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On the redistributive effects of Germany's feed-in tariff

Peter Grösche♦ and Carsten Schröder♠

Abstract. The present article assesses the redistributive effects of a key element of German climate change policy, the promotion of renewables in the electricity mix through the provision of a feed-in tariff. The tariff shapes the distribution of households' disposable incomes by charging a levy that is proportional to household electricity consumption, and by financial transfers channeled to households feeding green electricity into the grid. Our study builds on representative household survey data, providing information on various socio demographics, household electricity consumption and ownership of solar facilities. The redistributive effects of the feed-in tariff are evaluated by means of various inequality indices. All the inequality measures indicate that Germany's feed-in tariff is mildly regressive.

Key words: income distribution, redistribution, tax incidence, renewable resources, energy policy

JEL codes: D12, D31, H22, H23, Q27, Q48

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1. Introduction

Electricity is an elementary ingredient of our everyday life. Nearly all of our daily activities are somehow related to the consumption of electricity, starting with the alarm clock and the coffee-maker in the morning, and ending with turning on the light bulbs and the TV in the evening. Indeed, there is ample empirical evidence that household spending on electricity is price inelastic, and that the expenditure share for electricity, as for other necessity goods, is inversely related to household income. For example, according to the German “Sample Survey of Income and Expenditure 2008” (StaBuA 2010), a typical German household in the lowest income quintile spends about 3.7 percent of its net income on electricity, as opposed to 1.3 percent in the highest income quintile.

Under such conditions, higher electricity prices raise a relative higher monetary burden on households at the lower end of the income distribution. Accordingly, electricity price-raising environmental policies are likely to have regressive effects. In this regard, the key element of Germany’s climate change policy, the feed-in tariff to promote renewable electricity, is particularly interesting. Like in many other industrialized countries, for instance in Australia, Canada/Ontario, several US states or Spain, suppliers of green electricity in Germany receive a fixed payment per kWh for feeding the generated electricity into the public grid. The tariff is technology specific and depends on the year of installation of the generation facility. However, it generally exceeds the electricity spot market price, and provides financial incentives for green electricity generation. The difference between subsidy payment and spot market price is shifted to the electricity consumer, who pays a levy on top of the consumer price. [1]

The German approach is quite a success story in terms of green-electricity production: the share of renewables in the electricity mix increased from seven to 17 percent between 2000 and 2010. However, in the same time the subsidy payments rose from 1.2 billion Euro to about 12.3 billion Euro (UeNB 2010a, 2010b), associated with an increase of the levy from 0.6 cent per consumed kilowatt-hour (ct/kWh) to 2.05 ct/kWh. The design and the scope of the subsidy scheme have evoked a hot debate on its effectiveness. Critics argue that the feed-in tariff facilitates expensive technologies without fostering cost-reducing innovations, while its climate protection effect is nil, because the carbon-dioxide emission in Europe are capped by the European emission trading system, and the

[1] Renewable energy policy instruments in Germany are surveyed in Agnolucci (2006).

subsidized greening of the electricity mix simply relieves emission permits that are now used elsewhere.[2]

Besides effectiveness and efficiency, the distributive effects are another central question in gauging the desirability of environmental policies. For the political acceptability of a policy it is decisive who gathers its benefits and who bears its fiscal burden. In the late 1980's, Baumol and Oates (1988, p. 235) already emphasized the relevance of distributional effects for the evaluation of environmental policies:

> *"Obviously, the distributive side of externalities policy is of interest in and of itself in a world in which inequality and poverty have assumed high priority among social issues. In addition, without adequate consideration of this aspect of the matter, we may not be able to design policies that can obtain the support they require for adoption. Thus, by ignoring the redistributive effects of an environmental policy, we may either unintentionally harm certain groups in society or, alternatively, undermine the program politically."*

For such reasons, assessing the redistributive impacts of taxing energy, electricity, carbon or motor fuels has gained popularity in the literature. Fullerton (2008) and Parry et al. (2005) provide a review of previous works, and identify the economic channels through which the personal income distribution may be affected.[3] For several OECD countries, studies such as Pearson and Smith (1991), Casler and Rafiqui (1993), Brannlund and Nordstrom (2004), Wier et al. (2005), Scott and Eakins (2004), Callan et al. (2008), and Grainger and Kolstad (2009) have assessed the redistributive impacts of aforementioned environmental taxes. The general finding is that such taxes have mildly regressive distributional effects which can further be alleviated by revenue recycling, e.g. lump-sum transfer or tax relieves.

While most empirical studies assess the redistributive effects by comparing households' monetary tax burdens at different points (quintiles, deciles, percentiles) of the income distribution, studies using inequality measures to gauge distributive consequences of climate change policy are rare to find. The study of Oladosu and Rose (2007) examines the welfare effects of a carbon tax for a particular east-coast region in the United States. The reported Gini- and Theil indices evince that the tax yields a more equal income distribution, a result quite contrary to the usual findings. Further, Jorgenson et al. (1992) assess the distributional impacts of carbon taxes by means of a social welfare function. They report a modest regressive effect, while the magnitude varies with the level of inequality aversion in the society. Recently, Araar et al. (2011) have conducted a welfare analysis of

[2] Other practical issues include corruption, accounting finagling, or ease of implementation (see Nordhaus (2007)). Concerning the design of economically efficient feed-in-tariff see Lesser and Su (2008). Menanteau et al. (2003) examine the (static and dynamic) efficiency of different incentive schemes for promoting the development of renewable energy.

[3] For previous literature reviews see IPCC (1995: 419-421), OECD (1995), and Speck (1999)

different domestic emission trading systems using Canadian data. Using the Gini index, they find that overall “the policy effects on inequality is numerically small” (Araar et al., 2011, p. 239).

The redistributive effects of Germany’s feed-in tariff have attained surprisingly scant attention so far, despite equality, equity, and fairness being deeply rooted in the German society. Germany’s feed-in tariff is likely to be regressive, i.e. redistributing income shares from the lower to the upper part of the income distribution. Poorer households spend a higher share of their income on electricity than wealthy households, and a levy raised proportionally to electricity consumption emphasizes this differential. Moreover, the collected revenues are used for subsidizing renewable energy installations, investments typically undertaken by wealthier households.

The quantitative strength of the direct monetary redistributive effect of the feed-in tariff on households’ budgets hinges both on households’ electricity demand and the relationship between household income and green-electricity investments. We assess this redistributive effect by comparing inequality indices computed with and without the direct monetary consequences of the feed-in tariff on households’ budgets. As there is no such thing as a “best” inequality index, our analysis relies on four well-known measures: the Gini index, the Theil index, the Atkinson index, and the 90/10 percentile ratio. All statistics indicate a regressive effect, meaning that Germany’s feed-in tariff yields a more unequal income distribution. However, this effect is moderate in quantitative terms.

Our results build on several simplifying assumptions. First, we restrict our attention to the distributive effects of the feed-in tariff among households only, though any other investor in green electricity – such as utilities or funds –is entitled to receive the subsidy. Second, concerning the transfers, we exclusively focus on subsidies paid for solar panels (installed by private households). De facto, other forms of production (e.g., wind power) are subsidized as well. Wind power farms are often financed by private funds, and typically wealthier persons invest in such funds. Hence, there is an indirect way how the feed-in tariff affects the income distribution as well, but we lack information about the household's investment portfolio. However, both aforementioned assumptions should lead to an underestimation of the tariffs’ regressive effects. Third, behavioral responses and general equilibrium effects are ruled out, with ambiguous effects on inequality estimates.[4] Fourth, we focus on the monetary consequences of the tariff, and thus ignore how other (external) cost and benefits may affect social welfare.[5]

[4] Using Canadian data Araar et al. (2011) show that the inclusion of equilibrium effects of a carbon tax does not change its welfare implications.

[5] A broad discussion of the distribution of benefits is provided Baumol and Oates (1988) or Brooks and Sethi (1997). Already in 1978, Harrison and Rubinfeld have examined how the benefits from air pollution control strategy are distributed across income classes in the area of Boston.

The remainder of the paper outlines as follows. Section 2 introduces the inequality indices underlying the empirical analysis. We provide an overview over the used data in Section 3, and the empirical assessment of the redistributive effects in Section 4. Section 5 concludes. The paper further includes an Appendix, providing details of the data assembly and estimation methodology.

2. Measuring inequality

At first instance, the term “inequality” appears to be a somewhat blurry notion since it simply states that the distribution of a particular measure (i.e., income, expenditures, or wealth) deviates from a state of equality. The distribution of a particular measure is unequal if disparities in the measure exist between economic units such as households, individuals, or groups within a society. Inequality analyses typically rely on incomes, since economists consider the income distribution, particularly the distribution of disposable incomes, as a good proxy for the distribution of living standard. Along these lines, this paper selects the households’ disposable incomes to derive the distribution of living standard.

Comparing incomes across households requires the researcher to deal with the empirical fact that people living in households which differ in size and material needs. The subsequent paragraph describes the conversion of such a heterogeneous household-level distribution into a quasi-homogeneous distribution. Further, the researcher must decide how to measure inequality, meaning the selection of an appropriate inequality index. This sensible issue will be touched in the paragraph after next.

Adjusting household income for differences in needs and household weighting

Inequality analyses are typically based on incomes, as income is interpreted as a close proxy for living standard. However, a complication emerges if the population is heterogeneous and household units differ in size and needs. Then the same disposable income is associated with different levels of material living standard, and an ordering of households by income is not consistent with an ordering by material living standard. For example, it is unlikely that a four-member household and a single–person household, both endowed with the same disposable income of 2,000 Euro per month, attain the same material living standard. However, it is also unlikely that the four-person household needs four times the income of the one-member household to attain the same standard of material well-being, since larger households have the ability to share appliances and household equipment.

To capture such scale effects, household incomes are adjusted for differences in needs by means of equivalence scales, meaning that the household income is divided by the respective equivalence scale. Equivalence scales reflect intra-household sharing potentials and differences in family members' needs, and normalize the household income to the needs of a benchmark household, in our case a single-person household. In our empirical examination, we use the square root equivalence scale (OECD 2011): the number of household members to the power of 0.5. Accordingly, the above mentioned four-person household with a household income of 2,000 Euro attains a living-standard equivalent to a one-member household endowed with an income of 1,000 Euro, i.e. $2{,}000/4^{0.5}$. The result of this operation is a (needs-adjusted) equalized income which can now be assigned to each respective household member.[6] This procedure transforms the heterogeneous distribution of household incomes at the household level in a quasi-homogeneous distribution of individuals, which is underlying our inequality analysis. In the quasi-homogeneous distribution, income units are comparable in terms of material living standards as income is adjusted for differences in needs, and observations are comparable in size as persons are chosen as observation unit.

Inequality indices

The magnitude of income inequality is typically represented by a scalar, an inequality index.[7] By definition, it condenses all the particularities of an income distribution in a single number. Numerous inequality measures have been suggested in the literature, including ad-hoc measures (e.g., Gini index and percentile ratios), entropy-based measures (e.g. Theil index), and measures based on social-welfare functions (e.g., Atkinson and Dalton index). Each approach and measure possesses particular weaknesses and strengths. Accordingly, there is no such thing as a "best" inequality index. Moreover, it is not ruled out that two indices yield different rankings of income distributions. For these reasons, our inequality analysis builds on a set of four well-known inequality indices: the 90/10 percentile ratio, the Gini coefficient, the Theil index, and the Atkinson index, all being defined subsequently.

[6] Theoretical issues of alternative techniques to convert heterogeneous distributions in quasi-homogeneous distributions are discussed in Ebert and Moyes (2003) and Shorrocks (2004), while Bönke and Schröder (2010) provide an empirical examination of the role of alternative conversion techniques.
[7] An alternative (complementary) option is to depict the extent of inequality by means of graphical device such as the Lorenz curve or the Parade of Dwarfs. See Cowell (2011) for an overview.

90/10 percentile ratio

The 90/10 percentile ratio is a simple ad-hoc inequality measure. Let y_i be the income of person i, $i = 1, \ldots, n$. Then the 90/10 percentile ratio measures the range (in relative terms) between the income of a person in the 90th (y_{p90}) and a person in the 10th percentile (y_{p10}) of the income distribution:

$$(1) \qquad p_{9010} = \frac{y_{p90}}{y_{p10}}$$

For instance, a 90/10 percentile ratio of $p_{9010} = 4$ indicates that somebody at the 90th percentile has an income which is four times higher than the income of somebody who belongs to the 10th percentile.

Gini coefficient

The Gini coefficient, G, is probably the most frequently used inequality index in applied inequality research. Let $F(y)$ denote the proportion of the population with income less than or equal to y, and let $\bar{y}$ denote the mean income of the population. Then $\Phi(y)$ is the proportion of total income received by persons having an income not more than y, with:

$$(2) \qquad \Phi(y) = \frac{1}{\bar{y}} \int_0^y z dF(z),$$

where z is the integration variable (income). The Lorenz curve (F, Φ) graphs the population proportion F versus the income proportion Φ. The Gini index is defined as twice the area between the line of perfect equality (each household has the same income) and the Lorenz curve:

$$(3) \qquad G = 1 - 2\int_0^1 \Phi dF.$$

An index value of $G = 0$ indicates that income is perfectly equally distributed among the units (households or individuals), while $G = 1$ indicates perfect inequality, i.e. one unit possesses all the income. The Gini index puts a lot of weight to the middle part of the income distribution, and slowly reacts to changes in the top and bottom part of the income distribution.

Theil index

The Theil index belongs to the family of generalized entropy indices and is defined as

$$(4) \qquad T = \frac{1}{n}\sum_{i=1}^{n}\frac{y_i}{\overline{y}}\log\left(\frac{y_i}{\overline{y}}\right).$$

Entropy-based inequality measures rely on an analogy between inequality analysis and information theory. Information theory assigns probabilities to events and values the information that an event has occurred. The lower the probability for an event, the more weight is assigned to the information that the event has been observed. Theil has suggested a re-interpretation of the entropy concept: Events are interpreted as economic units (people or households) and probabilities as the income shares of the households from total income. The Theil index thus assigns a higher weight to low-income units than to high-income units.

Atkinson index

The Atkinson index explicitly relies on a particular type of social welfare function (SWF). The SWF reflects a society's preference towards (in)equality, generally meaning that the valuation a society gives to a person's income decreases with the increase of the person's economic position. The SWF is defined as

$$(5) \qquad W\left(y_1,\ldots,y_n\right) = \sum_{i=1}^{n}\frac{y_i^{1-\varepsilon}-1}{1-\varepsilon} \text{ when } \varepsilon \neq 1 \text{ and } \varepsilon > 0 \text{, and}$$

$$W\left(y_1,\ldots,y_n\right) = \sum_{i=1}^{n}\ln\left(y_i\right) \text{ for } \varepsilon = 1.$$

The parameter ε captures the degree of inequality aversion in the society. The higher is ε, the more sensitive to inequality is the society. The Atkinson index is defined as

$$(6) \qquad A_\varepsilon = 1 - \frac{EDE_\varepsilon}{\overline{y}},$$

where EDE_ε denotes the equally-distributed-equivalent income. EDE_ε provides the level of income per head which, if equally shared, would generate the same level of social welfare as the observed distribution and is defined as:

$$(7a) \qquad EDE_\varepsilon = \left[\sum_{i=1}^{n}\frac{1}{n}y_i^{1-\varepsilon}\right]^{1/(1-\varepsilon)} \text{, when } \varepsilon \neq 1 \text{ and } \varepsilon > 0 \text{, and}$$

$$(7b) \qquad EDE_{\varepsilon} = \sum_{i=1}^{n} \frac{1}{n} \ln\left(y_i\right), \text{ when } \varepsilon = 1.$$

Figure 1 gives a graphical representation of the idea underlying the Atkinson index. Point A depicts the distribution of income for two individuals, $\left(y_{1,0}, y_{2,0}\right)$. The related level of social welfare is represented by the social indifference curve, while the shape of the indifference curve is triggered by the parameter ε. Income would be perfectly equally distributed along the diagonal line. Associated with the observed incomes $\left(y_{1,0}, y_{2,0}\right)$ is the mean income $\overline{y}$. Since the society dislikes inequality, social welfare would increase if $\overline{y}$ were distributed equally (point C). On the other hand, EDE captures an equally distributed income that yields an equivalent level of social welfare as the original income distribution (point B). Hence, the distance between B and C is the amount of welfare a society is willing to sacrifice for reducing inequality, and the Atkinson index measures the percentage of mean income the society is willing to give up.

Figure 1 about here

Properties of inequality indices

A set of five key principles has been suggested in the inequality literature: weak/strong principle of transfers, income scale independence, population principle, and decomposability.[8] We proceed with an introduction of the principles, and then summarize the properties of the aforementioned four indices.

Weak principle of transfer (WPT)

Let an income distribution A be achieved by a simple redistribution of income from a distribution B, holding total income constant and ensuring that the Lorenz curve for A lies wholly inside that of B. Then, inequality measures that comply with *WPT* always indicate strictly less inequality for situation A than for B.

[8] Of course, the list of principles is not exhaustive. Other principles touch the issue of sensitivity of inequality measures to transfers in different parts of the income distribution (e.g., Shorrocks and Foster (1987)), or to isolated income changes (e.g., Barett and Salles (1998)), or deal with the issue of household-type heterogeneity (e.g., Ebert (2007), Shorrocks (2004), and Ebert and Moyes (2003)). For further details, see Cowell (2011, Chapter 3 and also pp. 186f).

Strong principle of transfer (SPT)

SPT requires that the inequality reduction due to an income transfer from a rich person to a poor person depends on the difference between the two persons' income. It does not matter which two individuals are involved in the transfer.

Principle of income scale independence (ISI)

An index complies with *ISI* if the index depends on the distribution of total income but not on the actual level of total income. More precisely, if every person's income changes by the same proportion, then the level of measured inequality should remain unchanged.

Population principle (PP)

An index meets *PP* if it depends on the distribution of total income but not on the number of persons in the population. Accordingly, if we merge two identical income distributions, inequality is unchanged if the index satisfies *PP*.

Decomposability (D)

Finally, according to *D*, the total inequality in an income distribution can be expressed as a function of inequality within its subgroups (e.g., household types) and inequality between the subgroups.

The properties of the used inequality measures are summarized in Table 1. Percentile ratios satisfy *ISI* and *PP*, yet violate both transfer principles and *D*. The Gini index satisfies *WPT*, *ISI*, and *PP*, but it fails to satisfy *SPT* and *D*. The Atkinson satisfies *WPT*, *ISI*, *PP*, and *D* but fails to meet *SPT*. Only the class of generalized entropy measures simultaneously satisfy *WPT*, *SPT*, *ISI*, *PP* and *D*.

Table 1 about here

3. Data set

Our data are drawn from the German Residential Energy Consumption Survey (GRECS 2008), a sample of 6,714 households, surveyed in spring 2010. GRECS provides socio-demographic information about household characteristics such as the household size, disposable income, age and education of the household head, and the accommodation. Further, information on households' annual electricity consumption and whether a household owns solar panels is reported. Such data are crucial for our purposes, and GRECS is the only household micro database including all the information jointly.[9] From annual electricity consumption we can quantify the levy burden. Ownership of solar panels indicates whether households generate revenues from the feed-in subsidy scheme.

Electricity consumption

Table 2 provides summary statistics for households' annual electricity consumption, decomposed by disposable income classes. The second column provides the number of observations in our data set, pertaining to the particular income class in 2008. The third column depicts mean electricity consumption in the income class, while the fourth column reports the range of the respective 95% confidence interval. Results from Table 2 clearly indicate that electricity consumption rises with income. For instance, in 2008 the typical household with a monthly income below 500 Euro consumed on average 1,915 kWh of electricity compared with more than 4,000 Euro when disposable income exceeds 4,000 Euro. However, the relationship of electricity consumption and income, as indicated by the third column, is not proportional: While households in the highest income class possess an income at least eight times higher as households in the lowest class, their electricity consumption is only twice as high. Complying with Engel's law, electricity consumption increases in income but its expenditure share declines (i.e. the income elasticity is between zero and one). These numbers confirm that electricity – like food, water and gas – is a necessity good.

Table 2 about here

Levy payment

The German feed-in tariff is funded by a levy on top of the consumer electricity price. The last two columns of Table 2 give the results of a back-of-the-envelope calculation to assess the levy payment of a typical household in each income class. In 2008, a levy of 1.1 ct per consumed kWh was charged, and the typical household in the second income class consumed on average 2,012 kWh. Accordingly, these households paid a levy of about 22.13 Euro per year. Since the levy is strictly connected to the electricity consumption, the absolute level of levy paid by the households rises with income, while the levy-induced monetary burden relative to income decreases with household disposable income.

The GRECS survey includes electricity billing data, but not all interviewed households provide their consumption data. The figures reported in Table 2 rely on 2,594 households. In the inequality

[9] For example, Germany's Sample Survey of Income and Expenditure contains „expenditures on electricity" as a variable, yet no information on equipment with solar panels.

analysis, we have imputed electricity consumption and resulting annual levy payment for all households where the information is missing using the correlation between household size, occupied living space and electricity consumption. More precisely, we run ordinary least square regressions for electricity consumption on dwelling and household size, and use the predicted values to impute electricity consumption in case of missing information. For details see the Appendix.

Solar facilities: distribution of ownership

Households consume electricity but also they may produce green electricity, for instance if they have solar panels installed on their roofs. We expect a positive relationship between the household's disposable income, the size and the quality of the household's accommodation, and the endowment with a solar installation. While less wealthy households typically rent a dwelling, and have little opportunity to install a solar panel, wealthy households are more likely to live in their own property, and have space and money to invest in such panels. Table 3 provides some evidence in support of this hypothesis. The columns show the monthly disposable household income, starting from below 500 Euro in the first column until 4,500 Euro (and more) in the last column. The percentage of households having a solar installation on their roof amounts to 3% in the lowest income category. This share rises in income: About 21% of the households belonging to the highest income category (meaning at least 4,500 Euro per month as disposable income) possess solar panels. We measure the association between the (categorical) income and whether the household has a solar installation (binary information) by Cramér's V ,

$$(8) \qquad V=\sqrt{\frac{\sum_i\sum_j\left(n_{ij}-e_{ij}\right)^2/e_{ij}}{N\cdot\left(\min\left(r,c\right)-1\right)}},\ 0\le V\le 1,$$

where n_{ij} denotes the number of observations in row i and column j of a contingency table, $e_{ij}=\left(n_{.i}\cdot n_{.j}\right)/N$ is the expected number of observations when variables are uncorrelated with N giving the total number of observations, and $\min\left(r,c\right)$ is the minimum of the number of rows and columns. In our case, the correlation between income category and the possession of solar panels is 0.1. However, the quantitatively small number should not be interpreted as a weak correlation. As can be seen from the definition of Cramér's V , its upper limit is less than 1.0 when numbers of rows and columns are different, which is the case as we have a two item variable for ownership of solar panels (yes, no) but a ten item variable for income.

Table 3 about here

Solar facilities: costs and revenues

Households receive payments from the feed-in tariff scheme if they feed generated electricity into the public grid. GRECS provides information about the household's dwelling characteristics, whether the building is equipped with solar panels, and the installation year of the panels. If a household owns the occupied dwelling and is equipped with solar panels, a net return from the panel has been calculated based on the following assumptions: (a) the size of the solar panel is 30 square meters, (b) electrical efficiency is 0.13 kilowatts per square meter, and (c) solar radiation is 900 kWh per year and square meter. Accordingly, we assume a capacity of 4 kilowatts peak per installed solar facility, yielding a supply of 3,510 kWh per year. Each produced kWh generates revenues from the feed-in tariff, while the actual subsidy per kWh depends on the year of facility installation. The payment dwindles over time, starting with 57.4 cent per generated kWh for installations made before 2005 and reaching 43.0 cent/kWh for installations made in 2009. Investment costs also depend on the year of installation, starting from 4,000 Euro per kW capacity in 2006 and reaching 3,400 Euro/kW capacity in 2009. [10] We annualize investment costs over 20 years (the time span the subsidy is guaranteed) with an interest rate of 3.9%. Received subsidy payments minus annualized investment costs yields the yearly net return of the solar installation, which we add to the household's disposable income.

Income imputation

Unfortunately, it is not possible to assess the feed-in tariffs redistributive effects from GRECS directly, as household income is not provided as a continuous variable. Instead, income is provided by a categorical variable, indicating whether the household's disposable income belongs to a particular income class. To circumvent the limitations arising from the categorical information, we transform the income data into a continuous variable: An auxiliary data set provides information on household income in continuous form, from which we estimate a household-type specific income distribution for Germany. We impute a household income in the GRECS data set from the fitted income distribution using a bootstrap procedure. The Appendix describes the imputation procedure in detail. We choose $R=1,000$ bootstrap replications, where each replication generates an imputed income for every household and an according bootstrap income distribution. In the subsequent analysis we precede with these imputed bootstrap distributions.

[10] Investment costs are surveyed on a regular basis by the respective solar industrial association. For more information, see www.solarwirtschaft.de/preisindex.

4. Empirical assessment of the feed-in tariffs' redistributive effects

The starting point for our distribution analysis is a benchmark scenario, where we compute inequality indices from the disposable income distribution without any adjustment for the feed-in tariffs distributional effects. Departing from the inequality estimates for the benchmark scenario, we assess the tariffs' distributional effects for several alternative scenarios. More precisely, for any alternative scenario, we adjust the income distribution for the levy burden and the provided feed-in payments from solar panels, and re-calculate the inequality indices. Then we gauge the distributional effects of the feed-in tariff scheme by comparing the adjusted income distribution in the scenarios with the benchmark.

Defining the scenarios

Our first scenario involves the distributional effects in year 2010, when a levy of 2.05 ct per consumed kWh electricity was charged. We then precede our investigation with 2011 with a levy of 3.53 ct/kWh. For future periods no "official" point estimates for the levy are published yet, so that we have extrapolated the relative increase of the levy for 2012 to 2015. In this respect, we use forecasts of generation and associated feed-in remunerations for renewable electricity, forecasts of the revenues from selling the provided electricity at the spot market, and estimates of the future electricity end-use consumption, in order to assess a likely future path of the levy charge (Table 4). To be more specific, it is expected that about 93.7 TWh of renewable electricity will be supplied in 2011, and the associated remunerations reach about 15.6 billion Euro. Selling this amount of electricity yields revenues of 5.5 billion Euro, so that 10.1 billion Euro must be financed via levies to be paid by the consumers. Dividing the funding gap of 10.1 billion Euro by the expected electricity end-use consumption of 407 TWh, we end up with an estimate for the levy in 2011 of 2.5 ct per kWh consumed electricity. The same calculation for the year 2012 yields a levy of 2.8 ct per kWh, an increase of more than 13%. However, since the actual levy charged in 2011 is 3.53 ct per kWh, an increase of 13% implies a levy of 4.0 ct/kWh. We update the 2012 estimate accordingly, and cross-check our estimate with the computations of the authority responsible for fixing the levy. While the authority expects the levy being in the interval 3.4 ct per kWh to 4.4 ct per kWh (UeNB 2010c), our estimate of 4.0 ct/kWh is exactly central in this interval.

For the future periods 2013 to 2015 the levy estimate can be computed in a like manner. For 2013, we estimate the levy to reach 4.3 ct/kWh, reaching 4.6 ct/kWh in 2014, and 4.9 ct/kWh in 2015. Since we lack external information about a reasonable interval for the levy in future periods, we are unable to cross-check our computations. Table 4 summarizes the scenario set-up.

Table 4 about here

Having determined a likely path for the levy levels in future years, the annual levy payments for each and every household must be determined. The easiest way is to assume a price inelastic demand for electricity, and thereby neglecting any responsiveness of consumer behavior to price changes. Though this assumption might appear strong, it is supported by the low price elasticities reported in previous studies. For example, Narayan et al. (2007) find a short-run price elasticity of -0.1068 for residential demand elasticities in G7 countries. For Swiss households Fillippini (1999) has estimated a price elasticity of -0.3, and according to Boonekamp (2007), households in the Netherlands exhibit a smaller price responsiveness with an elasticity of -0.13. Thus, electricity demand seems to be highly inelastic, at least in the short run and for reasonable price variations as in our scenarios.

We hence fix households electricity consumption at the 2008 values, and calculate for every household in our data set the respective total annual cost associated with the levy. That means, a household consuming e.g. 2 000 kWh per year paid 22 Euro as levy in 2008, the levy cost will amount to 70.60 Euro in 2011, and will add up to 98 Euro in 2015.

Results

The distributional effects of Germany's feed-in tariff are summarized in Table 5. The scenarios appear row-wise: In the benchmark scenario, inequality estimates are derived from the distribution of equalized disposable incomes before levy and fee-in tariff related transfers to owners of solar panels. In the adjacent two rows follow the 2010 scenario with a levy of 2.05 ct/kWh, and the 2011 scenario with a levy of 3.53 ct/kWh. Underneath appear the results of three scenarios for year 2012. These three scenarios reflect forecasts of an upper and a lower bound of the levy according to the responsible grid authority (UeNB 2010c), and also our own projection, which is exactly centered in this interval. The last three rows contain the scenarios for 2013 to 2015, where we expect the levy to rise from 4.3 ct/kWh to 4.9 ct/kWh.

For each scenario, seven measures are provided, appearing column-wise, the 90/10 percentile ratio, the Gini and Theil index, and the Atkinson index with inequality aversion parameters 0.5, 1.0, and 2.0. For each measure, two statistics are provided: the estimator of the mean, and the 95 percent bootstrap confidence interval (appearing in brackets underneath). We have also computed percentage deviations from the benchmark scenario for each and every measure (appearing in parentheses). For example, take the 2011 scenario. Here the bootstrap mean of equalized income,

$\overline{y}^* = \frac{1}{1,000}\sum_{R=1}^{1000}\overline{y}^R$, is 20,016 Euro. The brackets underneath provide the respective 95 percent confidence interval derived from the vector $\overline{y}^1,...,\overline{y}^{1000}$. The value in parentheses indicates that levies and transfers leads to a 0.296% reduction of mean equalized disposable income compared with the benchmark scenario.

Table 5 about here

In all alternative scenarios, mean equalized disposable income falls below its benchmark level. For example, while the average loss of equalized disposable income amounted to 25 Euro in year 2010, it is expected to be 59 Euro in 2011, and 90 Euro in year 2015. The drop in equalized income is due to the fact that levy-related fiscal revenues are transferred back to renewable energy producers in general and irrespective of the type of production (e.g., solar panels vs. windmills), while the present analysis solely considers transfers to private solar-panel owners.

The corresponding distributional effects are captured by the associated inequality indices. Except the 90/10 percentile ratio which always exceeds 1.0, all indices are multiplied with a factor of 100. As can be seen from the 90/10 percentile ratios, the feed-in tariff broadens the income divide between the bottom and the top of the distribution: While in the benchmark scenario the equalized disposable income of high-income households (90th percentile) is 3.259 times the income of low income households (10th percentile), the factor increases to 3.272 in the 2011 scenario and to 3.285 in the 2015 scenario. There are two basic causes explaining the rise of the 90/10 percentile ratio. First, electricity is a necessity good with an expenditure share which is decreasing in income. Accordingly, relative to income, the levy induced monetary loss is higher at the bottom compared to the top of the distribution. Second, the fraction of households owning solar panels is increasing in income. Accordingly, revenues accrue especially at the top of the distribution.

The results for the 90/10 percentile ratio indicate that Germany's feed-in tariff scheme is associated with a regressive effect on the distribution of equalized disposable income. This result is reconfirmed by the other inequality indices. The Gini index suggests that the regressive effect is quantitatively small. The bootstrap estimator of the mean is 27.092% in the benchmark scenario, and even in the 2015 scenario, the scenario with the highest levy, it has risen only by 0.518% to a level of 27.232%. However, when interpreting the result it should be kept in mind that the Gini index puts a lot of weight to the middle part of the income distribution, and thus is insensitive to changes at the very bottom and top. The Theil index, for example, is more sensitive to the redistributive effects of the feed-in tariff scheme: In the 2015 scenario, it is 1% higher as in the benchmark.

The Atkinson index allows an assessment of distributional effects for different levels of inequality aversion, as captured by the parameter ε. In a society with low preferences against income inequality (i.e., $\varepsilon = 0.5$), inequality increases by 1.02% from the benchmark to the 2015 scenario. In a society with a higher inequality aversion (e.g. $\varepsilon = 1.0$), the change in the Atkinson index amounts to 1.04%, and respectively to 1.10% if $\varepsilon = 2.0$.

The results from Table 5 indicate that the regressive effect rises with the levy level. Figure 2 gives supporting evidence, where we have plotted our inequality indices against the levy levels (in ct/kWh). The solid lines give the bootstrap estimate of the mean index, while the grey lines indicate the 95 percent confidence interval. For all four indices, we find an almost linear relationship between the levy and the level of measured inequality.

Figure 2 about here

The changes in the equally-distributed-equivalent income, EDE, provide a numerical representation of the additional welfare loss due to increasing income inequality. Remember from Figure 1 that $\bar{y}$ is the mean equalized income of a particular scenario, and is documented in column 1 in Table 5. By contrast, EDE captures the (equalized) income that gives rise to the same level of social welfare like the actual income distribution but is equally distributed among the members of the population. If a society has preferences in favor of a more equal income distribution, $\bar{y} > EDE$ and the differences denotes the social welfare loss (in monetary terms) that arise due to the inequality in the income distribution. In other words: a society is willing to sacrifice $\bar{y} - EDE$ in per capita income, in order to reduce income inequality. By rearranging equation (6) to

$$(6') \qquad EDE_\varepsilon = (1 - A_\varepsilon)\,\bar{y}$$

it follows that

$$\begin{aligned} EDE_\varepsilon - \bar{y} &= (1 - A_\varepsilon)\,\bar{y} - \bar{y} \\ EDE_\varepsilon - \bar{y} &= -A_\varepsilon \bar{y} \\ \bar{y} - EDE_\varepsilon &= A_\varepsilon \bar{y}, \end{aligned}$$

which can be calculated from the Atkinson index and the mean equalized income, both provided in Table 5. By comparing the magnitude of this difference over the several scenarios, we are able to gauge whether the regressive effects of the feed-in tariff are of political relevance or too small to be of importance.

Table 6 illustrates the welfare loss due income inequality. In the benchmark scenario, the welfare loss amounts to 1,245 Euro up to 4,507 Euro, depending on the level of inequality aversion in the society. The table also reveals the additional welfare losses resulting from the regressive effects of the feed-in tariff scheme. Consider for example the 2011 scenario. The levy of 3.53 ct/kWh and the subsidy payments to the owners of photovoltaic panels increase income inequality compared to the benchmark scenario. To remove this additional incurred inequality, the society is willing to sacrifice about 6 Euro to 23 Euros per capita, depending on the level of inequality aversion. In the 2005 scenario with a levy of 4.9 ct/kWh, the additional loss of welfare due to the increase income inequality is 7 Euros to 29 Euros. These additional welfare losses are very moderate. Yet, they come in addition to the reductions in mean disposable income.

Table 6 about here

5. Concluding remarks

There are dissenting views on the design and success of Germany's feed-in tariff scheme to promote renewable electricity generation. Advocators emphasize that it is appealing having led to a substantial rise of the share of renewable fuels in the electricity mix. By contrast, critics argue that the system is costly and inefficient. From a neutral position we can state that the share of renewable fuels in the electricity mix increased under the regime of the feed-in tariff from seven percent in 2000 to about 17 percent in 2011, but also imposed substantial cost to the electricity consumer due to subsidizing renewables.

This paper analyzes the question whether the feed-in tariff scheme increases income inequality in the society and thereby conflicts with the general social goal to reduce disparities in peoples' disposable incomes. We use four well-established inequality indices to assess the redistributive impacts of the feed-in tariff on the income distribution. All our calculations indicate that Germany's feed-in tariff is regressive, but that the redistributive effect is quantitatively small. From this general point of view, there is little doubt concerning the feed-in-tariff's political acceptability and performance. At the same time, we would like to point out that the tariff reduces the disposable incomes of households positioned at the very bottom of the distribution, and this may be viewed as particularly problematic: As electricity has characteristics of a necessity good, it cannot easily be substituted, and related expenditures make up a substantial fraction of low income households' budgets.

One last but very important point has to be stressed. The electricity consumers in Germany fund a subsidy system that redistributes about 13 billion Euro in 2011, with rising tendency. Our analysis shows that the per-capita contribution to this funding is minor from a distributional point of view. This paper does not contribute to the discussion whether the feed-in tariff attains its goals in a cost-efficient way. But we do believe that it must be a foregone conclusion to make the most of the electricity consumer's money in terms of renewable electricity.

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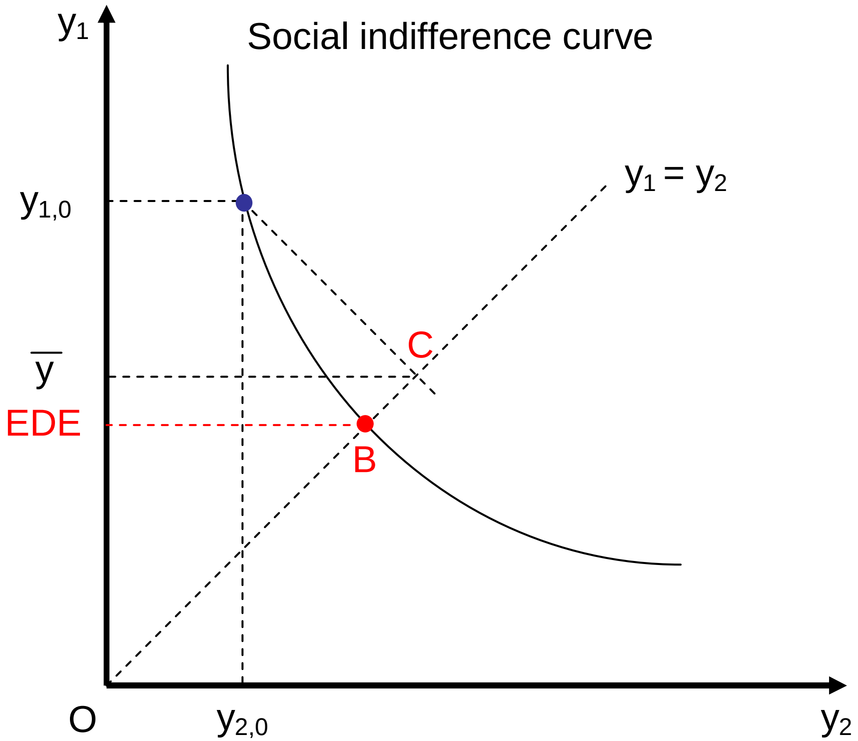
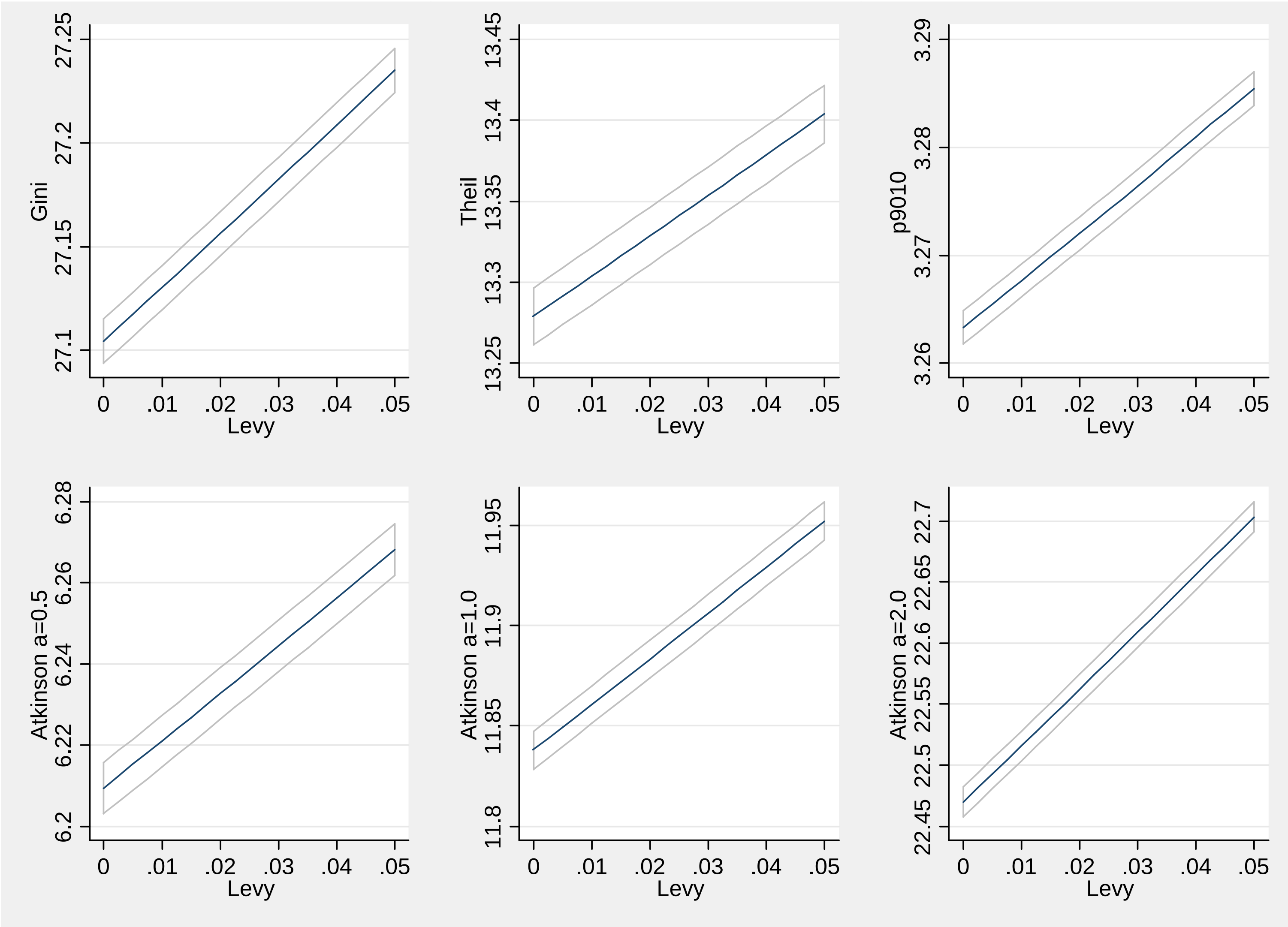


Figure 1. Equally-distributed-equivalent income (EDE)



Note. Database is GRECS. Own calculations. Solid line indicates the mean of bootstrap estimators, grey lines the 95 percent confidence interval.

Figure 2. Distributional effects of levy variation

Table 1. Properties of Inequality Measures

	Percentile ratio	Gini	Theil	Atkinson
Principle of Transfer	No	Weak	Weak and Strong	Weak
Income Scale Independence	Yes	Yes	Yes	Yes
Population Principle	Yes	Yes	Yes	Yes
Decomposability Principle	No	No	Yes	Yes

Source: Cowell (2011).

Table 2. Electricity Expenditures and Levy Cost

Monthly disposable income	Number of obs.	Electricity Consumption 2008		Annual levy 2008	
		Mean in kWh	95% confidence interval	Mean in Euro	95% confidence interval
< 500 €	9	1 915	[± 1 048]	21.06	[± 11.53]
500 € and below 1 000 €	122	2 012	[± 180]	22.13	[± 1.98]
1 000 € and below 1 500 €	236	2 240	[± 165]	24.65	[± 1.82]
1 500 € and below 2000 €	327	2 560	[± 165]	28.16	[± 1.81]
2 000 € and below 2 500 €	363	3 011	[± 167]	33.12	[± 1.84]
2 500 € and below 3 000 €	368	3 607	[± 199]	39.68	[± 2.19]
3 000 € and below 3 500 €	280	3 558	[± 201]	39.14	[± 2.21]
3 500 € and below 4 000 €	188	3 912	[± 260]	43.03	[± 2.86]
4 000 € and below 4 500 €	153	4 102	[± 297]	45.12	[± 3.27]
4 500 € and above	259	4 555	[± 260]	50.10	[± 2.86]

Note. Database is GRECS.

Table 3. Relationship between income and solar installation

Income (in €)	< 500	500 - 999	1 000 - 1 499	1 500 - 1 999	2 000 - 2 499	2 500 - 2 999	3 000 - 3 499	3 500 – 3 999	4 000 - 4 499	4 500 and more
Fraction of owners	3%	2%	6%	10%	12%	14%	11%	11%	11%	21%

Note. Column-wise the monthly disposable income; the second row refers to the percentage of households in the respective income category owing a solar installation. Association between income and solar installation as measured by Cramér's V is 0.1.

Table 4. Levy Calculation

		2011	2012	2013	2014	2015
Renewable Generation	[TWh]	92.3	99.1	104.4	112.1	117.6
Feed-In Payments	[bn. €]	15.6	17.4	18.4	19.7	20.4
Sales Revenues	[bn. €]	5.5	6.0	6.3	6.7	7.1
Financial Gap	[bn. €]	10.1	11.4	12.1	13.0	13.3
Electricity End-Use Consumption	[TWh]	407.8	408.1	404.5	399.0	392.8
Row 4 / Row 5	[ct/kWh]	2.5	2.8	3.0	3.2	3.4
Change to 2011		-	+13.3%	+21.3%	+31.3%	+37.3%
Levy	**[ct/kWh]**	**3.53**	**3.99**	**4.28**	**4.64**	**4.85**

Note: The levy actually charged in 2010 was 2.05 ct/kWh and 3.53 ct/kWh in 2011. The responsible authority expects the levy 2012 to be in the interval 3.4 ct/kWh to 4.4 ct/kWh (UeNB 2010c). Our estimate for 2012 of 3.99 ct/kWh is centred in this interval. For 2013 to 2015 we lack respective reference values.

Table 5. Distributional effects in different scenarios

Scenario		Equalized income	p90/p10	Gini	Theil	Atkinson 0.5	Atkinson 1.0	Atkinson 2
benchmark	BE of mean (variation in %)	20 075	3.259	27.092	13.269	6.204	11.827	22.452
	Conf. Interval	[20 071; 20 078]	[3.258; 3.262]	[27.078;27.101]	[13.264; 13.303]	[6.199; 6.215]	[11.817; 11.841]	[22.435;22.463]
2010 (2.05 ct/kwh)	BE of mean (variation in %)	20 050 (-0.126)	3.272 (0.400)	27.158 (0.243)	13.330 (0.462)	6.233 (0.472)	11.885 (0.484)	22.565 (0.502)
	Conf. Interval	[20 045; 20 053]	[3.271; 3.274]	[27.145; 27.167]	[13.320; 13.366]	[6.229; 6.243]	[11.876; 11.897]	[22.550; 22.580]
2011 (3.53 ct/kwh)	BE of mean (variation in %)	20 016 (-0.296)	3.279 (0.601)	27.196 (0.385)	13.367 (0.741)	6.251 (0.753)	11.918 (0.771)	22.634 (0.811)
	Conf. Interval	[20 011; 20 019]	[3.278; 3.281]	[27.183; 27.206]	[13.358; 13.403]	[6.246; 6.261]	[11.910; 11.931]	[22.619; 22.649]
2012 (low) (3.4 ct/kwh)	BE of mean (variation in %)	20 019 (-0.281)	3.278 (0.583)	27.193 (0.373)	13.364 (0.716)	6.249 (0.729)	11.915 (0.745)	22.628 (0.784)
	Conf. Interval	[20 014; 20 022]	[3.277; 3.281]	[27.180; 27.202]	[13.354; 13.400]	[6.245; 6.259]	[11.907; 11.928]	[22.613; 22.643]
2012 (4.0 ct/kwh)	BE of mean (variation in %)	20 005 (-0.350)	3.281 (0.668)	27.209 (0.431)	13.379 (0.830)	6.256 (0.843)	11.929 (0.862)	22.656 (0.909)
	Conf. Interval	[20 000; 20 008]	[3.280; 3.284]	[27.196; 27.218]	[13.370; 13.415]	[6.252; 6.267]	[11.920; 11.942]	[22.641; 22.672]
2012 (high) (4.4 ct/kwh)	BE of mean (variation in %)	19 996 (-0.395)	3.283 (0.723)	27.219 (0.470)	13.389 (0.905)	6.261 (0.920)	11.938 (0.940)	22.675 (0.994)
	Conf. Interval	[19 991; 19 999]	[3.282; 3.285]	[27.206; 27.228]	[13.380; 13.425]	[6.257; 6.271]	[11.930; 11.951]	[22.660; 22.691]
2013 (4.3 ct/kwh)	BE of mean (variation in %)	19 998 (-0.384)	3.282 (0.709)	27.217 (0.460)	13.386 (0.887)	6.260 (0.900)	11.936 (0.920)	22.670 (0.972)
	Conf. Interval	[19 994; 20 001]	[3.281; 3.285]	[27.204; 27.226]	[13.377; 13.422]	[6.255; 6.270]	[11.927; 11.949]	[22.655; 22.686]
2014 (4.6 ct/kwh)	BE of mean (variation in %)	19 991 (-0.418)	3.284 (0.750)	27.224 (0.489)	13.394 (0.943)	6.263 (0.958)	11.943 (0.979)	22.684 (1.036)
	Conf. Interval	[19 987; 19 994]	[3.283; 3.286]	[27.212; 27.234]	[13.385; 13.430]	[6.259; 6.274]	[11.934; 11.959]	[22.669; 22.700]
2015 (4.9 ct/kwh)	BE of mean (variation in %)	19 985 (-0.453)	3.285 (0.791)	27.232 (0.518)	13.401 (1.000)	6.267 (1.015)	11.950 (1.038)	22.699 (1.099)
	Conf. Interval	[19 980; 19 987]	[3.284; 3.287]	[27.219; 27.242]	[13.392; 13.437]	[6.263; 6.277]	[11.941; 11.963]	[22.683; 22.715]

Note. In parentheses: BE denotes bootstrap estimator. In parentheses: change compared with reference scenario (0) in percent. In brackets: 95% bootstrap confidence interval. Gini, Theil and Atkinson index as well as 90/10 percentile ratio are given in percentage points. Database is GRECS.

Table 6. Welfare loss due to income inequality

	Atkinson 0.5	Atkinson 1.0	Atkinson 2
Benchmark	1 245	2 374	4 507
2010	1 250	2 383	4 524
2011	1 251	2 386	4 530
2012 (low)	1 251	2 385	4 530
2012	1 252	2 386	4 532
2012 (high)	1 252	2 387	4 534
2013	1 252	2 387	4 534
2014	1 252	2 388	4 535
2015	1 254	2 388	4 536

Note. Own calculations. Database is GRECS.

Appendix to:

On the redistributive effects of Germany's feed-in tariff

1. Imputation of electricity consumption

The GRECS data set consists of 6 714 households, from which we observe electricity consumption for 2 594 households, and respectively lack information for 4 120 households. To impute missing consumption data, we estimate the following model with ordinary least squares:

$$(A1) \qquad electr.cons2008 = cons + \alpha_1 m^2 + \sum_{s=2}^{5} \alpha_s * \text{householdsize}_s$$

with m^2 as dwelling size measured in square meters, and with index s denoting household size ($s = 1,...,5+$). Accordingly, we have chosen the single person household ($s = 1$) as base category. The results are depicted in Table A1. Given the parsimonious specification, the coefficient of determination indicates a quite satisfactory explanatory power for cross sectional consumption data. The regression coefficients indicate that electricity consumption and household size are positively correlated, and that each additional square meter living space raises the electricity consumption by 7 kWh a year. Using the predicted values, we impute lacking electricity consumption figures.

Table A1 about here

2. Income imputation

As outlined in the main body of the paper, GRECS provides income only in the form of a categorical variable. In order to impute discrete disposable incomes in GRECS, we follow a procedure involving two stages. First, we estimate household-type specific income distributions for Germany using an auxiliary data set. Second, we transcribe the fitted distribution to the GRECS data set, and use the inverse distribution to impute an income to every household observation in the GRECS data set.

Stage 1: Estimating an income distribution

In order to estimate an income distribution for Germany, we draw auxiliary data from the German Socio-Economic Panel (GSOEP), a panel dataset of the population in Germany. The GSOEP contains information of more than 10 000 households, and more than 20 000 adult persons. Apart from household disposable incomes, the GSOEP provides information on household composition (number of adults and children), occupation, employment, earnings, etc.

We start with estimating a four parameter Generalized Beta distribution of the Second Kind (GBD2K). According to McDonald (1984, p.660), this distribution "provides the best relative fit" to empirical income data (for an assessment based on unit record data see Brachmann et al., 1996).

The GBD2K probability density function is defined as (McDonald, 1984)

$$(A2) \qquad h(y;a,b,p,q)=\frac{ay^{ap-1}}{b^{ap}B(p,q)\left(1+(y/b)^{a}\right)^{p+q}}$$

with $y>0$ denoting a random variable (here: household income), and with a,b,p,q the four parameters to be estimated. Finally, $B(.)$ is the beta function. For particular parameter values, the GBD2K includes some well-known distributions, one of which the log normal distribution (McDonalds, 1984, and Kleiber and Kotz, 2003). Particularly, if $q=1$ (and also $a=1$ respectively $p=1$), we have the special case of a Dagum distribution (Inverse Lomax respectively Fisk (log logistic) distribution); . if $a=1$ (and also $q=1$ respectively $p=1$), we have the Beta distribution of the Second Kind (Inverse Lomax respectively Lomax distribution); and if $p=1$ (and also $q=1$ respectively $a=1$), we have the Singh-Maddala distribution (Fisk respectively Lomax distribution).

Using the STATA ado-package "gb2fit" (Jenkins 2004), we estimate the parameters of GBD2K. By imposing constraints on the distribution parameters, we further test whether the underlying income distribution belongs to a particular special case of GBD2K. It turns out that we cannot reject the hypotheses $p=1$, meaning that the German income distribution is of type Singh-Maddala ($\text{Prob>Chi}^2=0.062$).The Singh-Madalla (SM) distribution has the cumulated density function

$$(A3) \qquad F(y;a,b,q)=1-\left[\frac{1}{1+(y/b)^{a}}\right]^{q}$$

and the probability density function

$$(A4) \qquad f(y;a,b,q) = \left(\frac{aq}{b}\right) \cdot \zeta^{-(q+1)} \cdot \left(\frac{y}{b}\right)^{a-1}$$

for $\zeta = 1 + \left(\frac{y}{b}\right)^{a}$. To allow for the possibility that income distributions are different across household types, we proceed with the SM distribution and allow its distribution parameters (a,b,q) to be depending on household size (see Biewen and Jenkins, 2005). The parameter estimates obtained from GSOEP 2009 including standard errors and significance levels are provided in Table A2. The single person household serves as the reference case and the other entries measure the deviation for the particular parameter estimate from the reference case. For instance, the estimate for the parameter q in case of three member households is $\hat{q}_3 = 1.191 - 0.442 = 0.749$. The corresponding estimates of cumulative density functions of disposable income are depicted in Figure A1.

Table A2 about here

FIgure A1 about here

In order to assess the fit of the estimated household-type specific income distributions, we compare actual GSOEP income observations with the predicted values obtained from the fitted SM distributions. For each household separately, Figure A2 plots the predicted disposable incomes (derived from the inverse SM distribution) against the observed disposable income of every household. The closer the observations are to the 45° line, the smaller is the difference between the predicted and the observed distribution. Visual inspection of Figure A2 reveals a satisfactory fit for all household types, the summary statistics in Table A3 gives additional confirmative evidence. In the columns entitled “GSOEP, Observed”, the Table provides several percentiles, the mean and Gini coefficient of the observed household-type specific income distributions in GSOEP. The adjacent column, “Estimate”, gives the same statistics directly derived from parameter estimates $\left(\hat{a}_s, \hat{b}_s, \hat{q}_s\right)$.

For example, take the entry “2 300” in column “2, GSOEP, observed,” row “P50”. It indicates that median disposable income of two-person households is 2,300 Euro per month. The number “2 334” to the right of (column “2, Estimate”) is the corresponding estimate taking the parameter vector

$\left(\hat{a}_2, \hat{b}_2, \hat{q}_2\right)$. For all household types, observed percentiles are always pretty close to their corresponding estimates. The same holds for mean disposable income and the Gini coefficient.

Figure A1 about here

As a final step, we must ensure that the relative frequency of households, belonging to a particular income class, is compatible between the estimated income distribution and the GRECS data set. Take, for example, the case of single-person households. From equation (2) and the parameter estimates $\left(\hat{a}_1, \hat{b}_1, \hat{q}_1\right)$ for single-person households, it follows that

$$\hat{F}(499) - \hat{F}(0) = 1 - \frac{1}{\left[1 + (500/1149.13)^{3.282}\right]^{1.191}} - 0 \approx 7.22\%$$

of the single-person households belong to the first income class, that

$$\hat{F}(999) - \hat{F}(500) = \left[1 - \frac{1}{\left[1 + (999/1149.13)^{3.282}\right]^{1.191}}\right] - \left[1 - \frac{1}{\left[1 + (500/1149.13)^{3.282}\right]^{1.191}}\right] \approx 36.94\%$$

belong to the second income class, and so on. Whenever we discover a deviation from these relative frequencies in our GRECS data set, we re-weight the observations as to comply with the estimate of the cumulative density function. Information on the imputed income distributions is contained in the column “GRECS, imputed” in Table A3. In general results deviate only marginally from the GSOEP estimates. Some minor differences can result when sample size in a particular cell (defined by income class and household size) is low.

Table A3 about here

Figure A3 about here

Stage 2: Imputing disposable income

The GRECS data provide information on disposable income by means of ten income classes. In order to transform this discrete information into a continuous variable, we make use of the fitted income distributions, described in the subsection above.

The position of a particular household within its respective income class is, however, unknown, while the imputation of an income using the estimated income distributions requires an ordering of the households within each income class. We circumvent this conflict by applying the following five-step bootstrap procedure.

(1) We assign a random number r_i to every household i, where i is of household size $s = 1,...,5+$, and belongs to income class $c \in \{1,...,10\}$, with $N_{s,c} = \sum_i i$.

(2) In the second step, all households of a particular size and within a particular income class are sorted by r_i in ascending order.

(3) In a third step, we assign a probability weight to each household i of type s in c, calculated as

$$(A5) \qquad \pi = \frac{F(s,c) - F(s,c-1)}{N_{s,c}}$$

with $F(s,c)$ denoting the cumulated density at the upper bound of income class c and $F(s,0) = 0$. Accordingly, we equally divide the probability mass pertaining to a certain income class among the households belonging to that class, and every household in this class receives the same probability weight.

(4) Now, the fourth step involves computing cumulative probability weight Π_i (i.e., the percentile position) for every household with respect to its income class and its rank r_i:

$$(A6) \qquad \Pi_i = F(s,c-1) + \sum_{j=1}^{r_i} \pi_j$$

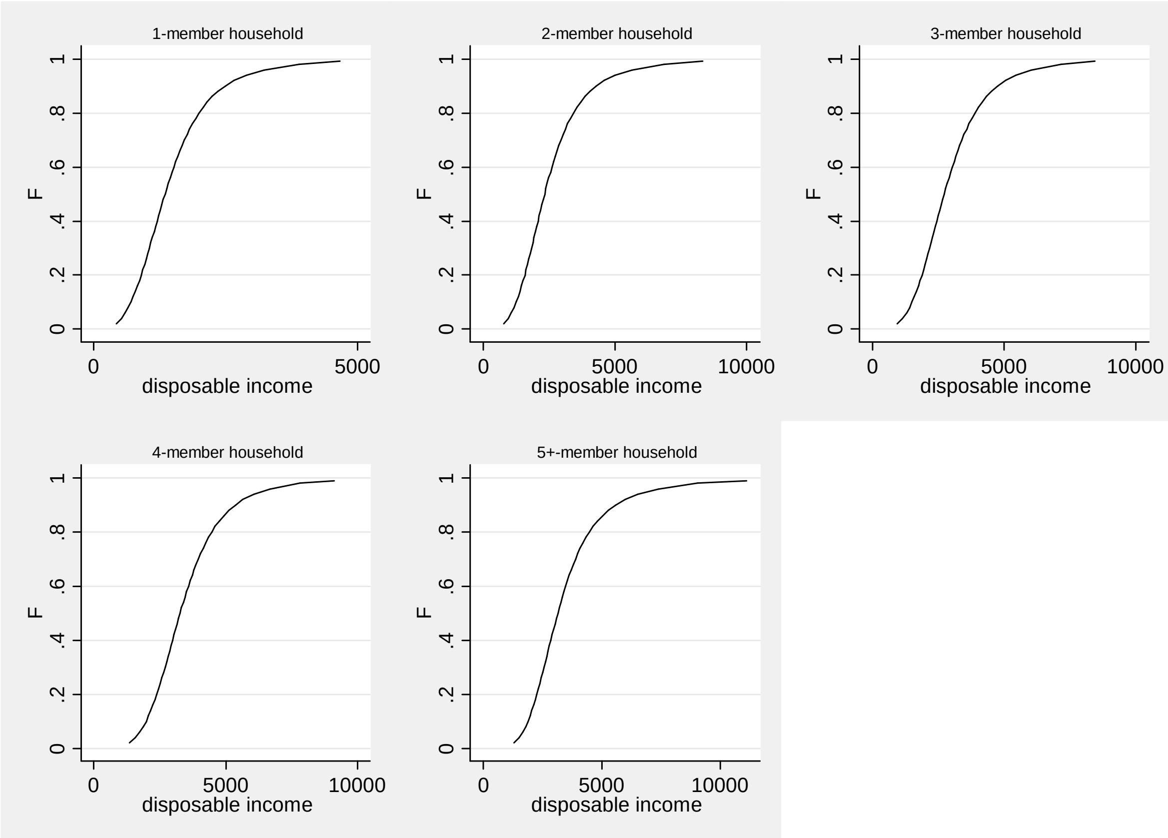
with $F(s,c-1)$ being the cumulative probability till the lower bound of i's income class, and $\sum_{j=1}^{r_i} \pi_j$ adds probability mass with respect to i's rank within its income class.

(5) Finally, the fifth step draws on the estimated distribution parameters with respect to i's household size s along with the cumulative probability Π_i, and uses the inverted SM distribution:

$$(A7) \qquad \hat{y}_i(s) = \hat{b}_s \left[\left(1 - \Pi_i\right)^{-(1/\hat{q}_s)} - 1 \right]^{1/\hat{a}_s}$$

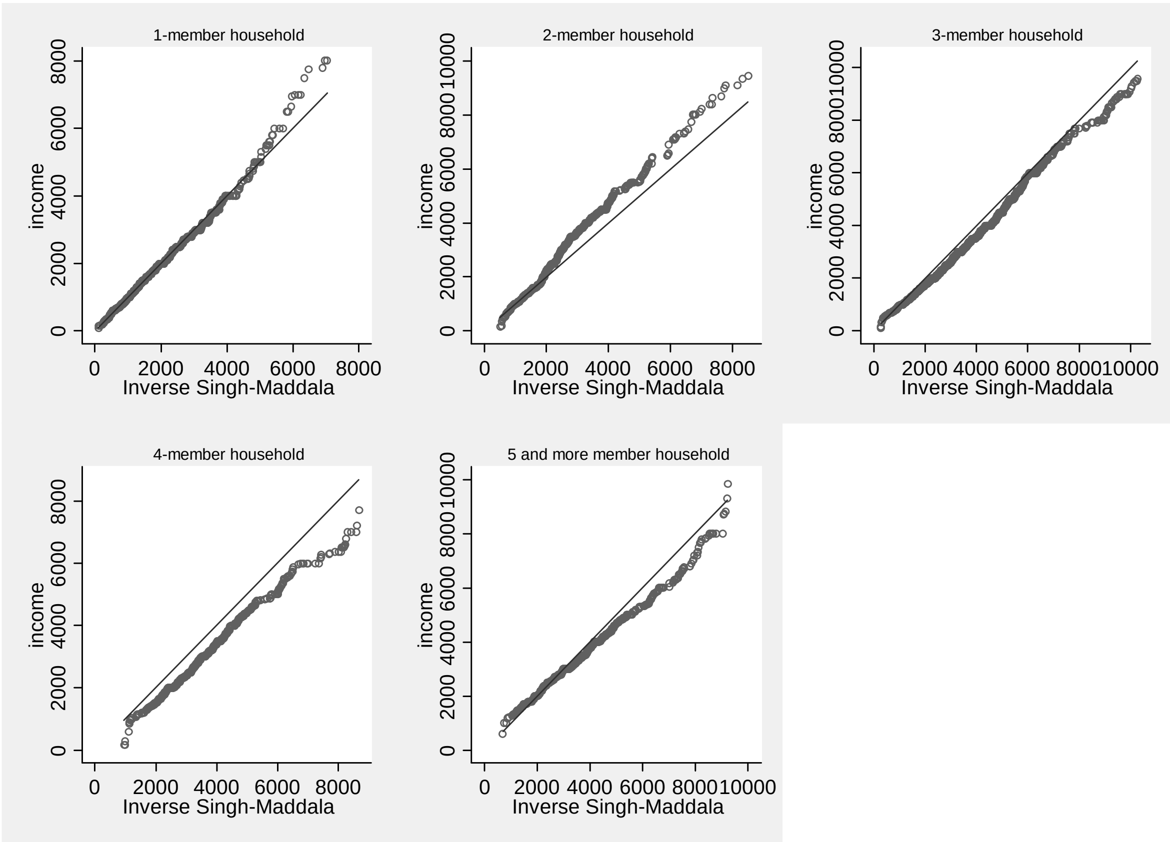
to impute income $\hat{y}_i$ for household *i* at percentile Π_i.

To ensure that the assignment of ranks within an income class does not drive results in the subsequent distribution analysis, we execute this bootstrap procedure 1 000 times, yielding a bootstrap sample of 1 000 distributions of disposable incomes.



Note. Database is GSOEP 2009. Own calculations.

Figure A1. Estimates of cumulative density functions



Note. Database is GSOEP 2009. Own calculations.

Figure A2. Probability plots

Table A1 Regression results for electricity consumption imputation

	Coefficient	Std. Err.	p-value
Dwelling Size	7.02	0.53	0.00
2 Persons	1 091.91	85.92	0.00
3 Persons	1 832.14	103.57	0.00
4 Persons	2 414.19	108.05	0.00
5+ Persons	3 602.42	148.40	0.00
Constant	1 396.65	77.84	0.00
F statistic	311.07		
R square	0.375		

Note. Database is GRECS. Number of observations is 2,954.

Table A2. Singh-Maddala estimates

Parameter		Estimated coefficient	Std. Err.	z	P>|z|
a	HH size 2	0.276	0.143	1.93	0.054
	HH size 3	0.370	0.171	2.16	0.031
	HH size 4	1.066	0.183	5.83	0.000
	HH size 5+	1.254	0.271	4.63	0.000
	Constant	3.282	0.106	30.84	0.000
b	HH size 2	902.287	90.176	10.01	0.000
	HH size 3	1456.315	136.271	10.69	0.000
	HH size 4	1867.864	115.800	16.13	0.000
	HH size 5+	1419.608	130.986	10.84	0.000
	Constant	1449.130	59.333	24.42	0.000
q	HH size 2	-0.172	0.123	-1.4	0.162
	HH size 3	-0.016	0.155	-0.1	0.917
	HH size 4	-0.147	0.135	-1.09	0.277
	HH size 5+	-0.442	0.134	-3.29	0.001
	Constant	1.191	0.103	11.55	0.000

Note. Database is GSOEP 2009 and electricity database. Own calculations. The constant refers to the reference household type, the one-member household.

Table A3. Goodness-of-fit

Household size	1			2			3			4			5+		
Statistic	GSOEP observed	Estimate	GRECS imputed	GSOEP observed	Estimate	GRECS imputed	GSOEP observed	Estimate	GRECS imputed	GSOEP observed	Estimate	GRECS imputed	GSOEP observed	Estimate	GRECS imputed
P5	600	559	560	1 024	1 022	1 025	1 300	1 240	1 240	1 675	1 668	1 674	1 600	1 523	1 527
P10	700	701	702	1 250	1 261	1 263	1 528	1 520	1 521	2 000	1 980	1 981	1 800	1 836	1 842
P20	861	895	897	1 600	1 583	1 584	1 900	1 893	1 894	2 430	2 385	2 387	2 284	2 223	2 230
P30	1 030	1 051	1 052	1 830	1 841	1 842	2 170	2 187	2 188	2 700	2 697	2 699	2 557	2 529	2 529
P40	1 200	1 198	1 199	2 030	2 084	2 084	2 443	2 460	2 463	3 000	2 983	2 986	2 890	2 816	2 817
P50	1 373	1 348	1 349	2 300	2 334	2 335	2 722	2 737	2 738	3 250	3 271	3 274	3 100	3 120	3 116
P60	1 522	1 515	1 516	2 600	2 614	2 615	3 000	3 041	3 042	3 538	3 586	3 589	3 500	3 458	3 459
P70	1 726	1 718	1 719	3 000	2 956	2 957	3 477	3 405	3 405	4 000	3 962	3 967	3 928	3 898	3 895
P80	2 000	1 996	1 998	3 500	3 434	3 435	4 000	3 901	3 906	4 500	4 473	4 478	4 300	4 500	4 500
P90	2 500	2 490	2 492	4 188	4 301	4 303	4 867	4 766	4 769	5 200	5 361	5 380	5 580	5 575	5 647
P95	3 000	3 039	3 042	5 300	5 289	5 298	5 789	5 711	5 727	6 028	6 329	6 373	7 092	6 964	7 005
P99	4 664	4 676	4 734	7 900	8 344	8 399	8 500	8 450	8 472	10 000	9 118	9 375	10 028	11 837	11 883
Mean	1 532	1 524	1 534	2 655	2 657	2 662	3 019	3 023	3 029	3 561	3 553	3 573	3 561	3 598	3 618
Gini	0.285	0.281	0.285	0.277	0.278	0.280	0.252	0.255	0.255	0.227	0.226	0.229	0.252	0.271	0.273

Note. P denotes percentile. Database is GSOEP 2009 and electricity database. Own calculations. All GSOEP estimates for weighted by GSOEP frequency weights and number of household members. Entries in column "Observed" are the actual values as observed in GSOEP 2009. Entries in column " Estimate" is directly derived from the estimates of the Singh-Maddala distribution. Entries in column "GRECS, imputed" are bootstrap estimators from the imputed incomes in GRECS. These estimators are derived using as weight the imputed weights (as explained in the text) times the number of household members (which is relevant for 5+ households only where observations can differ in household size).