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Abstract

The success of energy transition in addressing climate change depends on several factors, including the affordability of new technologies and the influence of peers within communities. However, concerns about affordability raise questions about how economic inequalities shape peer effects and whether they create barriers to equitable adoption. To this end, we explore how inequalities influence peer effects in the uptake of renewable heating sources. We leverage over 260,000 observations from unique and unpublished microdata from the Polish Clean Air Priority Programme – one of the largest retrofit schemes in Europe. Our results show that peer effects accelerate technology uptake, with each additional installation increasing the likelihood of subsequent adoption by 0.014 pp. Peer influence is affected by economic inequality. In more economically homogeneous regions, affluent individuals considerably impact their peers. In areas with higher economic disparities, this influence diminishes. Our findings highlight the role of heating technology type and adopter wealth in shaping peer effect magnitude. Less wealthy adopters of biomass stoves emerge as a significant driver of peer influence, especially in regions with lower income inequality. We advise direct transfers to address technology adoption inequalities, leveraging social capital in low-inequality regions and adopting individualised strategies in high-inequality areas.

Keywords: inequalities, peer effects, energy transition, residential sector, renewable energy

JEL: Q52, Q55, O33

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1. Introduction

Differences in economic status can either facilitate or hinder the transmission of social influence. Individuals often seek to follow the behaviour of those perceived as aspirational figures, driving the spread of certain practices and ideas (Morgenroth et al., 2015). Economic status shapes the effectiveness of such influence. Practical and financial constraints restrict the ability to adopt behaviours from other income groups. Consequently, peer effects and behaviour may vary in societies with different income inequalities. Understanding these dynamics is crucial in technology adoption, where economic constraints and the desire to follow peer behaviours often intersect (George et al., 2012; Gómez et al., 2024). Therefore, it is imperative to address the following question: how do economic inequalities influence the transmission and adoption of behaviours among different income groups?

To answer this question, we investigate the interplay between peer effects, economic inequality, and technological uptake. We use the residential energy transition as an example to study their interdependency, as this process explains how individuals and communities decide to adopt new technologies influenced by the behaviours of their peers (Bollinger and Gillingham, 2012). In our setting, the transmission of peer effects in adopting new heating technologies operates through observable behavioural patterns among neighbours within defined geographic areas. The mechanism of this influence is the visible action of their neighbours, as households observe whether their peers continue using traditional polluting coal stoves or opt for cleaner heating sources. The social visibility of these decisions creates a normative influence that either encourages or discourages change, reinforcing the role of peer effects in technology diffusion. However, the strength of this mechanism is contingent on economic disparities—greater income inequality may weaken the salience of peer influences if financial barriers prevent adoption even in the presence of strong social signals. Our study uses a large sample of 260,000 observations of unpublished microdata from the Clean Air Priority Programme (CAPP) in Poland. CAPP is a large-scale residential building retrofit initiative that offers technological subsidies for using cleaner energy sources. Our data contains information on contract assignment dates, household income, zip code-level addresses, and new heating sources. This rich dataset enables us to precisely assess the impact of economic inequality and financial incentives on households' decisions to adopt new heating technologies. Polish institutional context offers a solid foundation for researching the relationship between income inequality and adopting energy-efficient technologies. Poland has a significant economic disparity across its regions (Bukowski and Novokmet, 2017), providing a diverse landscape for exploring the impact of income inequality on technology adoption. Additionally, Poland's residential energy sector heavily relies on traditional energy sources like coal (Wierzbowski et al., 2017), making the shift to renewable energy technologies, such as heat pumps, particularly impactful.

Our contribution to literature is threefold. First, we fill the research gap on the relation between peer effects and economic inequalities. To this end, we examine how economic disparities impact the effectiveness of peer influences in adopting various technologies. Existing research has indicated that social and economic factors, e.g. education and knowledge, income and wealth or peer effects and social networks, influence technology adoption (Foster and Rosenzweig, 2010; O'Shaughnessy et al., 2023). Due to peer effects, people are more likely to install new technologies if residents, neighbours, or other network members have done so previously (Curtius et al., 2018; Graziano and Gillingham, 2015; Scheller et al., 2022; Sokołowski, 2023; Stewart, 2023). However, the role of economic inequality, particularly affecting the strength of peer effects in technology adoption, has received less attention (DiMaggio & Garip, 2012). Our analysis reveals significant and positive peer influences on technology uptake among the renewable heating adopters supported in the programme. Each additional installation raises the likelihood of a subsequent installation by 0.014 pp. Additionally, income inequality is paired with the decreased impact of peer influence on technology adoption. Specifically, affluent individuals significantly impact their peers' decisions to adopt new technologies in regions with lower income inequalities, with a 0.017 pp increase in adoption likelihood. Conversely, this peer effect diminishes substantially in areas with higher economic disparities.

Second, we contribute with a novel perspective to the just transition discourse by providing empirical evidence on the impacts of economic disparities on technology uptake and the effectiveness of subsidy programmes. Technological subsidies generally yield positive results regarding savings and subjective quality of life, although varied spatial and distributional effects are observed (Lamb et al., 2020; Langer and Lemoine, 2022). Mainly, regressive effects raise controversies, as the preselection of wealthier households for subsidies under climate policy imperative can exacerbate new inequalities, contradicting the "leaving no one behind" principle during the shift towards cleaner energy sources (Heffron and Sokołowski, 2024; Smith, 2017). According to the existing studies, income inequalities among those benefiting from technological subsidies mainly arise from low-income households' financial constraints (Willand et al., 2020; Stewart, 2021). Barriers like the inability to accumulate savings for a down payment or higher operational costs generate further inequalities (Tozer et al., 2023), excluding less affluent households from benefitting from investments. Therefore, early adopters are often wealthier and possess knowledge of administrative procedures, technical capabilities, and access to network resources (Hansen et al., 2022; Stewart, 2023). These disparities extend to the influence of peer effects on technology adoption. We find that the influence of peer effects on the adoption of heating technologies varies by the type of technology and the adopter's wealth level. Less wealthy adopters with biomass stoves are the most influential in regions exhibiting low inequalities. For them, a biomass adopter in a region increases the likelihood of subsequent adoption by 0.016 in areas with lower income inequality and by 0.01 pp in more unequal regions.

Our third contribution is methodological, as we focus on wealth, rather than income, as the primary dimension of economic status in peer effect transmission. We make this distinction to address endogeneity concerns and prove a framework for analysing the heterogeneous effects of peer influence and economic inequalities on technology adoption. While income is commonly used in studies of technology uptake and peer effects (O'Shaughnessy et al., 2023), it might be subject to endogeneity issues in the context of income disparities. In contrast, wealth, particularly fixed assets like real estate, is a more stable and exogenous measure of household economic status (Guren et al., 2021). To this end, we propose using the wealth score from observable, fixed characteristics of the building and its' location as a proxy for wealth, which is less likely to be influenced by short-term shocks or endogenous factors associated with technology adoption decisions (Aladangady, 2017). We validate our wealth score to confirm its robustness as a proxy for economic status. Our results demonstrate that households with higher wealth are more likely to reside in regions with greater income inequality, exhibit preferences for more advanced technologies like heat pumps, and face fewer financial constraints than low-wealth households.

Finally, our research underscores the crucial role of peer networks within socioeconomic groups in promoting sustainable practices and the impact of economic inequalities in dampening these networks' effectiveness. Economic disparities tend to confine individuals within their socioeconomic groups, holding back the exchange of behaviours and limiting the broader adoption of sustainable technologies. Public policy should play a crucial role in mitigating these inequalities. Therefore, our findings underscore the need for policy interventions that reduce economic disparities, amplify the influence of peer effects, and promote a more equitable transition to sustainable technologies.

2. Data and methodology

We use a rich and novel individual-level dataset that covers over 260,000 CAPP participants across nine out of 16 Polish regions between 2018 and 2022.[1] These Polish regions included in our sample represented diversity regarding geographic location, population density, age of housing stock, air quality level, forest cover, and particular environmental policy context, i.e., antismog resolutions.

The data are from the Regional Environmental Protection and Water Management Funds, directly responsible for CAPP implementation. The combined dataset contains information on the date of contract assignment, household income, zip code-level address, building surface, year of construction, new heating source, and amount of subsidy received. Based on the socioeconomic diversity of regions included in the study and the large sample of representatives, we claim that our results can be generalised for the whole programme.

We acknowledge that our data sources have limitations. Some observations are incomplete; for example, they lack income or heating source information.[2] This is because, at the beginning of the program, paper applications were also possible, which required manual entry into the database, and some data were not transferred to the digital system. Moreover, there were various reporting standards within each Regional Environmental Protection and Water Management Fund, so merging and cleaning the overall database to a robust form resulted in removing incomplete observations. Nonetheless, the data used in this study is representative of the whole country. We present the distributions of income, building construction year, and participants' ages in the sample and the whole country at the county level in Appendix B (see Figures B1-B3).

2.1. The Clean Air Priority Programme

The Clean Air Priority Programme is Europe's third-largest retrofit subsidy.[3] The program is aimed to improve air quality and reduce greenhouse gas emissions by replacing heat sources and improving the energy efficiency of single-family residential buildings (National Fund for Environmental Protection and Water Management, 2024). It was established in 2018 as a part of the complex reaction to the air quality crisis in Poland (Frankowski, 2020). The announced long-term horizon and financial support (24 billion EUR until 2029) made it one of the most strategically oriented, publicly-led, multi-institutional retrofit initiatives in Polish public policy (Matczak et al., 2023). Features distinguishing CAPP from other nationwide European retrofit initiatives include focusing on single-family buildings, heating source replacement, and supporting fossil fuel technologies such as gas and, until 2022, even coal (Williams et al., 2023). During the implementation process, CAPP was strengthened by complementary financial schemes, such as loans, tax relief, and a dedicated program for energy-poor households in local authorities with the highest air pollution. Since its introduction in 2018 and ongoing improvements, it has been relatively effective in meeting its primary objective and enhancing air quality in Poland (Sokołowski and Bouzarovski, 2022).

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[1] We thank Client Earth for sharing the data for this research. We note that Client Earth has applied for data from all the regions, but five regions refused to share the data, and two others provided data of a quality that was insufficient to include them in the analysis.

[2] Approximately 215,000 have income information, and about 240,000 have heating source information.

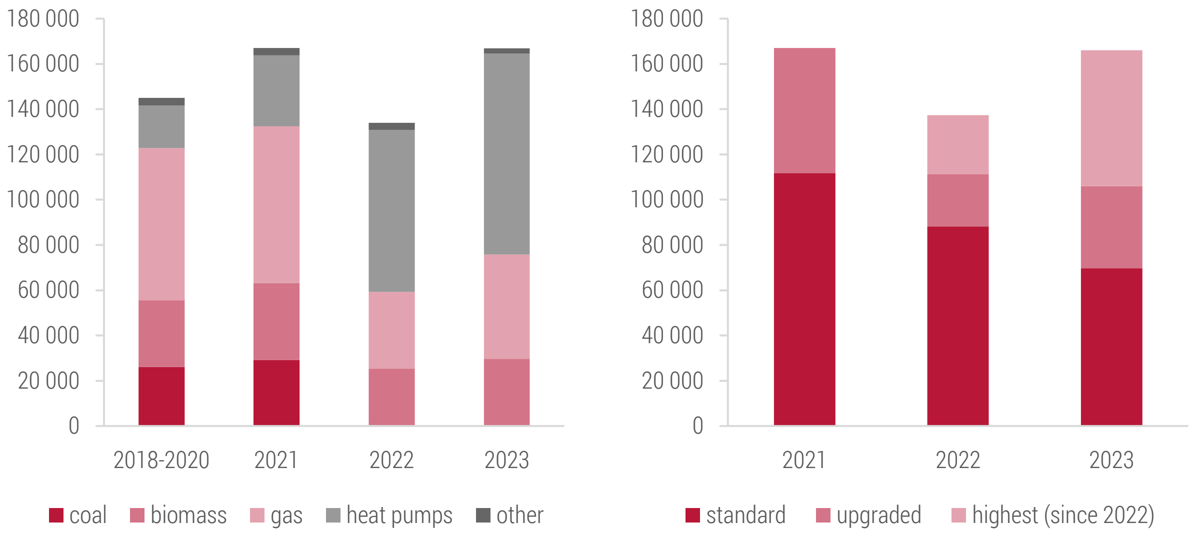
[3] After Federal support for energy-efficient buildings in Germany and the French energy retrofit programme MaPrimeRénov.

CAPP began as a technologically neutral program that supported all heating installations and improved energy efficiency. By the end of 2021, about 2/3 of the submitted applications were concerned with new coal and gas installations (Figure 1, panel a). In this way, the CAPP complemented the state's gasification strategy, favoured by local governments and state-owned energy companies (Frankowski and Herrero, 2021). However, the situation changed in 2022, as the outbreak of war in Ukraine and concerns regarding fossil prices, combined with an emerging market penetration of this technology (Rosenow et al., 2022), boosted the popularity of heat pumps. CAPP amendments also supported this with favourable financing conditions for heat pump uptake. While in the first version, an average household could count on a subsidy of less than EUR 2,000 for an air heat pump, at the end of 2023, it was more than EUR 4,000 for air heat pumps with an increased energy efficiency class, and almost two times more (EUR 7,700) in households with the lowest income. As a result, in 2023, heat pumps and biomass stoves accounted for over 70% of the supported heating sources in the CAPP.

Figure 1. Distribution of technologies and subsidy groups in CAPP (number of applications)

a) Technologies supported in CAPP

b) Subsidy-level group participation in CAPP



Source: own elaboration based on CAPP data.

As the program developed, it became more income-progressive (Figure 2, panel b). The amount of subsidies for individual technologies conditional on the household income per person determines the required level of investment and, consequently, the participation of different income groups in the programme. In the first three years of CAPP, funding intensity depended solely on income level.[4] A significant change occurred in mid-2021 when subsidy levels were reduced to two categories (basic and upgraded) and when the maximum householder income of the beneficiary decreased from 27,650 EUR to 22,026 EUR (Appendix 1). Five months later, at the beginning of

[4] Specifically, there were seven income groups. The higher the income group, the lower the subsidy. Households were assigned to the first income group when the household monthly income per person was below 130 EUR (subsidy up to 90% of eligible investment costs) and to the 7th income group, where the household monthly income per person was above 350 EUR (subsidy up to 30% eligible investment costs).

2022, the highest subsidy level was also introduced.[5] Since 2023, due to inflation and rising prices, subsidies for individual technologies have been indexed (to increase progressivity, especially for heat pumps). A maximum funding threshold of about 30,000 EUR[6] has been set for less affluent households, along with the provision of pre-financing options. However, no analyses have specified the programme's adaptation pathways and knowledge transfer among different income groups.[7]

2.2. Peer effects

We follow Bollinger and Gillingham's (2012) standard approach to measuring peer effects as lagged changes in the installed base of a particular technology.[8] In our setting, the transmission of peer effects in adopting new heating technologies operates through observable behavioural patterns among neighbours within defined geographic areas. The mechanism of this influence is the visible action of their neighbours, as households observe whether their peers continue using traditional polluting coal stoves or opt for cleaner heating sources.

Our analysis focuses on two technologies: heat pumps and biomass stoves. We chose these technologies for three main reasons. First, we consider heat pumps and biomass more sustainable than traditional fossil fuels like coal and natural gas, making these technologies relevant in the energy transition (Lindroos et al., 2021). Second, heat pumps and biomass stoves represent technologies adopted by more affluent and less affluent communities, making them appropriate for studying peer effects across different income brackets (Heiskanen and Matschoss, 2017). Third, the adoption patterns of these technologies make them better candidates for studying peer effects, unlike natural gas, where the decision to adopt may be less influenced by peer behaviour and more by infrastructure constraints (Nielsen et al., 2024).

To investigate the relationships between income level and peer effects, we first calculated deciles of income using the Household Budget Survey (Statistics Poland, 2019) for each year and assigned programme participants to the appropriate decile.[9] Second, we used administrative data from the Polish Ministry of Finance (Chrostek et al., 2020) to assign the Gini coefficient and average income by municipality level. We differentiate between municipalities with "high inequality" (above the 75th percentile of the Gini coefficient) and "low inequality" levels (below the 25th percentile of the Gini coefficient). The structure of municipalities in terms of inequality remains very similar in the

[5] These three groups vary not only in the percentage of subsidy regarding particular installations (higher in terms of upgraded and the highest group) but also in the total amount of the possible subsidy. At the end of 2023, households in the standard group can receive up to 14,500 EUR in the upgraded group, 21,800 EUR, and 29,700 EUR in the highest group.

[6] We assume a conversion rate between EUR and PLN of 4.54, an average for 2023, published by the Polish Ministry of Finance.

[7] Appendix B provides a detailed analysis of program participants' incomes and timing of participation.

[8] Following Bollinger and Gillingham (2012), we translate our results into a probability of a subsequent adoption. We use the average number of buildings in a given area as the denominator and add one additional adoption as the numerator. This creates a ratio representing the relative intensity of adoption in that area. We then multiply this ratio by the corresponding regression coefficients. The result indicates how many percentage points the probability of subsequent installations increases due to this additional adoption.

[9] We calculate equivalent income according to OECD methodology. Self-declared income of participants is presented in Figure B4 in Appendix B.

nine regions included in the study and the seven regions excluded due to data unavailability.[10] The structure of installed heating sources by region is comparable (see Figure B5 in Appendix B).

To measure peer effects, we calculated and the share of households living in a given area who decided to install a new heating source. Therefore, we divided the area of Poland into one-kilometre squares using the Population and Housing Census 2021 layer, geolocated each program participant according to the precise location and matched them to corresponding squares. Then, we assigned the number of buildings within each square using Census data. Finally, we calculated each square's cumulative number of program participants by quarters of the year between 2018 and 2022.[11] The final dataset consists of 14,525 observation units (squares) with 20 observations of time in each square.

Next, we made two assumptions to calculate the share of households changing the heating source. First, we assumed each program participant belongs to a separate household. Second, each building represented different households.[12] Therefore, our baseline peer effect measure is the share of people living in buildings that changed the heating source (we will refer to them as adopters). Moreover, we keep the number of buildings within a square constant to ensure that variation in measurement comes only from the increased number of adopters:

$$SH_{iq} = \frac{Adopters_{iq}}{BUILD_i} \quad (1)$$

where, i is square ID, and q is the quarter of the year.

Three main issues arise when identifying causal peer effects: endogenous group formation, correlated unobservable variables, and simultaneity (Manski, 1993). In our case, the following must happen to make the endogenous group formation an issue. First, after the programme details announcement, individuals must have decided to build their houses next to each other. Second, they must have participated in the program to receive a subsidy and switch heating source. However, considering the total costs of building (or buying) a house and other non-financial aspects (neighbourhood quality, proximity of schools and other public services, etc.), it is unlikely that program participation is biased by endogenous group formation. This is especially unlikely since we excluded gas stoves from the support, where such practice (due to top-down, publicly-led infrastructural investments) could occur more often. Instead, we focus on distributed generation heating technologies. Therefore, we claim that programme participation is exogenous to group formation. In our case, group formation is based on the geographical location of the buildings and is, therefore, exogenous.

Next, we deal with correlated unobservable variables using a first-difference estimator (so unobserved square-related constant in time characteristics cancel out; (Wooldridge, 2010). Finally, we address the issue of simultaneity by letting the agents' decisions depend on past decisions made by their peers. Namely, we estimate the following model:

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[10] The structure in our sample contains 26% low-inequality and 25% high-inequality municipalities; the structure in the minority of regions not included in the sample is 24% low-inequality and 25% high-inequality municipalities.

[11] Applications submitted to the programme must be processed within 30 days, but this period may be extended by 30 more days in certain cases. Considering the additional time needed to prepare applications, the quarter of the year is a natural time span to observe the emergence of peer effects.

[12] CAPP does not support multi-family buildings with three apartments or more.

$$SH_{i,q} = \beta SH_{i,q-1} + X_{i,q} + \mu_q + \eta_i + \upsilon_{iq} \quad (2)$$

where, $X_{i,q}$ is the number of participants by income group in the square i in quarter q, μ_q is quarter fixed effects, η_i is constant for square i and υ_{iq} is the i.i.d. error term. Coefficient of interest β identifies the relationship between past and current installations (peer effect). Consistent estimates with static panel data models require strict exogeneity assumption (no correlation between independent variable and past error terms $\mathbb{E}[SH_{i,q}\, \upsilon_{it}\,] = 0\; \forall q \neq t$). This assumption cannot be met when lags are included as regressors. Therefore, we use a panel data GMM estimator approach with forward-orthogonal deviations transformation (Arellano & Bover, 1995). Consequently, we estimate the first differenced model of the form:

$$\Delta\, SH_{i,q} = \beta \Delta SH_{i,q-1} + \Delta X_{i,q} + \mu_q + \Delta \upsilon_{iq} \quad (3)$$

To meet the assumption of serially uncorrelated shocks $\left(\mathbb{E}[\upsilon_{iq}\upsilon_{it}\,] = 0\; \forall q \neq t\,\right)$ and error components $\left(\mathbb{E}[\eta_i] = \mathbb{E}\left[\upsilon_{iq}\right] = \mathbb{E}[\eta_i \upsilon_{iq}] = 0\right)$ we utilise past realisations of $\Delta\, SH_{i,q}$ as instruments to correct a bias arising from $\mathbb{E}\left[\Delta SH_{i,q-1}\Delta \upsilon_{iq}\right] \neq 0$. In particular, we use second and higher-order lags as instruments, as they meet both relevance and orthogonality conditions. We follow the procedure provided by Kiviet (2020) to choose the appropriate specification of the model. We use Windmeijer's (2005) correction following a two-step procedure to obtain robust standard errors.[13]

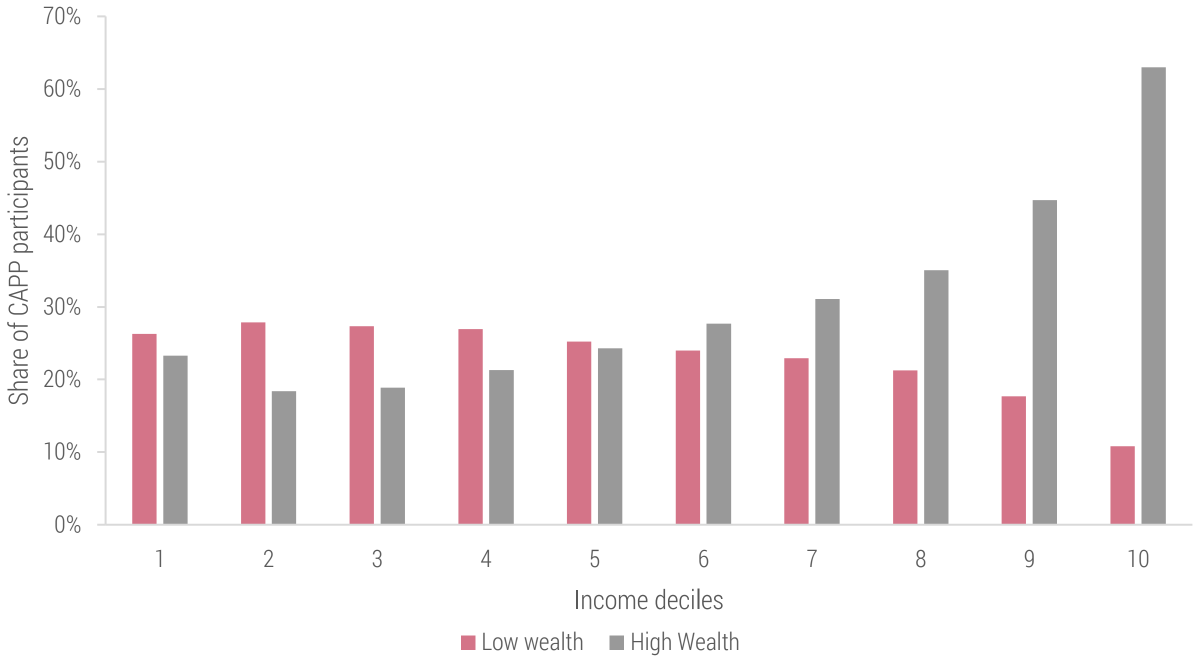
2.3. Wealth score

We focus on wealth rather than income as a primary dimension of analysis to address endogeneity concerns and provide a more robust basis for examining heterogeneous effects of peer influence and inequalities. Income is more likely subject to endogeneity concerns in our context due to unobserved factors, such as individual characteristics, regional economic conditions, or policy interventions. In contrast, wealth should offer a more exogenous and stable proxy for household economic status. We use the value of a house as a proxy for wealth since fixed assets constitute about 95% of households' assets in Poland (National Bank of Poland, 2015). We derive the wealth score from observed, fixed characteristics such as the age of the building, the typology of the municipality, and the building's surface area (European Commission and Organisation for Economic Co-operation and Development, 2015).[14] These variables are unlikely to be influenced by short-term shocks or endogenous factors related to the outcome variables in our analysis, thus reducing concerns about reverse causality. Our methodological framework leverages the relative exogeneity of the wealth score to provide insights into the role of economic disparities in shaping outcomes.

[13] We estimate the models with the Stata *xtdpdgmm* package by Kripfganz (2019).

[14] We obtain reasonable correlation between wealth score and households self-declared income (Table B1 in Appendix B)

Figure 2. The allocation of individuals to wealth groups by income deciles.



Source: own elaboration based on CAPP data.

We conducted regression analyses to validate our wealth score using a multinomial probit model, treating households with moderate wealth as the reference category.[15] The results confirmed the robustness of our scoring method. First, we found that households classified as high wealth were more likely to be located in regions with high Gini coefficients, reflecting inequality patterns in Poland (Tammaru et al., 2020). Second, households with high wealth demonstrated a lower likelihood of installing biomass stoves than heat pumps, suggesting preferences aligned with higher financial flexibility and access to advanced technologies. Third, the wealth score corresponded closely with income distribution: low-wealth households were likelier to fall below the fifth income decile, whereas high-wealth households were likelier to exceed this threshold (Figure 2). This correlation highlights a key characteristic of Polish households: wealth disparities strongly mirror income inequalities. Given Poland's relatively recent transition to a free-market economy, much of the observed wealth inequality stems directly from income disparities (Bukowski and Novokmet, 2017).

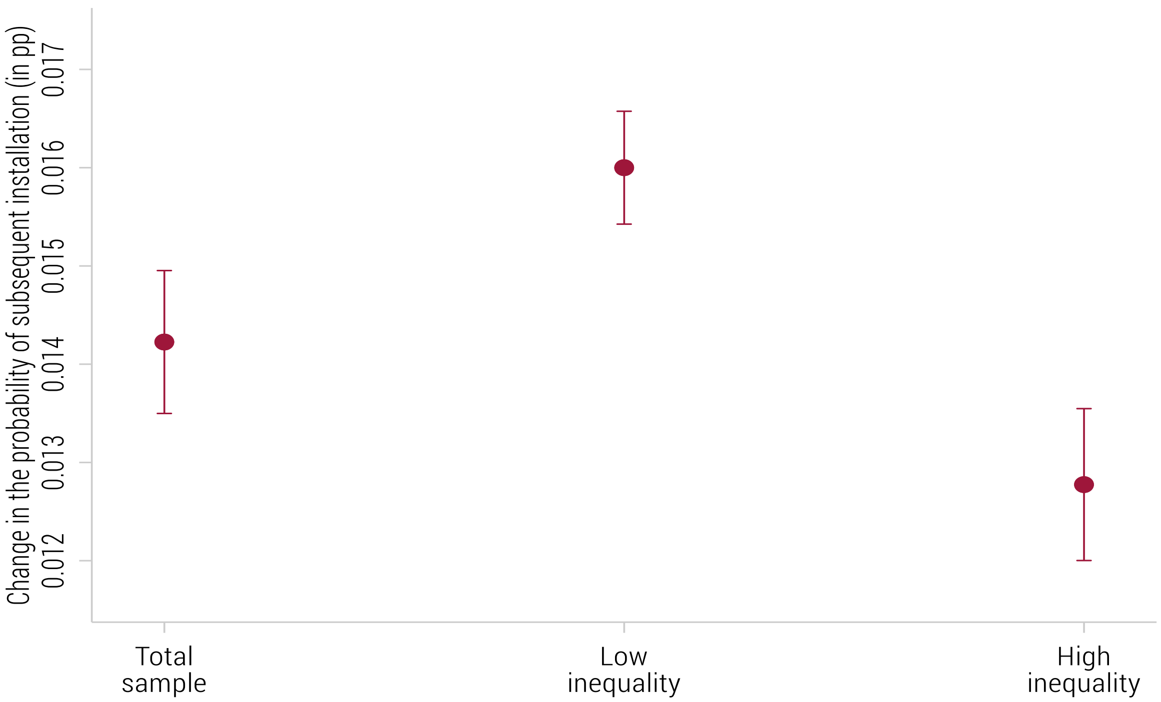
[15] Detailed results and the model description are in Appendix B, Figure B1.

3. Results

This section studies the causal relationships between income level and peer effects. To this end, we start by regressing peer effects on the total sample of participants (equation 3). A few key findings emerge.

First, we find strong and positive peer effects on technology adoption among program participants. According to our estimates, adding one installation increases the probability of the subsequent installation by 0.014 pp (Figure 3 and Table B2 column 1). When broken down by regional inequality levels, the magnitude of peer effects is slightly higher in regions with lower inequalities, where one additional installation increases the probability of subsequent adoption by 0.016 percentage points.

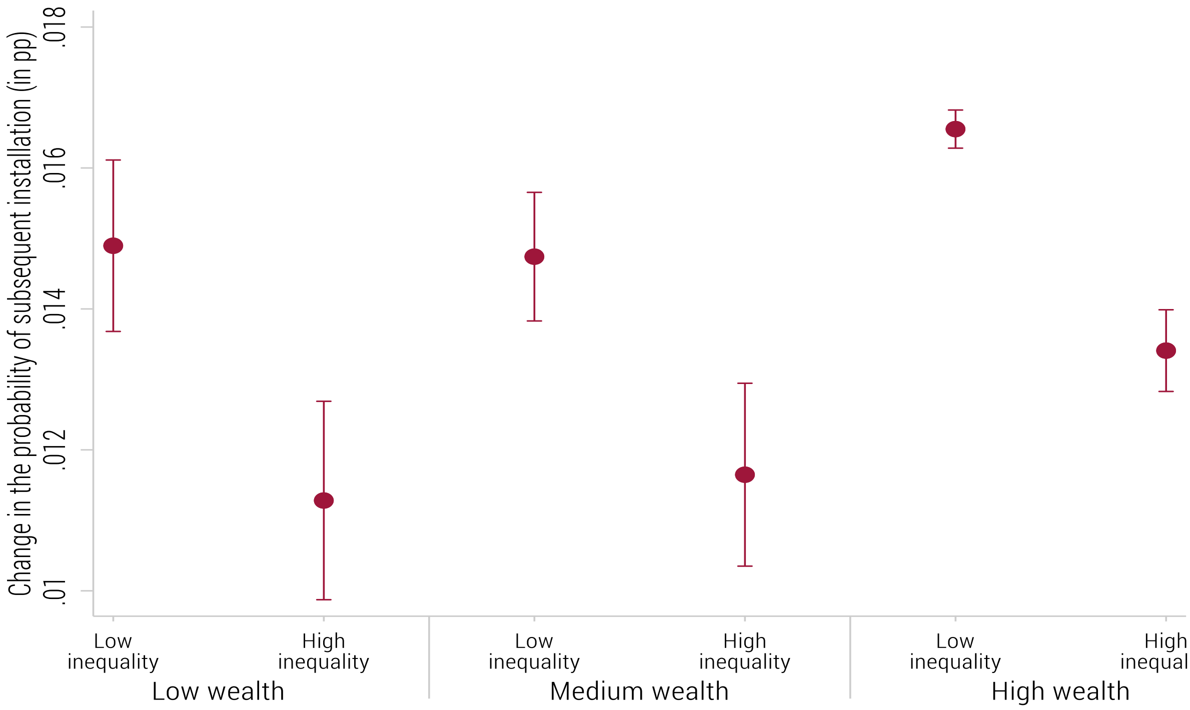
Figure 3. Peer effects in the total sample and areas with low and high inequalities (pp change)



Source: own elaboration based on CAPP data. The figure presents the estimated probability of the following installation based on regressions in column 1 of Table B2 in the Appendix.

Second, peer effects are most pronounced among affluent individuals. Still, the differences in wealth groups are relatively small (Table B2 columns 2-4), suggesting that peer influence's impact is consistent across different economic levels. Additionally, the strength of peer effects between individuals from the highest and lowest wealth strata decreases in regions with higher inequalities (Figure 4 and Panels B-C of Table B2, columns 2 and 4). Namely, the probability that individuals with high wealth follow each other in regions with lower inequalities increases by 0.017, while in the more unequal regions by 0.013 (Figure 4 Panel B-C of Table 1, column 4). Similarly, the probability that individuals with low wealth follow each other in regions with low inequalities is 0.015 and in regions with high inequalities, 0.011. We interpret this trend as a reflection of the more fragmented social networks in economically unequal societies, where the disparity might impede the flow of information and reduce the cohesive influence of peer groups (Rockenbauch & Sakdapolrak, 2017).

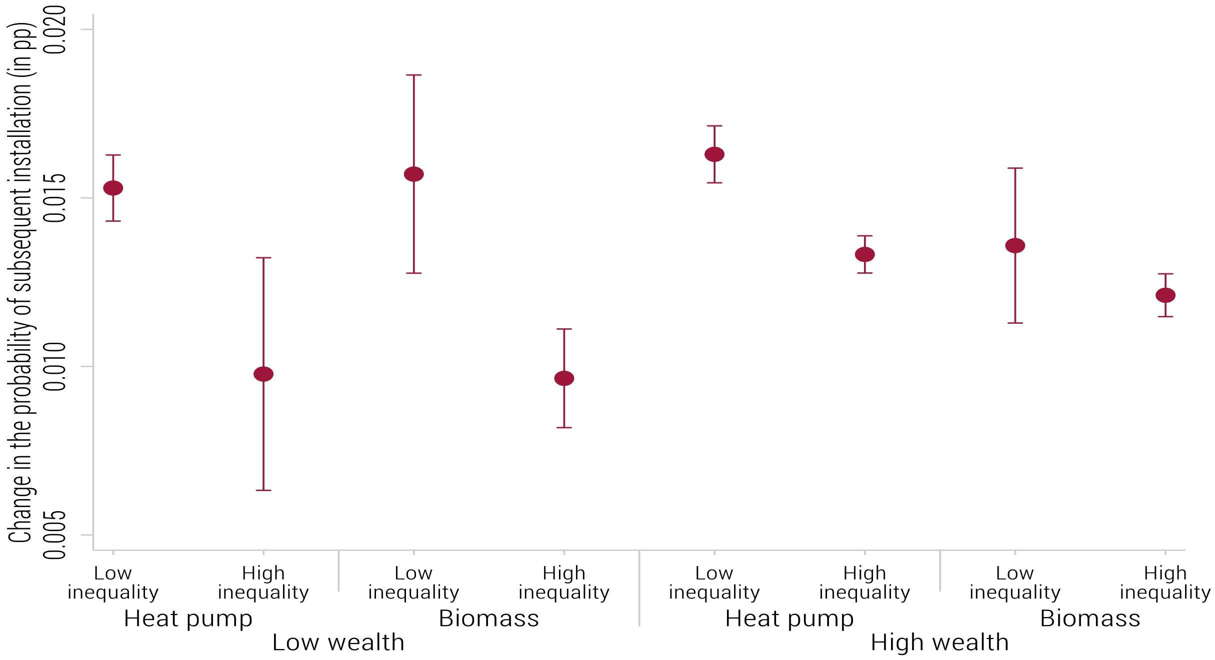
Figure 4. Peer effects in the total sample and areas with low and high inequalities (pp change)



Source: own elaboration based on CAPP data. The figure presents the estimated probability of the following installation based on regressions in column 2-4 of Table B2 in the Appendix.

Third, the magnitude of peer effects depends significantly on the choice of the heating source and the wealth status of adopters (Figure 5). We observe the strongest effects among less affluent individuals in regions characterised by low-income inequality. Biomass stove adopters showed the largest peer effects among individuals with low wealth, particularly in regions with low inequality (Table B3, Panel B). Specifically, for every additional biomass stove adopted by an individual with low wealth in such areas, the probability of a similar person adopting a new heating source increased by 0.016 pp. It represents a substantial increase compared to the 0.01 pp effect observed in high-inequality areas. In contrast, wealthy individuals adopting heat pumps exhibited consistent but lower peer effects, which did not vary significantly across regions with different levels of inequality (Table B3, Panels B and C, column 2). We see it as an indicator that amplifying peer effects in low-inequality areas primarily benefits low-income adopters (Baynes et al., 2015).

Figure 5. Peer effects across wealth groups, heating sources and areas with low and high inequalities (pp change)



Source: own elaboration based on CAPP data. The figure presents the estimated probability of the following installation based on regressions in Table B3 in the Appendix.

3.1. Robustness

We conduct a series of tests to verify the stability and reliability of our model's specification under different time lags. Initially, we have utilised quarterly data. However, to ensure that our results are not overly sensitive to this particular choice, we expand our examination by incorporating an alternative monthly time lag. It is important to note that the magnitude of the coefficients in autoregressive models is strongly related to the proximity of the lag to the original event. Closer lags represent more recent events that strongly influence the current state. In contrast, longer lags can accumulate more noise over time, making it harder for the model to distinguish between meaningful signals from random fluctuations. Therefore, we expect monthly lags to have higher coefficients than quarterly lags.

The significance of the results generally persists. For instance, peer effects for all individuals in the total sample are robust across both time lags (Panel A of Tables B2 and B7, column 1 in Appendix B). Importantly, the difference between the magnitude of the effects between low and high inequality areas persists if favour for the former ones (Panels B and C of Table B6 in Appendix B).

When using a monthly lag in different income groups across regions with varying inequality levels, peer effects remain significant across all individuals, demonstrating robust social influence even on a short-term basis (Table B6 in Appendix B). High-income groups across different inequality levels consistently exhibit strong peer effects, indicating, e.g. that their financial flexibility might allow for quicker adjustments to peer adoption behaviours (Panels A and B of Table B6, column 4 in Appendix B).

The month lag in the context of different heating sources and regional inequality levels shows that the results remain robust across different specifications. For low-income groups using heat pumps, the one-month lag reveals a more pronounced effect in specific contexts, such as high inequality areas, where peer effects remain significant in the shorter term (Table B7, column 1 in Appendix B). The results for high-income groups using heat pumps and biomass remain robust (Table B7, columns 2 and 4 in Appendix B).

Overall, the alternative lags confirm the positive peer effects observed in the quarterly data and show enhanced significance. However, choosing the appropriate lag is essential to estimating the proper size of the peer effect. Therefore, we use quarterly lags as baseline specifications based on the programme's legal set-up.

Subsequently, we divide individuals into low-, medium, and high-income groups according to self-declared income instead of wealth score (Tables B4 and B5 in Appendix B). The results are consistent with our preferred specification and confirm the main findings.

4. Discussion and conclusions

In this paper, we investigated the adoption dynamics of new technologies based on peer effects. To study this relation, we used the example of the Clean Air Priority Programme, Europe's third-largest retrofit subsidy initiative, aimed at improving air quality and reducing greenhouse gas emissions in Poland. We found significant peer effects within the same wealth groups, especially in regions with low economic disparities. These findings suggest that economic inequality is an important factor in the effectiveness of peer networks in promoting technology adoption, which has solid scientific and practical implications.

Our results suggest that progressive support mechanisms within energy transition programs, such as the Clean Air Priority Program (CAPP), could significantly reduce barriers to adoption. Subsidies and financial incentives tailored to income levels, such as pre-financing schemes, can make sustainable technologies accessible to a broader demographic, fostering a more equitable energy transition (Hanke et al., 2023). From a policy perspective, enhancing the progressivity of support mechanisms facilitates adoption among lower-income groups and strengthens peer network effects across diverse socioeconomic strata (Tozer et al., 2020). This dual benefit ensures a more balanced diffusion of technologies, potentially accelerating the transition to sustainable energy sources. Furthermore, our study contributes to the discourse on evidence-based policymaking by shedding light on the intersection of socioeconomic inequality and environmental policy effectiveness (Vona, 2023), and it provides actionable insights for designing retrofit programs that promote social equity and environmental resilience. A more effective strategy in areas with low economic inequality would involve leveraging social capital networks to support the energy transition (e.g., neighbourhood organisations, parishes), as technology adoption tends to occur more rapidly in such contexts. In contrast, in areas with higher economic inequalities, a more effective approach to promoting the adoption of renewable energy sources would likely involve individualised, targeted outreach to individuals capable of replacing their heating sources.

Our study contributes to creating evidence-based policies focused on the role of socioeconomic factors in environmental policy and technology adoption. By highlighting the role of economic inequalities and the potential of peer effects as catalysts for sustainable change, we underline the need for policy interventions that promote technological innovation and foster social inclusivity and equity. At the European level, instruments like the Social Climate Fund, later transposed to the national level through technological subsidies and direct support, can play a pivotal role. Directing the fund toward income support for vulnerable households—rather than exclusively toward technological subsidies—can mitigate the risk of benefits disproportionately favouring wealthier groups. By aligning financial support with the needs of low-income populations, policymakers can reduce inequities and enhance the overall impact of energy transition initiatives (European Parliament and the Council of the European Union, 2024).

Our findings suggest that centralising data collection and oversight could enhance the implementation and monitoring of programmes like CAPP. At the beginning of 2025, fragmented administration across multiple institutions risks data inconsistencies and procedural inefficiencies. A single coordinating entity could streamline processes, ensure data quality, and maintain public trust. Broader discussions on centralisation and coordination within environmental funding systems are warranted to optimise program effectiveness. However, the CAPP programme was stopped at the end of 2024 and is set to be restarted in 2025 with revised rules. Preliminary reports and press releases suggest that the new structure might shift from progressive to regressive support mechanisms, favouring wealthier participants and reducing access to economically vulnerable groups (Murator, 2025). This reversal undermines the programme's earlier systematic efforts to foster equity and inclusivity in the energy transition and risks exacerbating existing inequalities. Discontinuing such a crucial program or maintaining it without its progressive features creates significant disruption, potentially stalling progress in adoption rates, weakening peer network effects, and slowing the diffusion of sustainable technologies. Our results strongly support prioritising an equitable programme design and ensuring any changes do not marginalise participants with low incomes.

We acknowledge our study limitations. We recognise that the scope of our analysis is confined to the CAPP and its participants, which may not fully reflect the diversity of contexts influencing technology adoption in other settings. For instance, smaller financial schemes or regulatory approaches may yield different dynamics. Furthermore, while we examined peer effects through observed patterns of technology uptake, this approach does not capture the full complexity of social interactions and individual motivations that influence decisions. Future research should integrate qualitative social science methods, including interviews with program stakeholders, to provide richer insights into these dynamics. Finally, while using a wealth score mitigates concerns about income-associated endogeneity, it does not allow for causal inference regarding the drivers of heterogeneity. Instead, we aimed to identify differential patterns across wealth categories. Future research could address this limitation by employing methods that leverage exogenous variation in economic factors to establish causal relationships.

References

Aladangady, A., 2017. Housing Wealth and Consumption: Evidence from Geographically-Linked Microdata. American Economic Review 107, 3415–3446. https://doi.org/10.1257/aer.20150491

Arellano, M., Bover, O., 1995. Another look at the instrumental variable estimation of error-components models. Journal of Econometrics 68, 29–51. https://doi.org/10.1016/0304-4076(94)01642-D

Baynes, J., Herbohn, J., Smith, C., Fisher, R., Bray, D., 2015. Key factors which influence the success of community forestry in developing countries. Global Environmental Change 35, 226–238. https://doi.org/10.1016/j.gloenvcha.2015.09.011

Bollinger, B., Gillingham, K., 2012. Peer Effects in the Diffusion of Solar Photovoltaic Panels. Marketing Science 31, 900–912. https://doi.org/10.1287/mksc.1120.0727

Bukowski, P., Novokmet, F., 2017. Top Incomes during Wars, Communism and Capitalism: Poland 110.

Chrostek, P., Klejdysz, J., Skawiński, M., 2020. Wybrane aspekty systemu podatkowoskładkowego na podstawie danych administracyjnych 2017 (No. No 4-2020), MF Opracowania i Analizy.

Curtius, H.C., Hille, S.L., Berger, C., Hahnel, U.J.J., Wüstenhagen, R., 2018. Shotgun or snowball approach? Accelerating the diffusion of rooftop solar photovoltaics through peer effects and social norms. Energy Policy 118, 596–602. https://doi.org/10.1016/j.enpol.2018.04.005

DiMaggio, P., Garip, F., 2012. Network Effects and Social Inequality. Annual Review of Sociology 38, 93–118. https://doi.org/10.1146/annurev.soc.012809.102545

European Commission, Organisation for Economic Co-operation and Development (Eds.), 2015. Eurostat-OECD compilation guide on land estimation: 2015 edition, 2015 edition. ed. Publications Office, Luxembourg. https://doi.org/10.2785/59692

European Parliament and the Council of the European Union, 2024. Directive 2003/87/EC of the European Parliament and of the Council of 13 October 2003 establishing a system for greenhouse gas emission allowance trading within the Union and amending Council Directive 96/61/EC.

Foster, A.D., Rosenzweig, M.R., 2010. Microeconomics of Technology Adoption. Annual Review of Economics 2, 395–424. https://doi.org/10.1146/annurev.economics.102308.124433

Frankowski, J., 2020. Attention: smog alert! Citizen engagement for clean air and its consequences for fuel poverty in Poland. Energy and Buildings 207, 109525. https://doi.org/10.1016/j.enbuild.2019.109525

Frankowski, J., Herrero, S.T., 2021. "What is in it for me?" A people-centered account of household energy transition co-benefits in Poland. Energy Research & Social Science 71, 101787. https://doi.org/10.1016/j.erss.2020.101787

George, G., McGahan, A.M., Prabhu, J., 2012. Innovation for Inclusive Growth: Towards a Theoretical Framework and a Research Agenda. Journal of Management Studies 49, 661–683. https://doi.org/10.1111/j.1467-6486.2012.01048.x

Graziano, M., Gillingham, K., 2015. Spatial patterns of solar photovoltaic system adoption: The influence of neighbors and the built environmentz. Journal of Economic Geography 15, 815–839. https://doi.org/10.1093/jeg/lbu036

Guren, A.M., McKay, A., Nakamura, E., Steinsson, J., 2021. Housing Wealth Effects: The Long View. The Review of Economic Studies 88, 669–707. https://doi.org/10.1093/restud/rdaa018

Hanke, F., Grossmann, K., Sandmann, L., 2023. Excluded despite their support - The perspectives of energy-poor households on their participation in the German energy transition narrative. Energy Research & Social Science 104, 103259. https://doi.org/10.1016/j.erss.2023.103259

Hansen, A.R., Jacobsen, M.H., Gram-Hanssen, K., 2022. Characterizing the Danish energy prosumer: Who buys solar PV systems and why do they buy them? Ecological Economics 193, 107333. https://doi.org/10.1016/j.ecolecon.2021.107333

Heffron, R.J., Sokołowski, M.M., 2024. Resolving energy policy failure: Introducing energy justice as the solution to achieve a just transition. Energy Policy 187, 114042. https://doi.org/10.1016/j.enpol.2024.114042

Heiskanen, E., Matschoss, K., 2017. Understanding the uneven diffusion of building-scale renewable energy systems: A review of household, local and country level factors in diverse European countries. Renewable and Sustainable Energy Reviews 75, 580–591. https://doi.org/10.1016/j.rser.2016.11.027

Kiviet, J.F., 2020. Microeconometric dynamic panel data methods: Model specification and selection issues. Econometrics and Statistics 13, 16–45. https://doi.org/10.1016/j.ecosta.2019.08.003

Kripfganz, S., 2019. Generalized method of moments estimation of linear dynamic panel data models. Proceedings of the 2019 London Stata Conference.

Lamb, W.F., Antal, M., Bohnenberger, K., Brand-Correa, L.I., Müller-Hansen, F., Jakob, M., Minx, J.C., Raiser, K., Williams, L., Sovacool, B.K., 2020. What are the social outcomes of climate policies? A systematic map and review of the ex-post literature. Environmental Research Letters 15, 113006. https://doi.org/10.1088/1748-9326/abc11f

Lindroos, T.J., Mäki, E., Koponen, K., Hannula, I., Kiviluoma, J., Raitila, J., 2021. Replacing fossil fuels with bioenergy in district heating – Comparison of technology options. Energy 231, 120799. https://doi.org/10.1016/j.energy.2021.120799

Manski, C.F., 1993. Identification of Endogenous Social Effects: The Reflection Problem. The Review of Economic Studies 60, 531–542. https://doi.org/10.2307/2298123

Matczak, P., Frankowski, J., Putkowska-Smoter, R., Wróblewski, M., Łoś, I., 2023. Tackling (Not Only) Air Pollution: Cross-sectional Tensions behind State-led Energy Retrofit Program in Poland. Society & Natural Resources 1–22. https://doi.org/10.1080/08941920.2023.2212286

Morgenroth, T., Ryan, M.K., Peters, K., 2015. The Motivational Theory of Role Modeling: How Role Models Influence Role Aspirants' Goals. Review of General Psychology 19, 465–483. https://doi.org/10.1037/gpr0000059

Murator, 2025. Czyste powietrze 2025 - od kiedy? Jakie zmiany w nowej wersji programu? [WWW Document]. URL https://muratordom.pl/aktualnosci/czyste-powietrze-2025-od-kiedy-program-jakie-zmiany-w-udzielaniu-dotacji-aa-eYD1-ebor-r9eZ.html (accessed 1.12.25).

National Bank of Poland, K., 2015. Zasobność gospodarstw domowych w Polsce.

National Fund for Environmental Protection and Water Management, 2024. Clean Air Priority Programme.

Nielsen, K.S., Cologna, V., Bauer, J.M., Berger, S., Brick, C., Dietz, T., Hahnel, U.J.J., Henn, L., Lange, F., Stern, P.C., Wolske, K.S., 2024. Realizing the full potential of behavioural science for climate change mitigation. Nat. Clim. Chang. 1–9. https://doi.org/10.1038/s41558-024-01951-1

O'Shaughnessy, E., Grayson, A., Barbose, G., 2023. The role of peer influence in rooftop solar adoption inequity in the United States. Energy Economics 127, 107009. https://doi.org/10.1016/j.eneco.2023.107009

Rockenbauch, T., Sakdapolrak, P., 2017. Social networks and the resilience of rural communities in the Global South: a critical review and conceptual reflections. Ecology and Society 22.

Rosenow, J., Gibb, D., Nowak, T., Lowes, R., 2022. Heating up the global heat pump market. Nature Energy 7, 901–904. https://doi.org/10.1038/s41560-022-01104-8

Scheller, F., Graupner, S., Edwards, J., Weinand, J., Bruckner, T., 2022. Competent, trustworthy, and likeable? Exploring which peers influence photovoltaic adoption in Germany. Energy Research & Social Science 91, 102755. https://doi.org/10.1016/j.erss.2022.102755

Smith, S., 2017. Just Transition. A Report for the OECD. OECD.

Sokołowski, J., 2023. Peer effects on photovoltaics (PV) adoption and air quality spillovers in Poland. Energy Economics 125, 106808. https://doi.org/10.1016/j.eneco.2023.106808

Sokołowski, J., Bouzarovski, S., 2022. Decarbonisation of the Polish residential sector between the 1990s and 2021: A case study of policy failures. Energy Policy 163, 112848. https://doi.org/10.1016/j.enpol.2022.112848

Statistics Poland, 2019. Household Budget Survey.

Stewart, F., 2023. Power to (some of) the people: inequalities in the uptake of low-carbon energy technologies, and how to fix them at a local level. University Of Strathclyde, Strathclyde.

Stewart, F., 2021. All for sun, sun for all: Can community energy help to overcome socioeconomic inequalities in low-carbon technology subsidies? Energy Policy 157, 112512. https://doi.org/10.1016/j.enpol.2021.112512

Tammaru, T., Marcin´czak, S., Aunap, R., van Ham, M., Janssen, H., 2020. Relationship between income inequality and residential segregation of socioeconomic groups. Regional Studies 54, 450–461. https://doi.org/10.1080/00343404.2018.1540035

Tozer, L., Hörschelmann, K., Anguelovski, I., Bulkeley, H., Lazova, Y., 2020. Whose city? Whose nature? Towards inclusive nature-based solution governance. Cities 107, 102892. https://doi.org/10.1016/j.cities.2020.102892

Tozer, L., MacRae, H., Smit, E., 2023. Achieving deep-energy retrofits for households in energy poverty. Buildings and Cities. https://doi.org/10.5334/bc.304

Vona, F., 2023. Managing the distributional effects of climate policies: A narrow path to a just transition. Ecological Economics 205, 107689. https://doi.org/10.1016/j.ecolecon.2022.107689

Wierzbowski, M., Filipiak, I., Lyzwa, W., 2017. Polish energy policy 2050 – An instrument to develop a diversified and sustainable electricity generation mix in coal-based energy system. Renewable and Sustainable Energy Reviews 74, 51–70. https://doi.org/10.1016/j.rser.2017.02.046

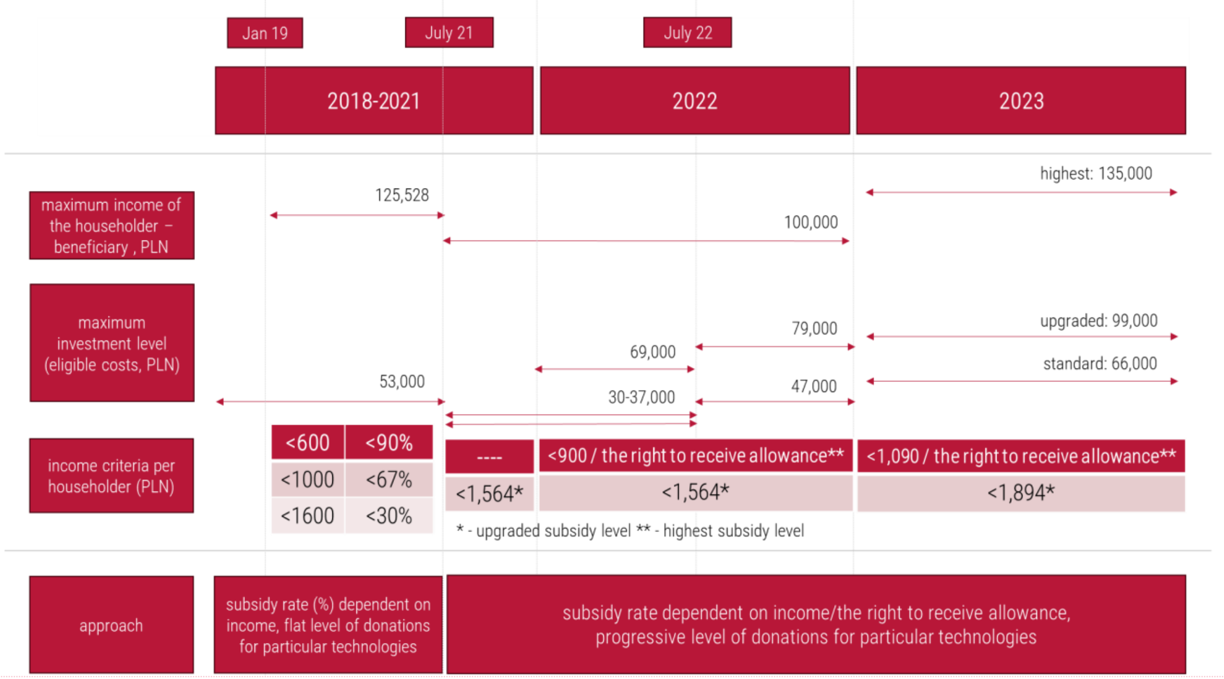
Willand, N., Moore, T., Horne, R., Robertson, S., 2020. Retrofit Poverty: Socioeconomic Spatial Disparities in Retrofit Subsidies Uptake. Buildings and Cities 1, 14–35. https://doi.org/10.5334/bc.13

Williams, R., Kralli, A., Jagtenberg, H., Smith, M., 2023. Subsidies for fossil heating appliances in the EU and UK. Trinomics, Rotterdam.

Wooldridge, J.M., 2010. Econometric analysis of cross section and panel data. MIT press.

Appendix A – Methodological details

Figure A1. Evolution of the CAPP financial criteria



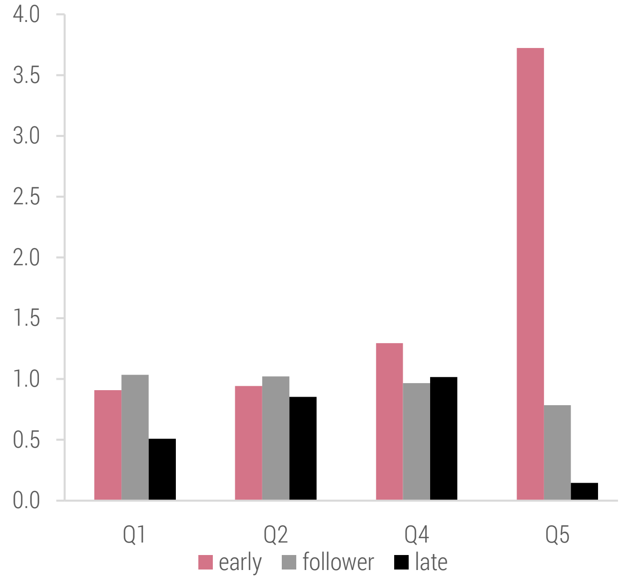
Source: own elaboration based on CAPP documentation

Appendix B – Additional results and descriptive statistics

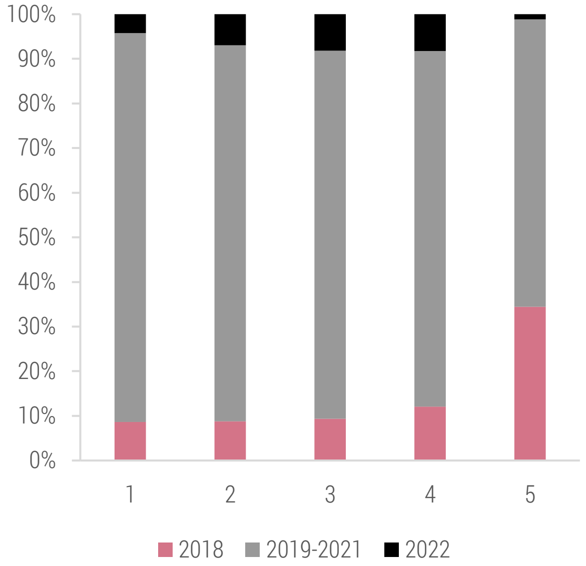
Figure B1. Likelihood and the distribution of program participation by income quintile and program timing

The characteristics of program participants differ significantly in terms of the timing of program participation. It is the consequence of tightening up the rules of participation in the program. Interestingly, the first income quintile group was two times less likely to be late adopters than the third. Relatively high-income participants dominated the programme's first stage, resulting from the lack of a household income limit for participation in CAPP. Over 50% of early adopters (i.e., those who changed their heating source in the programme's first year, 2018) belonged to the fifth income quintile (Figure B1, left and right panel). The likelihood that an early technology adopter belonged to the fifth income quintile was almost four times higher than that they belonged to the third quintile (Figure 3, left panel). The differences between the remaining quintile groups were minor, but higher quintile groups (Q5) were slightly more likely to change the heating source than lower quintile groups (Q1-Q2). Most participants at that stage were follower adopters (those who changed the heating source between 2019 and 2021; Figure 2, bottom panel). The differences among follower adopters were negligible in terms of likelihood, meaning that none of the income groups were dominant at this stage of the program (Figure B1, left panel). The likelihood that a late adopter (those who changed the heating source in 2022) belongs to the fifth quintile is about ten times lower than that she belongs to the third quintile (Figures B1, left and right).

a) Early, follower or late adopters by income quintile



b) Programme participation by income quintile and timing



Note: likelihoods are normalised with Q3.
Source: own elaboration based on CAPP data.

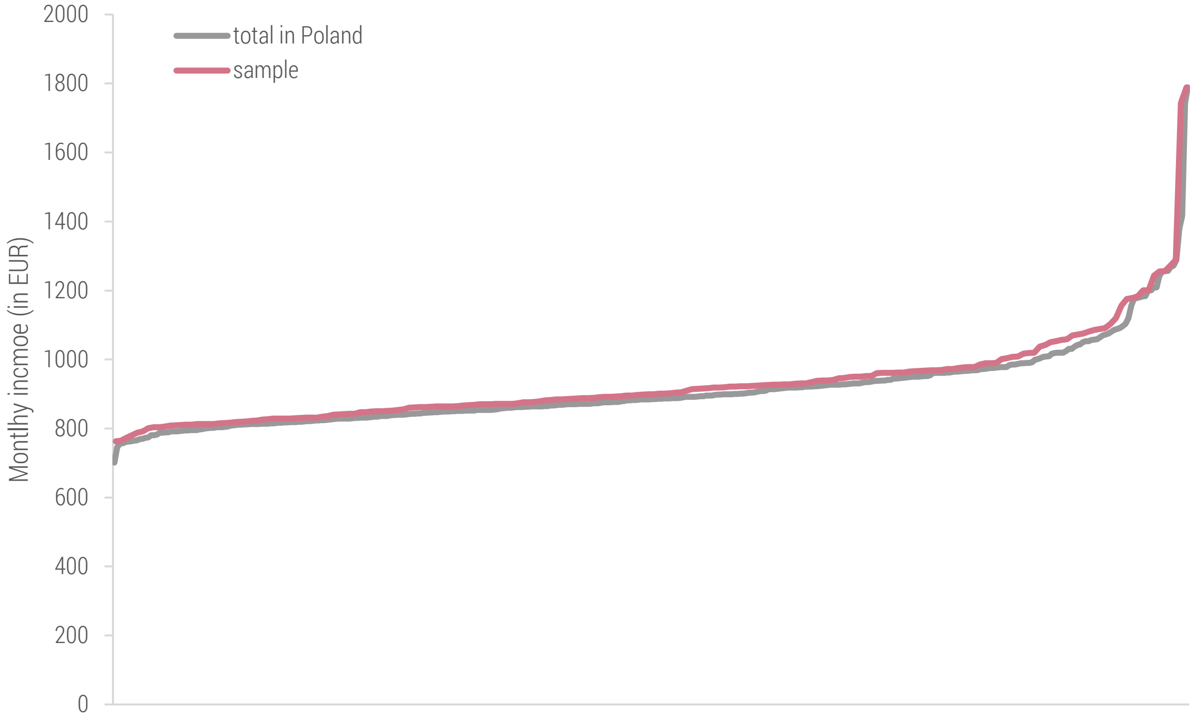
Table B1 Correlation between wealth score and household characteristics

	Low wealth	High wealth
Low Gini region	-0.222** (0.094)	-0.498*** (0.093)
High Gini region	-0.336*** -0.118	0.524*** (0.095)
Heating source – biomass stove	-0.041 (0.034)	-0.960*** (0.032)
Low Gini region # Heating source – biomass stove	0.037 (0.055)	-0.028 (0.058)
High Gini region # Heating source – biomass stove	-0.072 (0.067)	-0.069 (0.055)
Income decile: 1st	0.335*** (0.061)	0.111** (0.056)
Income decile: 2nd	0.069 (0.066)	-0.244*** (0.064)
Income decile: 3rd	0.152** (0.065)	-0.173*** (0.062)
Income decile: 4th	0.131** (0.065)	-0.137** (0.061)
Income decile: 6th	-0.026 (0.070)	0.117* (0.061)
Income decile: 7th	0.107 (0.074)	0.256*** (0.065)
Income decile: 8th	-0.000 (0.079)	0.300*** (0.068)
Income decile: 9th	-0.113 (0.122)	0.617*** (0.099)

Income decile: 10th	-0.818*** (0.193)	1.347*** (0.119)

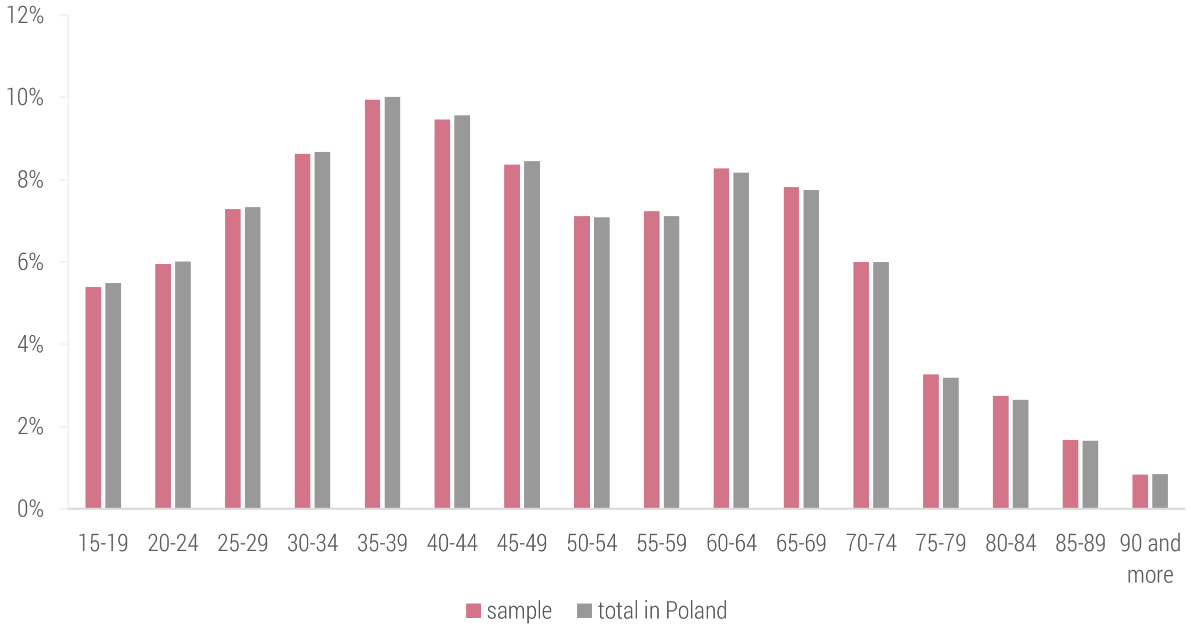
Source: own elaboration based on CAPP data.

Figure B2. The distribution of monthly income by county in the sample and the whole country in 2018



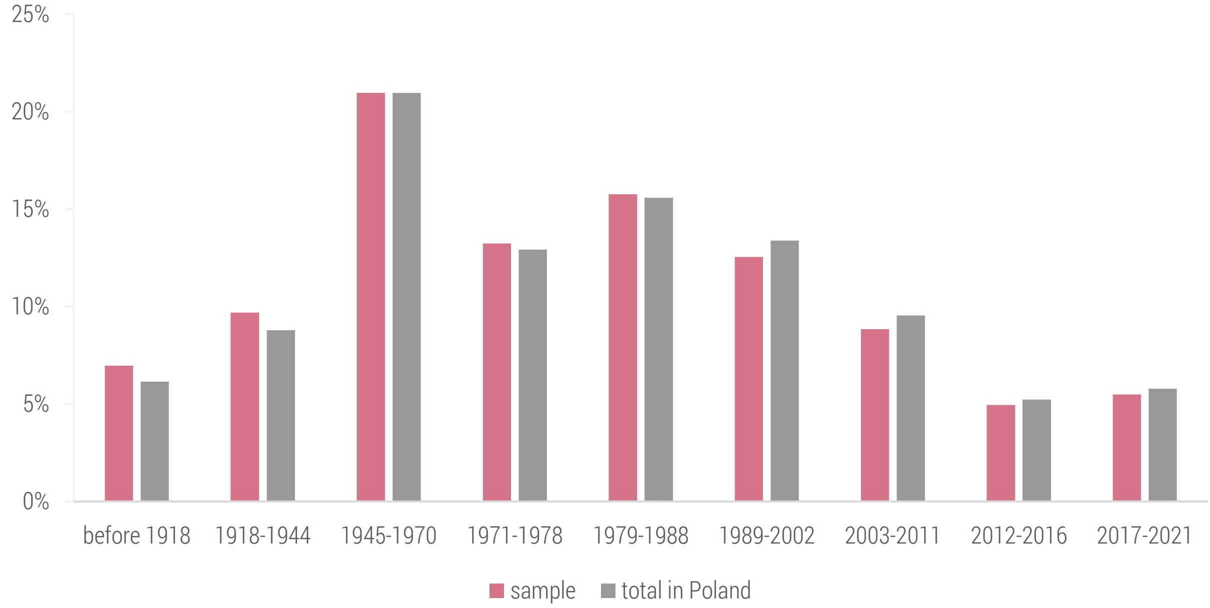
Source: Own elaboration based on CAPP and Statistics Poland data.

Figure B3. Distribution of age groups in the sample and the whole country in 2022



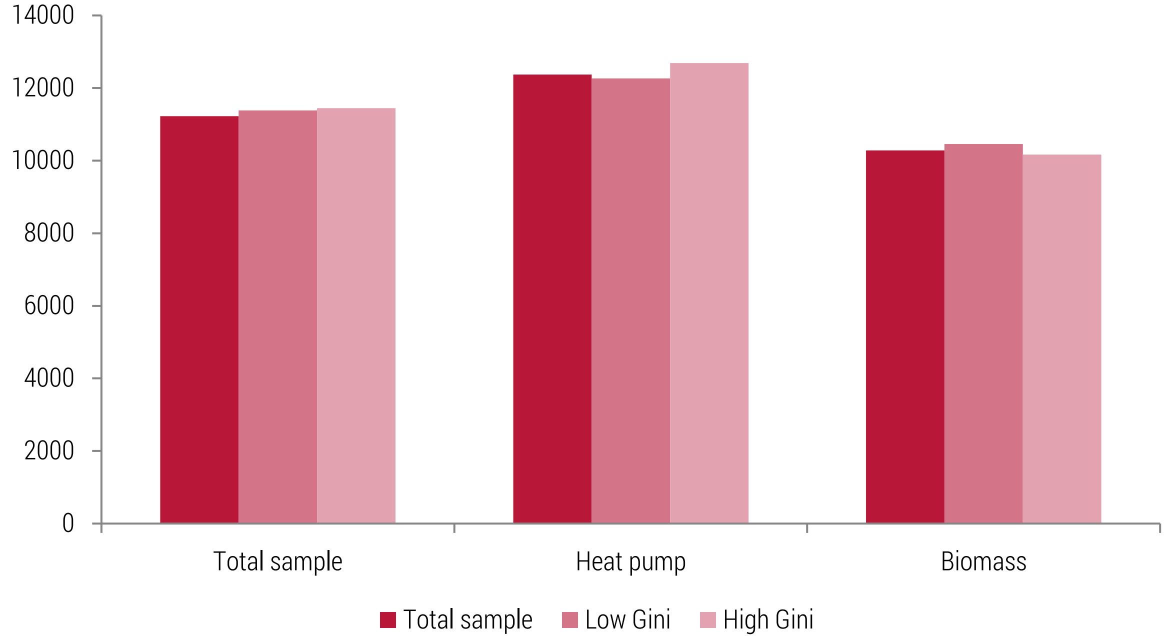
Source: Own elaboration based on CAPP and Statistics Poland data.

Figure B4. Distribution of building construction years in the sample and the whole country in 2022



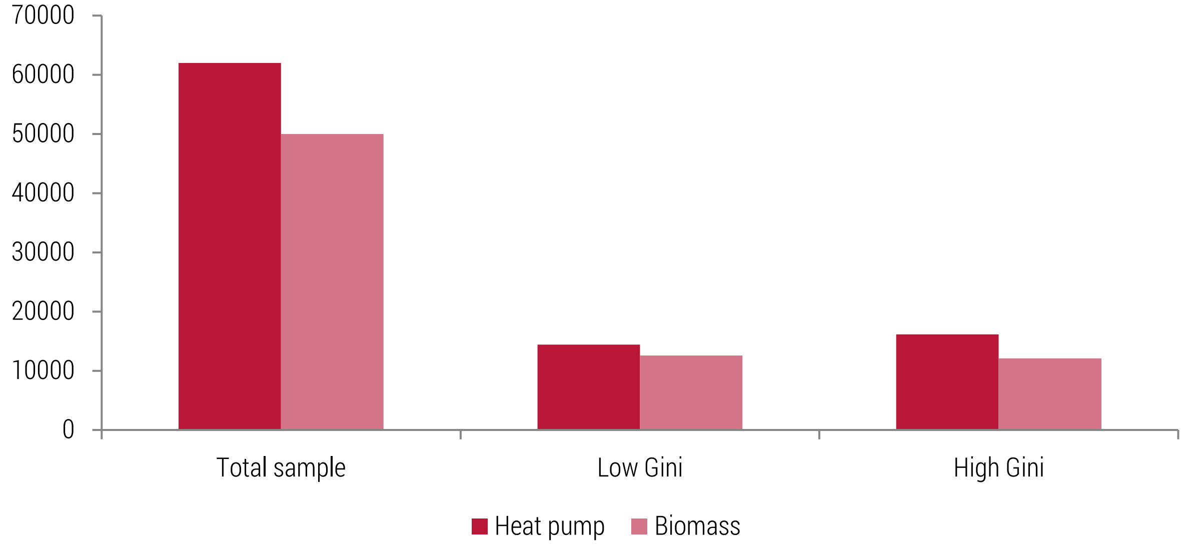
Source: Own elaboration based on CAPP and Statistics Poland data.

Figure B5. The average self-declared income by heating source and area of residence (in thousands of Euro)



Source: own elaboration based on CAPP data.

Figure B6. Number of installations by heating source and area of residence



Source: own elaboration based on CAPP data.

Table B2. Peer effects by income group and regions with high/low inequalities – individuals grouped by wealth score

Share of adopters:	(1) Total sample	(2) Low wealth	(3) Medium wealth	(4) High wealth
Peer effects:				
Panel A: Total sample				
All individuals	0.882***			
	(0.023)			
Low wealth		0.834***		
		(0.032)		
Medium wealth			0.851***	
			(0.024)	
High wealth				0.921***
				(0.029)
Panel B: Low inequality areas				
All individuals	0.928***			
	(0.017)			
Low wealth		0.864***		
		(0.036)		
Medium wealth			0.855***	
			(0.027)	
High wealth				0.960***
				(0.008)
Panel C: High inequality areas				
All individuals	0.907***			
	(0.028)			
Low wealth		0.801***		
		(0.051)		
Medium wealth			0.827***	
			(0.047)	
High wealth				0.952***
				(0.021)

*Notes: *** p<0.01, ** p<0.05, * p<0.1 Standard errors in parentheses.*

Table B3. Peer effects by income group and heating source, and regional inequality level – individuals grouped by wealth score

	(1)	(2)	(3)	(4)
Share of adopters:	Low incomes (heat pump)	High incomes (heat pump)	Low incomes (biomass)	High incomes (biomass)
Peer effects:				
Panel A: Total sample				
Low wealth (heat pump)	0.819***			
	(0.057)			
High wealth (heat pump)		0.936***		
		(0.026)		
Low wealth (biomass)			0.867***	
			(0.035)	
High wealth (biomass)				0.815***
				(0.023)
Panel B: Low inequality areas				
Low wealth (heat pump)	0.887***			
	(0.029)			
High wealth (heat pump)		0.945***		
		(0.025)		
Low wealth (biomass)			0.911***	
			(0.087)	
High wealth (biomass)				0.788***
				(0.068)
Panel C: High inequality areas				
Low incomes (heat pump)	0.694***			
	(0.125)			
High wealth (heat pump)		0.946***		
		(0.020)		
Low wealth (biomass)			0.685***	
			(0.053)	
High wealth (biomass)				0.860***
				(0.023)

*Notes: *** p<0.01, ** p<0.05, * p<0.1 Standard errors in parentheses.*

Table B4. Peer effects by income group and regions with high/low inequalities – individuals grouped by self-declared income

	(1)	(2)	(3)	(4)
Share of adopters:	Total sample	Low income	Medium income	High income
Peer effects:				
Panel A: Total sample				
All individuals	0.882***			
	(0.023)			
Low incomes		0.911***		
		(0.026)		
Medium incomes			0.849***	
			(0.020)	
High incomes				0.910***
				(0.040)

Panel B: Low inequality areas				
All individuals	0.928***			
	(0.017)			
Low incomes		0.929***		
		(0.024)		
Medium incomes			0.881***	
			(0.012)	
High incomes				0.927***
				(0.019)
Panel C: High inequality areas				
All individuals	0.907***			
	(0.028)			
Low incomes		0.883***		
		(0.020)		
Medium incomes			0.891***	
			(0.031)	
High incomes				0.936***
				(0.064)

*Notes: *** p<0.01, ** p<0.05, * p<0.1 Standard errors in parentheses.*

Table B5. Peer effects by income group and heating source, and regional inequality level – individuals grouped by self-declared income

	(1)	(2)	(3)	(4)
Share of adopters:	Low incomes (heat pump)	High incomes (heat pump)	Low incomes (biomass)	High incomes (biomass)
Peer effects:				
Panel A: Total sample				
Low incomes (heat pump)	0.876***			
	(0.029)			
High incomes (heat pump)		0.938***		
		(0.057)		
Low incomes (biomass)			0.874***	
			(0.028)	
High incomes (biomass)				0.832***
				(0.058)
Panel B: Low inequality areas				
Low incomes (heat pump)	0.937***			
	(0.029)			
High incomes (heat pump)		0.956***		
		(0.007)		
Low incomes (biomass)			0.961***	
			(0.014)	
High incomes (biomass)				0.740***
				(0.005)
Panel C: High inequality areas				
Low incomes (heat pump)	0.885***			
	(0.032)			
High incomes (heat pump)		0.937***		
		(0.084)		
Low incomes (biomass)			0.823***	
			(0.039)	

High incomes (biomass)				0.467*
				(0.245)

*Notes: *** p<0.01, ** p<0.05, * p<0.1 Standard errors in parentheses.*

Table B6. Peer effects by income group and regions with high/low inequalities – one month lag

	(1)	(2)	(3)	(4)
Share of adopters:	Total sample	Low income	Medium income	High income
Peer effects:				
Panel A: Total sample				
All individuals	0.962***			
	(0.004)			
Low wealth		0.967***		
		(0.012)		
Medium wealth			0.944***	
			(0.012)	
High wealth				0.965***
				(0.008)
Panel B: Low inequality areas				
All individuals	0.967***			
	(0.005)			
Low wealth		0.957***		
		(0.013)		
Medium wealth			0.969***	
			(0.007)	
High wealth				0.983***
				(0.002)
Panel C: High inequality areas				
All individuals	0.958***			
	(0.006)			
Low wealth		0.945***		
		(0.015)		
Medium wealth			0.941***	
			(0.016)	
High wealth				0.960***
				(0.007)

*Notes: *** p<0.01, ** p<0.05, * p<0.1 Standard errors in parentheses.*

Table B7. Peer effects by income group and heating source, and regional inequality level – one month lag

	(1)	(2)	(3)	(4)
Share of adopters:	Low incomes (heat pump)	High incomes (heat pump)	Low incomes (biomass)	High incomes (biomass)
Peer effects:				
Panel A: Total sample				
Low incomes (heat pump)	0.946***			
	(0.010)			
High incomes (heat pump)		0.976***		
		(0.017)		
Low incomes (biomass)			0.980***	
			(0.049)	

High incomes (biomass)				0.978***
				(0.055)
Panel B: Low inequality areas				
Low incomes (heat pump)	0.966			
	(10.113)			
High incomes (heat pump)		0.979***		
		(0.002)		
Low incomes (biomass)			0.966***	
			(0.076)	
High incomes (biomass)				0.914***
				(0.002)
Panel C: High inequality areas				
Low incomes (heat pump)	0.962***			
	(0.009)			
High incomes (heat pump)		0.972***		
		(0.030)		
Low incomes (biomass)			0.946***	
			(0.044)	
High incomes (biomass)				0.775***
				(0.086)

*Notes: *** p<0.01, ** p<0.05, * p<0.1 Standard errors in parentheses.*

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