-172.90	-177.17
Feed-in tariff	+1217.53	-185.68	-115.86	-131.91	-92.05	-100.35
Investment subsidy	+1281.90	-91.93	-13.09	-67.65	-6.15	-49.90
Lump-sum	+1238.32	-83.61	-5.46	-61.53	+0.08	-45.11
Panel C: Income tax						
Net metering (*status quo*)	+1093.77	-250.38	-197.70	-139.51	-199.54	-162.95
Feed-in tariff	+1119.11	-184.13	-123.48	-102.40	-127.29	-118.84
Investment subsidy	+1224.37	-95.71	-22.89	-53.17	-29.19	-60.67
Lump-sum	+1187.33	-87.06	-14.39	-48.35	-20.87	-54.90

Notes: This table reports welfare changes (€/household) by adoption status, home ownership, and dwelling type, under three financing schemes and four subsidy instruments.

7 Discussion

7.1 Optimal policy design

Policymakers consider three objectives when designing a subsidy. The first is the social cost efficiency of the policy in promoting adoption. The second is the fiscal budget of subsidies. The third relates to the equity of subsidy benefits.

In Section 6, I compared different policies conditional on the same adoption rate, which helps to illustrate the intensive effect. In practice, however, the *capacity* target is more reasonable as it directly links to the climate goal of reducing a certain amount of carbon emissions. The adoption capacity and adoption rate are related as shown in the equation below.

$$\text{Total capacity} = \text{Capacity per adoption} \times \text{Number of adoption} \tag{15}$$

Whether the target is set in terms of the adoption rate or total installed capacity, the intensive effect reported in Table 4 remains unchanged, as it depends on the distribution conditional on adoption. While the adoption and welfare distributions in Tables 5 and 6 differ numerically, the qualitative results hold. The key difference is that, to achieve the same level of installed capacity across different subsidy instruments, each policy must induce a different adoption rate due to the intensive effect. Hence, the required subsidy level changes, which, as shown later, provide new insights into the comparison between investment-based and production-based subsidies.

Denote the grid cost paid by each household is G_i. Conditional on the same capacity target, the three objectives are:

1. Social cost minimization:
$$\min \sum_i (G_i + C_i) \tag{16}$$
2. Fiscal budget minimization:
$$\min \sum_i \mathcal{R}_i^{gs} \tag{17}$$
3. Equity maximization:
$$\max \frac{1}{2n^2 \overline{\mathrm{EV}^{gs}}} \sum_i \sum_{-i} |\mathrm{EV}_i^{gs} - \mathrm{EV}_{-i}^{gs}| \tag{18}$$

For the equity objective, I introduce a *"Gini coefficient"* based on the equivalent variation across households under different subsidies. I use the equity across EV instead of welfare W because the welfare is negative under the setting of this paper, and this would mislead the results. Also, the grid cost in this paper is set to be equally shared, and the subsidy tax changes on the financing scheme. Hence, I only focus on the welfare distribution of adoption behavior.[24] See Figure 6 for the results.

Social cost Two countervailing cost effects arise. The first is the installation cost, which exhibits economies of scale. When larger PV systems are incentivized, total installation costs decline, making production-based subsidies—particularly the feed-in tariff—relatively cheaper. However, larger PV systems also result in greater electricity feed-in to the grid, thereby increasing the grid investment. Consequently, investment-based subsidies, especially the lump-sum transfer, incur lower grid investment costs. When both are considered, the total cost differences across policies are negligible. The net metering policy incurs both moderate installation and grid costs, and results in the lowest total social cost.

[24] An alternative method is to compute the real Gini coefficient

$$\frac{1}{2n^2 \overline{\mathrm{Income}^{gs} - \mathrm{EV}_{-i}^{gs} - G_{-i}}} \sum_i \sum_{-i} |(\mathrm{Income}_i^{gs} - \mathrm{dW}_{-i}^{gs} - G_{-i}) - (\mathrm{Income}_{-i}^{gs} - \mathrm{dW}_{-i}^{gs} - G_{-i})|, \tag{19}$$

which will not change the results. However, the Gini difference across subsidies is negligible because the welfare change of PV adoption is small compared to the total income of a household.

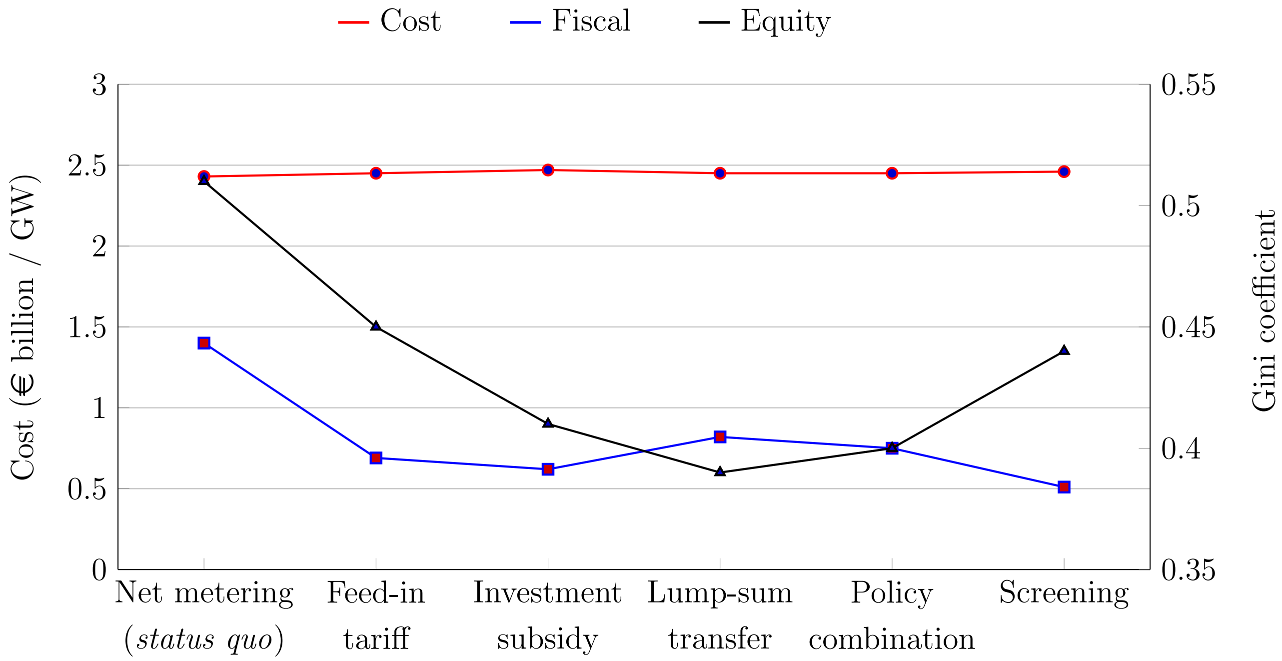


Figure 6: Optimal Policy

Note: This figure compares the social cost, fiscal budget, and Gini coefficient across four single policies, policy combination and policy screening to achieve a gigawatt (GW) PV capacity.

Fiscal budget At first glance, it may seem surprising that the feed-in tariff, which reimburses the future production, is less expensive than a lump-sum transfer, even though I assume that households heavily discount future benefits with a discount factor of 0.85 following De Groote and Verboven (2019). This happens because the intensive effect becomes crucial when the capacity target is considered (the same adoption rate results in different adoption capacity). In particular, under the lump-sum transfer, the subsidy level does not affect the PV size per adoption. Hence, the only way to achieve the capacity target is to raise the adoption rate. As a result, the government must increase the subsidy level not only for marginal adopters but also for infra-marginal ones, which is costly because a lump-sum transfer motivates small PV sizes. This subsidy cost would be lower for the proportional investment subsidy, which has a somewhat intensive effect and can induce households to install larger capacities by changing the subsidy level.

One might wonder whether setting a lump-sum transfer as an upper limit, so that a household receives the full transfer only when its installation cost exceeds this limit, and otherwise receives a reimbursement equal to its actual installation cost, could address the lack of an intensive effect. In theory, this is equivalent to reimbursing installation costs up to a capacity cap. However, this variation of lump-sum transfer only affects households that would otherwise install PV smaller than the cap, and increasing this cap quickly becomes prohibitively expensive. In the data sample, this constraint does not bind, meaning that whether or not this transfer plays as an upper limit does not change the equilibrium outcome. To achieve the same intensive effect of a proportional investment subsidy, the lump-sum transfer needs to be more than double.

In contrast, the feed-in tariff, with the largest intensive effect, allows the government to reach the same capacity target with a lower subsidy level and lower adoption rate. Consequently, even when households apply a high discount factor, the feed-in tariff incurs a lower fiscal cost than the lump-sum transfer, but still slightly higher than the investment subsidy. However, this €70 million per GW subsidy gap between the feed-in tariff and the investment subsidy vanishes when the discount factor rises to 0.87 (which is still low enough), suggesting that the intensive effect is so strong that it might even dominate the impact of a small discount factor.

Equity The regressive effects are consistent with the results in Table 6. In short, investment-based subsidies disproportionately benefit lower-income households relative to production-based ones. Policies that remove financial constraints lead to a more equitable distribution of subsidy benefits, and a lump-sum transfer performs best in terms of equity. Because lump-sum transfer also minimizes social costs, it must also yield the highest total welfare net of all costs and subsidy payments.

However, this welfare distortion can be corrected through a careful design of the subsidy's financing mechanism. For instance, if the subsidy is financed by an income tax, high-income households contribute more to the subsidy than they receive, and the regressive effects become trivial in determining the type of subsidy. Nevertheless, if the subsidy is financed through a surcharge on electricity consumption, the choice of subsidy is crucial. Specifically, combining a net metering policy with a surcharge should be avoided, as it is highly regressive.

While the regressive effects across income groups are mostly discussed, inequality in other dimensions also matters. For instance, some high-income households may be largely disadvantaged under an income tax because they live in apartments where solar PV installation is not feasible. These households contribute much through higher tax payments but face the same adoption constraints as low-income households. To the contrary, a low-income PV adopter receives the subsidy while contributing little. Hence, there is no single policy that corrects inequality in all dimensions, and the policy choice depends on which dimension of equality policymakers seek.

Policy combination So far, I have only considered a single subsidy instrument. However, in practice, policy combinations are common. I find that combining instruments can yield outcomes that lie between those of the single policies. For instance, Figure 6 illustrates a combination of a lump-sum transfer and a feed-in tariff. This combination is designed to minimize total fiscal cost while allowing the Gini coefficient to increase by only 0.01. Under this constraint, the fiscal cost is reduced by approximately €70 million per gigawatt compared with the lump-sum transfer alone, but it is more expensive than the feed-in tariff.

Screening I further propose a more cost-efficient policy combination by leveraging the heterogeneity of households. Specifically, because the price sensitivity ratio $\beta^C_{q_i}/\beta^R_{q_i}$ monotonically decreases with household income quintiles, it is possible to design a production-based subsidy and an investment-based subsidy such that there is a cut of of income quintile q, and the income quintile lower than the threshold $\underline{q}$ chooses investment-based subsidy and those higher than the threshold $\bar{q}$ chooses production-based subsidy. The incentive-compatible constraint holds as long as the subsidy satisfies:

$$\frac{\beta^C_{\bar{q}}}{\beta^R_{\bar{q}}} < \frac{\mathcal{R}^{production-based}}{\mathcal{R}^{investment-based}} < \frac{\beta^C_{\underline{q}}}{\beta^R_{\underline{q}}} \tag{20}$$

The screening mechanism that combines the investment subsidy and the feed-in tariff can reduce total fiscal expenditure by approximately €110 million per gigawatt compared with only the investment subsidy. This improvement arises because households select the "best" policy that maximizes their utility, which in turn allows for a lower subsidy level than under a single policy. The social cost remains the same as a single policy, but it is at the expense of a higher Gini coefficient. A Pareto improvement on all three objectives cannot be reached. Through this screening mechanism, the policy does not need to explicitly specify income thresholds or other conditions, and it avoids administrative costs for eligibility verification. Moreover, this screening mechanism helps alleviate the substantial upfront financial burden associated with investment subsidy while preserving its fiscal advantages.

7.2 Robustness check

Exogenous capacity choice I first examine the robustness of the results with respect to model specification. In the benchmark, I estimate a nested logit model with an outside option and capacity divided into five categories. As an alternative, I estimate a standard logit model. In this specification, households are allowed to install capacity in increments of 400W, but the adopted capacity is exogenously determined.[25] To assign this exogenous capacity, I regress the observed installed capacity of PV adopters on households' one-year lagged electricity consumption, house surface area, and household size. Hence,

$$K_{it} = \alpha_0 + \alpha_1 D_{i,t-1} + \alpha_2 \,\mathrm{Surf}_i + \alpha_3 \,\mathrm{HHsize}_i + \varepsilon_{it}. \tag{21}$$

I then use the predicted value $\hat{K}_{it}$ as the capacity that household i would install in the estimation sample. Based on this, I specify a logit model in which the individual utility of adoption is given by:

$$u_{i1t} = \delta_{i1t} + \epsilon_{i1t}. \tag{22}$$

with the condition value

$$\delta_{i1t} = \beta^R_{q_i} \mathcal{R}^{sq}_{i1t} - \beta^C_{q_i} C_{i1t} + +\mathbf{\Phi}\mathbf{w}_i + \boldsymbol{x_{i1t}\gamma}. \tag{23}$$

The cost and future revenue are calculated similarly to those in the nested logit model, using the predicted installed capacity. Control variables include year and alternative-location fixed effects.[26] The conditional value of non-adoption remains normalized to zero. Household characteristics are unchanged, but the parameter matrix is now independent of the capacity alternative. The full sample is used. The estimation results are reported in Table 8, which are similar to those in the main specification in Table 3.

Different discount factor In the benchmark model, I use a discount factor of 0.85. One may question whether the results are sensitive to this assumption. To address this concern, I estimate the model using alternative discount factors of 0.9, 0.95, and 0.97. The results in Table 9 indicate that the main findings remain robust.

7.3 Heterogeneous discount factors

I have shown that lower-income households are more sensitive to costs than to future income, and that this finding is robust across various model specifications. However, the source of this heterogeneity remains unclear. A natural explanation is that poorer households have more financial constraints, so that they are more sensitive to investment costs.

[25] 400W is the standard size of a solar panel. I also tried other sizes, such as 100W and 240W, which give similar results.

[26] In this logit specification, capacity can still be categorized. The difference is that households no longer choose among capacity categories as in the nested model.

Another possible reason is that households discount future benefits at different rates. Specifically, lower-income households may have a smaller discount factor, reflecting that they are more short-sighted and/or more risk-averse. Figure 7 draws the ratio of cost sensitivity to future income sensitivity for discount factors ranging from 0.8 to 1. It shows that the same discount factor for all households always results in a higher comparative cost sensitivity for lower-income households.

However, the same ratio across income quintiles could be achieved when households have different discount factors. For instance, when the ratio equals one, the implied discount factors for the first to fifth quintiles are 0.83, 0.83, 0.84, 0.92, and 0.94, respectively.[27] With such heterogeneous discount factors, the observed differences in price sensitivity would vanish. The policy implication between reimbursing solar PV installation costs or awarding future production remains, but now the variation arises from differences in intertemporal preferences. In this case, the same amount of future income provides less incentive for lower-income households, as they discount future benefits more.

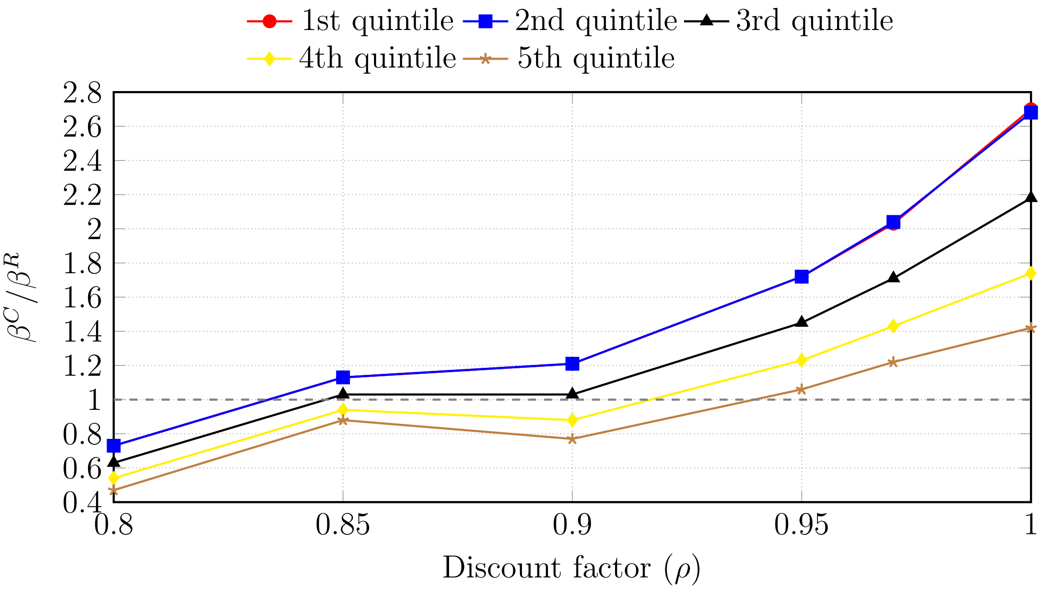


Figure 7: Price Sensitivity Ratio

Note: This figure shows the ratio between cost sensitivity and future revenue sensitivity in absolute terms, β^C/β^R, across discount factors (ρ) from 0.8 to 1, for five income quintiles.

[27] This implies a discount factor difference of 0.11 between the first and fifth quintiles, which is substantial. Even under the smallest difference scenario, where the discount factors are 0.90 for the first quintile and 0.97 for the fifth, the difference is 0.07.

7.4 Limitation

Like any research, this paper has several limitations. First, the analysis is conducted in a partial equilibrium framework, ignoring labor market effects and the environmental benefits of reduced emissions, which may be especially relevant for low-income households. Second, with limited time variation, I cannot disentangle the sources of households' heterogeneous responses to subsidies. Third, data limitations prevent me from capturing heterogeneity in rooftop conditions, installation costs across companies and locations, and variation in electricity retail contracts, all of which may influence adoption. Future research can build on these questions.

8 Conclusion

This paper analyzes the equilibrium outcomes of residential solar PV subsidies in a nested discrete choice framework by introducing heterogeneous preferences and endogenous PV capacity choice. Using Dutch administrative data, I quantify households' adoption behavior and the distributional consequences under diverse policy designs.

The results show that different subsidies vary in their effects on capacity choices. While the quantitative magnitudes may change with the data sample, these intensive effects provide two new policy implications. First, the installed PV size of the PV adopters influences the average installation cost through economies of scale and affects their level of self-consumption. Second, the intensive effect determines how effectively each policy achieves the PV capacity target. In particular, investment-based policies struggle to encourage large installation sizes. Hence, the subsidy level must be increased to meet the capacity target through higher adoption rates (extensive effect). This is fiscally costly and cancels out the advantage of investment-based policies compared with production-based ones, whose future benefits are heavily discounted.

For the distributional effect of subsidy, I show that a universal subsidy raises adoption rates proportionally more among lower-income households, but in absolute terms, richer households still adopt more. However, since low-income households are more cost-sensitive and face physical or financial obstacles, changing from an investment-based subsidy, such as a lump-sum transfer and investment subsidy, would incentivize more adoption of low-income households than a production-based subsidy, such as a feed-in tariff or net metering. This finding is consistent with Zwick and Mahon (2017), showing small firms are more incentivized by immediate tax credit, and this suggests a broader application for policy design in other sectors.

I then propose a novel policy screening design. This "targeted" method moves beyond choosing a single or a combination of policy instruments that is universal to all people, but instead allows households to select from a menu of policies based on their heterogeneous preferences. Such self-selection achieves the highest level of cost efficiency.

The way subsidies are financed also plays a crucial role. Financing through lump-sum taxes is regressive, since costs are spread equally but benefits are skewed toward higher-income households. Financing through surcharges is initially less regressive, as richer households consume more electricity and pay more surcharge, but it becomes more regressive than a lump-sum tax when adoption increases, and the net metering policy is deployed. Income taxation mitigates the regressive effect by shifting the burden toward high-income households. However, when a welfare distribution between PV adopters and non-adopters is considered, the conclusion reverses that high-income non-adopters would suffer most from an income tax, and a lump-sum tax becomes the least regressive.

To conclude, this paper shows the trade-off between different subsidy instruments and highlights the need for careful subsidy design. There are three main lessons. First, policy has not only extensive but also intensive effects. Second, households respond heterogeneously to different subsidy structures. Third, both the payment and financing of subsidies shape the distributional consequences.

Appendix

A Dutch electricity markets

Electricity activities include production, wholesaling, transmission and distribution, and retailing. Transmission and distribution are not liberalized; therefore, electricity markets typically refer to wholesale and retail markets. Electricity is traded on many wholesale markets, including over-the-counter markets, long-term forward and futures markets, day-ahead markets, intraday markets, and balancing markets. There are also ancillary markets that operate as backups to maintain grid stability and efficiency. The *day-ahead wholesale market* is one of the most important markets for electricity trading in the Netherlands. The day-ahead wholesale market works as follows: at day $d-1$ before noon, electricity sellers and buyers bid price on the volume of electricity they are willing to buy or sell for each hour h of the day d. After the gate closes, the market operator matches the bids in a merit order, meaning that dispatch starts from the cheapest fuel. Then, the market operator determines the market-clearing price for each hour by the marginal cost of the most expensive supply bid needed to meet the demand, and all the selected bids are settled at the same price. Without further explanation, the wholesale electricity price in the rest of the paper refers to the price set in the day-ahead wholesale market. As renewable energy has zero marginal cost, it shifts the supply curve to the right (from blue to red) and lowers the market-clearing price. See Figure 8.

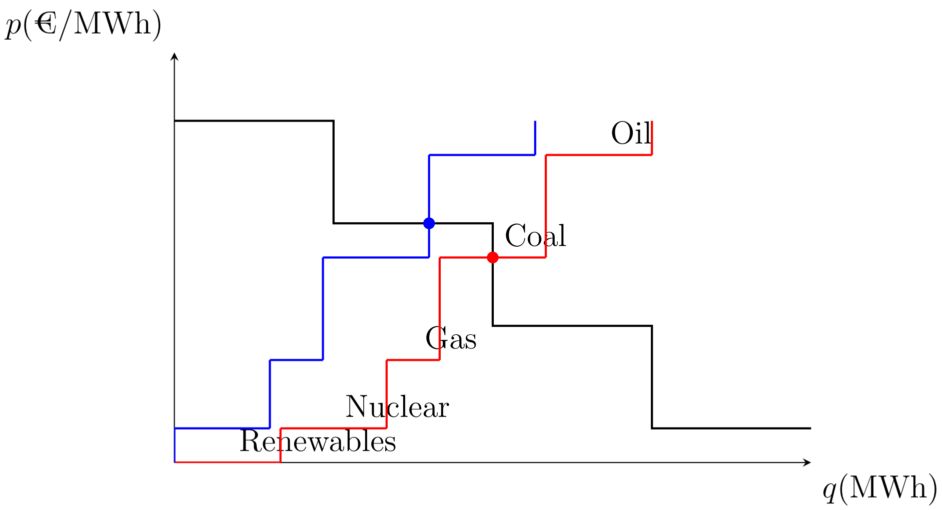


Figure 8: Day-ahead Market Auction

Notes: This figure shows how the day-ahead wholesale electricity price is determined in a blind auction. The operator collects upward supply bids and downward demand bids. The market-clearing price and quantity are determined by the intersection of the supply and demand curves. The figure is illustrative and does not represent the actual market structure in the Netherlands.

Most energy companies are integrated, meaning they engage in both electricity production and retailing. However, in this paper, I assume that wholesale and retail activities are independent. Hence, Retail activity refers to energy companies purchasing electricity from the wholesale markets and reselling it to households. Most households are not directly exposed to wholesale electricity prices. Instead, energy companies set energy prices that are typically calculated as a weighted average of wholesale prices.

The retail price, however, includes not only the energy price but also a fixed grid cost charged by grid operators and taxes paid to the government. Government taxes are levied on the volume of net electricity consumption (hence the consumption from the grid minus the volume fed back into the grid), including energy tax and sustainable energy surcharge (ODE-heffing).[28] As energy is a basic need, each household receives

[28] ODE tax was collected to subsidize renewable investment from 2013 and has been canceled as a separate tax and included in the energy tax since 2023.

a lump-sum tax refund. This refund is the same for every household, independent of their electricity consumption, income, house type, and solar PV adoption status. Finally, the retail price is subject to a value-added tax (henceforth, VAT) of 21 percent.[29] As fixed costs are independent of the amount of electricity consumption and net metering, from now on, VAT included retail price R only refers to the volumetric retail price (hence energy price r, plus taxes) and excludes fixed delivery and grid costs, and tax refund. Denote τ_e as the sum of energy tax and sustainable energy surcharge per kWh, and τ_v as VAT. The per unit tax on electricity consumption is defined as

$$\tau = r * \tau_v + \tau_e(1 + \tau_v) \tag{24}$$

The retail price per kWh is

$$R = r + \tau \tag{25}$$

Before 2022, 72% of the retail price was taxes and levies. Only 28% was for energy price. In 2022 and 2023, temporarily low taxes and high electricity prices reduced the ratio of taxes to 42%. See Figure 9.

In the Netherlands, the electricity bill is issued annually, while the settled price is determined based on the type of retail contracts. There are three types of retail contracts: fixed, variable,[30] and dynamic. The fixed contract charges a fixed retail price per kWh for a certain period between one to three years, while the variable contract has a variable price per kWh that changes twice to four times a year and can be canceled monthly.[31] The dynamic contract is new in the Netherlands, starting from the second half of the year 2022. It provides a price that changes daily or hourly based on the day-ahead wholesale electricity prices, plus a purchase fee per kWh. By the end of 2023, 27 out of 50 suppliers provide dynamic contracts. In total, 50% of households choose fixed contracts, 47% variable contracts, and only 3% dynamic contracts.

[29] VAT rate was 19% until October 2012 and temporarily reduced to 9% between July and December of 2022 because of the energy crisis.

[30] Model contract is a special variable contract that each energy company is obliged to offer, and the conditions of the model contract are the same across all suppliers so consumers are easy to compare and switch between different suppliers. However, the energy prices could differ. Besides model contracts, energy companies can also choose to offer other variable contracts that have different conditions and rates.

[31] Variable rates were adjusted on Jan 1 and July 1 until the energy crisis, when suppliers could adjust more frequently based on market conditions.

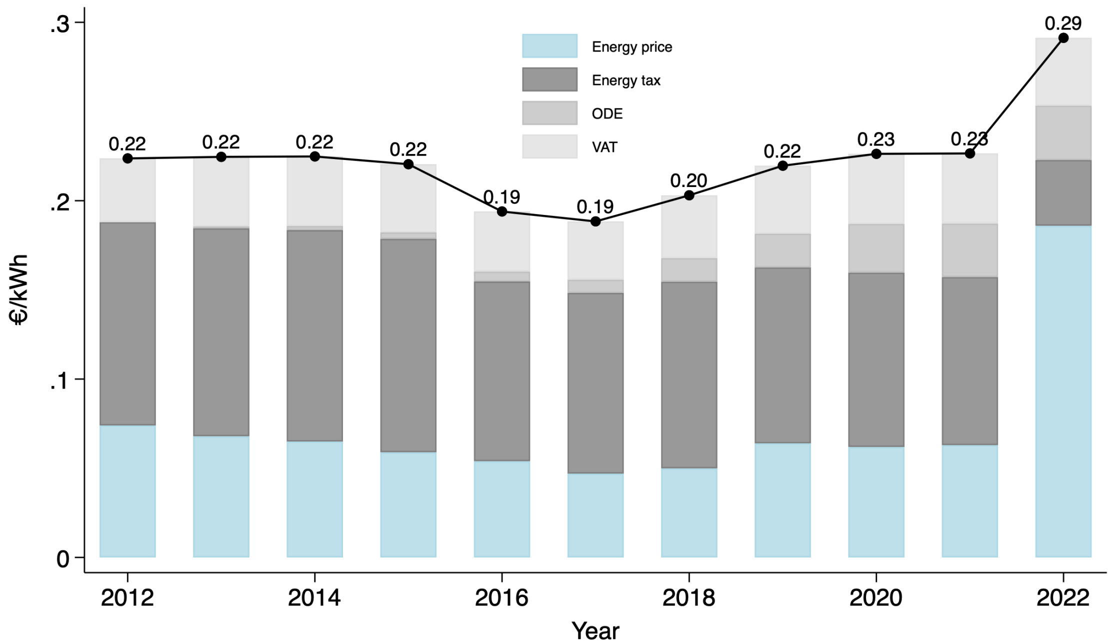


Figure 9: Retail Electricity Price (€/kWh)

Notes: This figure shows the average variable retail price and its breakdown in the Netherlands from 2012 to 2022.

B Solar Efficiency and Self-consumption

This section describes the calibration method for solar efficiency and self-consumption rate, which are used for structural estimation and policy discussions.

Self-consumption Define $Y_{d,h}$ as the solar production on hour h of day d. Define Y as the total annual solar production, $Y = \sum_d \sum_h Y_{d,h}$. $\mathbf{y} = \{\frac{Y_{d,h}}{Y}\}$ is the production profile. $X_{d,h}$ and $Z_{d,h}$ are the electricity consumption and feed-in with the same notation. the profile $\mathbf{x}$ and $\mathbf{z}$ are defined similarly. Self-consumption rate is

$$\alpha = \frac{Y - Z}{Y} \tag{26}$$

αY is the total self-consumption, so the total consumption of PV adopters equals grid consumption plus self-consumption, $X_1 + \alpha Y$.

There are no official data on the self-consumption rate, which is estimated to be between 20-40% in the Netherlands (Londo et al., 2020). In this paper, I estimate the self-consumption rate rather than arbitrarily choosing a number for two reasons. First, the data, assumptions, and estimation methods explained later are transparent, ensuring traceable estimates. Second, the self-consumption rate is indispensable to estimate solar efficiency, which is essential to evaluate the profitability of solar systems and affect the adoption decision of households estimated in Section 4. Finally, this is useful when understanding the adoption patterns in Section 5 and welfare implications among different incentive policies in Section 6. Hence, a self-evident estimate guarantees consistency throughout the paper.

The data used for estimating the self-consumption rate are grid consumption and feed-in profiles for households with and without solar panels. Hence, $\mathbf{x_0} = \{x^0_{d,h}\}, \mathbf{x_1} = \{x^1_{d,h}\}, \mathbf{z} = \{z_{d,h}\}$. The main assumption to estimate α is that the electricity consumption profile does not change with PV adoption. In other words, there is no significant difference between the consumption profile of PV adopters and non-adopters, defined as $\mathbf{c_1} = \{c^1_{d,h}\}$ and $\mathbf{c_0} = \{c^0_{d,h}\}$, respectively. The assumption means

$$\mathbf{c_0} = \mathbf{c_1} \tag{27}$$

This is a strong assumption, but it is reasonable when net metering applies, as the surplus electricity returned to the grid can 100% offset the electricity supplied from the grid at a retail price. Hence, there is no incentive to shift demand. One concern is that consumers may adapt their consumption behavior to retail price structure: consumers shift demand to the period when the price is lower. However, the data does not support this argument, showing that consumers who are charged single, double, or night fare do not behave differently. Another concern is that consumers use more electricity when they have independent producers. I do not rule out the possibility that total consumption changes with adoption, but I restrict consumption to unaffected profiles.[32] Solar production $Y_{d,h}$ is unobservable, meaning I cannot calculate each element in consumption profiles of PV adopters $\mathbf{c_1}$. To address this issue, I use the fact that solar panels do not work at night, so consumption during those periods is only supplied from the grid.[33]

$$c^1_{d,h} = \frac{X^1_{d,h}}{X_1 + \alpha Y} = \frac{X^1_{d,h}}{X_1 + \frac{\alpha}{1-\alpha} Z} = \frac{x^1_{d,h}}{1 + \frac{\alpha}{1-\alpha} \cdot \frac{Z}{X_1}}, \tag{28}$$

Z/X_1 is the total feed-in over the total grid consumption for PV adopters, which is calculated as 0.64. For non-adopters, grid consumption is equal to total electricity consumption. Hence, $\mathbf{c_0} = \mathbf{x_0}$. The OLS regression implied by equation (27) and (28) is

$$x^0_{d,h} = \frac{x^1_{d,h}}{1 + 0.64 \cdot \alpha/(1-\alpha)} + \epsilon_{d,h}, \quad d, h \in \{d, h | z_{d,h} = 0\} \tag{29}$$

[32] The violation of this assumption may overestimate the self-consumption rate as consumption is more likely to increase in the daytime when solar produces.

[33] Due to high investment costs and the net metering policy, household energy storage is uncommon in the Netherlands and is therefore not considered in this paper.

Even though α enters equation (29) in a non-linear way, $\frac{1}{1+0.64\cdot\alpha/(1-\alpha)}$ can be estimated by a simple OLS regression, and the estimated self-consumption rate $\hat{\alpha}$ is uniquely determined. The result is $\hat{\alpha} = 0.33$, suggesting that households, on average, directly use 33% of electricity produced by residential solar systems. The number aligns with the range suggested by Londo et al. (2020), hence a reasonable estimate.

Solar Efficiency CBS provides data on households' solar PV adoption status, capacity, and yearly electricity grid consumption and feed-in from 2019 to 2022. I do not observe the specific installation time. To estimate yearly solar production, I identify households installing PV in 2020 and track their electricity feed-ins in 2021. Similarly, for PV installed in 2021, I track the feed-ins in 2022. All other observations are dropped.

Let i index household and y index year. Denote K_i the solar installed capacity. By definition, $\iota = Y_{i,y}/K_i$, and $Y_{i,y} = Z_{i,y}/(1-\alpha)$. Hence,

$$\iota = \frac{Z_{i,y}}{(1-\alpha)K_i} \tag{30}$$

Hence, the OLS regression is

$$Z_{i,y} = \iota(1-\alpha)K_i + \mathcal{E}_{i,y} \tag{31}$$

$\widehat{\iota(1-\alpha)}$ is estimated to be 0.61, indicating that one additional kWp in PV capacity would, on average, result in an additional 610 kWh feed-in to the grid per year. Using the self-consumption rate $\hat{\alpha} = 0.33$ estimated in equation (29), a simple calculation yields $\hat{\iota} = 0.91$.[34] Hence, in the Netherlands, 1kWp of PV capacity can, on average, produce 910kWh per year. Households directly consume 33% of generated electricity, and the remaining 67% is returned to the grid.

[34]Self-consumption rate can be estimated by data from 2020 to 2023, while the necessary data to estimate solar efficiency only span from 2021 to 2022. For consistency, I only use data in 2021 and 2022. The self-consumption rate is solved to be $\alpha = 0.35$ in 2021, and $\alpha = 0.32$ in 2022. The total feed-in is 59% of installed capacity in 2021 and 62% in 2022. The simple regression of grid-in volume over installed capacity can explain over 90% of the total variation.

C Robustness

Table 8: Robustness: Logit Specification

	(1)	(2)	(3)
β^R (€10^3)	0.417*** (0.007)	0.458*** (0.008)	0.357*** (0.009)
$-\beta^C$ (€10^3)	-0.208*** (0.008)	-0.232*** (0.008)	-0.174*** (0.009)
$\Delta\beta^R_{q_1}$		-0.194*** (0.005)	0.349*** (0.027)
$\Delta\beta^R_{q_2}$		-0.182*** (0.002)	0.324*** (0.013)
$\Delta\beta^R_{q_3}$		-0.054*** (0.001)	0.093*** (0.009)
$\Delta\beta^R_{q_4}$		-0.011*** (0.001)	-0.014* (0.008)
$-\Delta\beta^C_{q_1}$	-0.163*** (0.004)		-0.434*** (0.021)
$-\Delta\beta^C_{q_2}$	-0.149*** (0.002)		-0.394*** (0.010)
$-\Delta\beta^C_{q_3}$	-0.049*** (0.001)		-0.125*** (0.007)
$-\Delta\beta^C_{q_4}$	-0.011*** (0.001)		-0.001 (0.007)
Apartment	-2.443*** (0.015)	-2.443*** (0.015)	-2.444*** (0.015)
HH age	-0.004*** (0.0002)	-0.004*** (0.0002)	-0.004*** (0.0002)
House age	0.083*** (0.001)	0.083*** (0.001)	0.083*** (0.001)
Wealth (€10^5)	-0.011*** (0.0004)	-0.011*** (0.0004)	-0.012*** (0.0004)
Income (€10^4)	0.006*** (0.001)	0.008*** (0.001)	0.007*** (0.001)
House size ($100m^2$)	0.200*** (0.006)	0.200*** (0.006)	0.200*** (0.006)
HH size	-0.005** (0.002)	-0.005** (0.002)	-0.005** (0.002)
Year 2022	0.623*** (0.012)	0.602*** (0.012)	0.646*** (0.012)
Constant	-3.060*** (0.422)	-3.329*** (0.422)	-2.706*** (0.424)
# of Obs	4,245,808	4,245,808	4,245,808

Notes: This table reports Logit estimation results for PV adoption from 2020 to 2022. Standard errors in parentheses are clustered at the household level. Fixed effects are included in the estimation but not reported. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 9: Robustness: Different Discount Factor

	$\rho = 0.9$	$\rho = 0.95$	$\rho = 0.97$
β^R (€10^3)	0.230*** (0.011)	0.157*** (0.007)	0.127*** (0.006)
$-\beta^C$ (€10^3)	-0.177*** (0.011)	-0.167*** (0.011)	-0.155*** (0.011)
$\Delta\beta^R_{q_1}$	0.166*** (0.032)	0.113*** (0.019)	0.092*** (0.019)
$\Delta\beta^R_{q_2}$	0.162*** (0.015)	0.110*** (0.010)	0.090*** (0.008)
$\Delta\beta^R_{q_3}$	0.083*** (0.008)	0.056*** (0.005)	0.046*** (0.004)
$\Delta\beta^R_{q_4}$	0.031*** (0.006)	0.020*** (0.004)	0.016*** (0.004)
$-\Delta\beta^C_{q_1}$	-0.300*** (0.038)	-0.297*** (0.038)	-0.290*** (0.038)
$-\Delta\beta^C_{q_2}$	-0.296*** (0.016)	-0.292*** (0.016)	-0.287*** (0.016)
$-\Delta\beta^C_{q_3}$	-0.144*** (0.009)	-0.142*** (0.009)	-0.140*** (0.009)
$-\Delta\beta^C_{q_4}$	-0.052*** (0.007)	-0.050*** (0.007)	-0.049*** (0.007)
Apartment	-2.395*** (0.048)	-2.393*** (0.048)	-2.392*** (0.048)
HH age	-0.003*** (0.001)	-0.003*** (0.001)	-0.004*** (0.001)
House age	0.089*** (0.003)	0.089*** (0.003)	0.089*** (0.003)
Wealth (€10^5)	-0.001*** (0.000)	-0.001*** (0.000)	-0.013*** (0.001)
Income (€10^4)	0.008*** (0.002)	0.008*** (0.002)	0.008*** (0.002)
House size ($100m^2$)	0.061*** (0.003)	0.061*** (0.003)	0.061*** (0.003)
HH size	0.007*** (0.002)	0.006*** (0.002)	0.006*** (0.002)
Year 2022	0.730*** (0.020)	0.712*** (0.021)	0.696*** (0.021)
σ	0.760(0.009)	0.752(0.010)	0.746(0.010)
# of Obs	2,314,295	2,314,295	2,314,295

Notes: This table reports Logit estimation results for PV adoption from 2020 to 2022. Standard errors in parentheses are clustered at the household level. Constants and other fixed effects are included in the estimation but not reported. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

D Welfare Change

Table 10: Welfare Change: Tenants Adopt (€, per HH)

	< 20%	20–40%	40–60%	60–80%	> 80%
Panel A: equivalent variation					
Net metering (*status quo*)	+26,23	+27,56	+61,00	+118,89	+177,27
Feed-in tariff	+38,57	+40,25	+70,59	+111,44	+145,13
Investment subsidy	+46,07	+48,39	+72,69	+104,09	+129,76
Lump-sum	+49,12	+50,87	+73,18	+101,79	+122,35
Panel B: welfare change with lump-sum tax					
Net metering (*status quo*)	-367.43	-366.10	-332.66	-274.77	-216.39
Feed-in tariff	-250.34	-248.67	-218.32	-177.47	-143.79
Investment subsidy	-103.93	-101.61	-77.31	-45.91	-20.24
Lump-sum	-87.27	-85.53	-63.21	-34.60	-14.05
Panel C: welfare change with surcharge					
Net metering (*status quo*)	-208.58	-260.15	-283.98	-305.97	-330.02
Feed-in tariff	-127.99	-164.46	-179.57	-204.33	-239.54
Investment subsidy	-40.32	-57.78	-57.14	-59.88	-70.08
Lump-sum	-29.40	-45.64	-44.86	-47.31	-59.41
Panel D: welfare change with income tax					
Net metering (*status quo*)	-85.51	-146.50	-205.95	-284.29	-570.57
Feed-in tariff	-43.44	-87.50	-125.33	-184.46	-403.72
Investment subsidy	+3.49	-17.93	-29.03	-49.53	-155.19
Lump-sum	+10.41	-9.44	-19.31	-37.90	-136.76

Notes: This table gives the welfare changes relative to the baseline across five income quintiles of alternative solar support policies.

Table 11: Welfare Change of PV Adopters (€, per HH)

	< 20%	20–40%	40–60%	60–80%	> 80%
Panel A: lump-sum tax					
Net metering (*status quo*)	+746.88	+721.80	+973.59	+1232.25	+1451.56
Feed-in tariff	+1012.94	+987.69	+1144.84	+1236.74	+1297.65
Investment subsidy	+1180.73	+1155.65	+1240.54	+1254.79	+1268.98
Lump-sum	+1212.31	+1181.88	+1247.80	+1238.21	+1215.69
Panel B: surcharge					
Net metering (*status quo*)	+978.78	+953.70	+1205.49	+1464.15	+1683.46
Feed-in tariff	+1096.94	+1046.91	+1178.74	+1223.75	+1254.43
Investment subsidy	+1224.35	+1186.40	+1258.15	+1257.48	+1254.94
Lump-sum	+1251.87	+1209.95	+1263.82	+1240.67	+1202.93
Panel C: income tax					
Net metering (*status quo*)	+892.30	+820.25	+1002.29	+1157.08	+1122.85
Feed-in tariff	+1119.67	+1059.94	+1165.90	+1181.56	+1056.41
Investment subsidy	+1236.15	+1193.16	+1251.48	+1226.14	+1143.73
Lump-sum	+1262.70	+1216.00	+1257.75	+1212.16	+1101.80

Notes: This table reports household welfare changes (€per household) under alternative policies across five income quintiles, financed through different mechanisms (lump-sum tax, surcharge, and income tax).

Table 12: Welfare Change of Non-adopters (€, per HH)

	< 20%	20–40%	40–60%	60–80%	> 80%
Panel A: lump-sum tax					
Net metering (*status quo*)	-231.90	-231.90	-231.90	-231.90	-231.90
Feed-in tariff	-170.19	-170.19	-170.19	-170.19	-170.19
Investment subsidy	-88.36	-88.36	-88.36	-88.36	-88.36
Lump-sum	-80.35	-80.35	-80.35	-80.35	-80.35
Panel B: surcharge					
Net metering (*status quo*)	-157.82	-193.80	-237.68	-302.46	-370.88
Feed-in tariff	-111.79	-137.28	-168.37	-237.83	-284.23
Investment subsidy	-58.03	-71.26	-87.40	-111.22	-136.38
Lump-sum	-52.91	-64.67	-79.47	-101.13	-124.01
Panel C: income tax					
Net metering (*status quo*)	-84.13	-131.05	-200.93	-303.34	-563.41
Feed-in tariff	-61.75	-96.17	-147.47	-222.63	-413.49
Investment subsidy	-32.06	-49.93	-76.56	-115.59	-214.67
Lump-sum	-29.15	-45.40	-69.62	-105.11	-195.20

Notes: This table reports welfare changes (€per household) for non-adopters under alternative solar support policies across five income quintiles, financed through different mechanisms (lump-sum tax, surcharge, and income tax).

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