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# POWERING UP CLEANER CHOICES: A STUDY ON THE HETEROGENOUS EFFECTS OF SOCIAL NORM-BASED ELECTRICITY PRICING ON DIRTY FUEL PURCHASES

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# Powering Up Cleaner Choices: A Study on the Heterogenous Effects of Social Norm-Based Electricity Pricing on Dirty Fuel Purchases

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**Abstract:**
This paper examines the heterogeneous effects of the experimental introduction of increasing-block-tariffs (IBT) for residential electricity on the propensity to purchase dirty fuels using panel household data (RLMS-HSE) in a number of regions of Russia. The study demonstrates that despite the design of the IBT being based on prescribed social norms and accounting for various household and dwelling characteristics, the adverse effects of this policy (in the form of increased propensity to purchase dirty fuels) are still more pronounced among households with higher base energy consumption, those receiving subsidies for utilities, and those in a vulnerable social position where the household head's primary occupation is childcare or housekeeping. Additionally, the paper finds that households headed by females are actually 20% less likely to purchase dirty fuels due to the introduction of IBT. The findings suggest that policymakers should fine-tune the calculation of social norms to minimize the negative impacts of IBT. Furthermore, the study's results may be relevant and useful for policymakers in other developing and transition economies that aim to implement various energy reforms, including IBT.

**JEL:** Q41, Q48, L98, L94
**Keywords:** residential electricity pricing, increasing-block-tariffs, heterogeneous treatment effects, social norms, dirty fuels, post-Soviet economy, Russia, natural experiment

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## 1. Introduction

The major industrial nations of the world are directly accountable for climate change, with Russia being one of the prominent countries on the list. According to Worldometers.info (2022), Russia is the fourth largest polluter in the world, following China, the United States, and India. The high levels of pollution in Russia are largely attributed to its carbon-intensive electricity generation, which is primarily produced through the utilization of natural gas and coal, the conventional sources of energy (Turdaliev, 2023). The main policy instruments, besides a transition to clean energy sources, to tackle resource-intensive electricity generation are the various pricing mechanisms, which also include the increasing-block-tariff (IBT) schemes.

The energy regulators tried to implement the IBT schemes in Russia back in 2013, by introducing a two-step IBT for residential electricity in a number of experimental regions. The plan was then to introduce IBT across the whole country by 2014 (Veretennikova, 2014). However, the results of the experiment did not appear to be successful, and it was decided to postpone the country-wide IBT implementation indefinitely (Veretennikova, 2014; Antonov, 2018). However, besides some vague remarks that the experiment was unsuccessful, the results of the experiment were never published by the officials. Thus, no rigorous policy assessment of this event was available.

Turdaliev (2023), and Turdaliev (2021) try to address this issue by investigating how the introduction of IBT in the experimental regions of Russia has affected electricity consumption, and the propensity to invest in major electrical appliances among residential consumers. The author finds, that the introduction of IBT in the experimental regions led to about a 1% reduction in electricity consumption, and about a 20% increase in the propensity to purchase major electrical appliances compared to households with flat electricity tariffs.

Following the arguments that the population in developing and transitioning economies may change their patterns of energy use in favor of less-clean options like coal, kerosene, wood, and the like as a result of policies (like IBT) that increase the price of fundamental energy sources like gas and electricity Turdaliev and Janda (2023), examine the propensity of households to purchase dirty fuels following the introduction of the IBT for residential electricity in these experimental regions of Russia. They document a large increase in the propensity to purchase dirty fuels in the regions where the IBT electricity pricing was introduced. Specifically, they estimate an increase of more than 60% in the case of households located in the experimental regions when compared to similar households located in the regions with flat electricity tariffs.

Even though, the impact of the introduction of the IBT for residential electricity in Russia was studied in a number of papers, the heterogeneous effects of this policy have not been studied, despite them being crucial for the proper policy analysis. For instance, as argued by Harold et al., (2018), it is important for energy suppliers, and policymakers to understand how the impacts of such policies vary across different socioeconomic and household level characteristics.

Moreover, even though literature documenting the various effects of the IBT for electricity, as well as estimates of the price and income elasticities under the IBT is quite abundant (see, for instance, Turdaliev, 2023 for literature review), the literature documenting the heterogenous effects of the IBT policies, especially with regards to the household's socio-economics is scarce.

For instance, one of the first to study the energy consumption of households in the presence of block tariffs for electricity, and analyze the heterogeneity of its impact was Wills (1981). The author concludes, that the price elasticity of electricity demand in Massachusetts (USA) is -0.18 for consumers that heat water, and their dwellings using primarily electricity, and -0.52 for consumers that combine electricity with some other type of energy source during the period of 30 years (1941-1970).

Reiss and White (2005) also reveal a substantial heterogeneity of households' sensitivity to the introduction of a five-part tariff for electricity in California following the electricity supply crisis in 2000-2001. The authors document a significant difference in demand elasticities for households with different heating and cooling systems. In particular, households with electric space heating or air conditioning demonstrate a much higher electricity price sensitivity compared to households without such systems.

Alberini et al., (2011) estimate static and dynamic models of electricity and gas demand using a mixed panel/multi-year cross-section of dwellings/households in the 50 largest metropolitan areas in the United States. In contrast to Reiss and While (2005), they do not find evidence of significantly different elasticities across households with electric and gas heating systems.

Mills and Schleich (2012) conclude that families with young children are more likely to utilize energy-saving strategies in the home, but senior households are less likely to employ conservation strategies. Additionally, they found that education levels influence household energy conservation behavior-households with higher levels of education being more prone to energy conservation practices.

In their study on the effect of social norm feedback on energy consumption, Dolan and Metcalfe (2015) conducted two natural field experiments in the UK with samples of 569 and 2142 households for each experiment. While their findings suggested that households with larger dwellings are less likely to reduce their energy use as a result of the feedback, they did not find any significant heterogeneous effects for wealth or gender of the household head.

Studying the block-tariffs pricing for residential electricity in China Sun and Lin (2013) conclude that higher income consumers are less sensitive to the introduction of the

IBT than those with lower income. Sun (2015) also studies the factors affecting the price sensitivity of residential electricity consumption following the introduction of tiered pricing for household electricity in China. The author finds that such factors as household income, the installation of solar water heaters, and tiered-pricing awareness, significantly affect household electricity-saving behavior.

Hung and Chie (2017) study the long-run performance of increasing block pricing in Taiwan's residential electricity sector. The authors show that cross-subsidization under IBT has resulted in inefficient over-consumption by poor households and inefficient under-consumption by wealthy households. They also conclude that the financial burden increased with the decreases in household income and that a relatively high proportion of subsidies mistakenly went to non-poor households.

Zhang et al., (2017) study the impacts of the increasing-block pricing for electricity on urban households in the Guangdong province of China. The paper concludes that the urban households in Guangdong respond only to a large increase in marginal price, and do not respond to a smaller increase. More specifically, an increase of about 8% in the marginal price for electricity results in a statistically insignificant response, while an increase of about 40% results in about a 35% decrease in electricity use.

Liu and Lin (2020) also study the heterogenous impacts of IBT pricing for electricity in Shanghai and Shenzhen. They conclude that households that are large, apply time-of-use (TOU) pricing, purchase energy-efficient appliances, have adequate knowledge of electricity saving and IBT contents, or understand the situation of electricity cross-subsidy, are more likely to be influenced by the IBT to save electricity.

Finally, Lin and Zhu (2021) also employ a similar analysis and study the factors affecting the electricity-saving behavior of households in China due to the introduction of

IBT. The study concludes that the energy-saving effect is more pronounced among residents with low incomes, low electricity consumption, and residents over 50 years old.

As can be seen, the literature studying the heterogenous impacts of IBT for electricity concentrates mostly on the income and environmental preferences of the household. Studies that analyze the heterogenous effects of IBT with regard to household socio-economics are rather scarce. Moreover, to the best of the author's knowledge studies that analyze the heterogenous effects of IBT with respect to the purchase of dirty fuels are non-existent. This paper addresses this gap in the literature by analyzing the heterogenous effects of IBT on the propensity to purchase dirty fuels following the introduction of the IBT for residential electricity in three regions of Russia.

I do document the presence of heterogeneous effects of the IBT for residential electricity on the propensity to purchase dirty fuels among Russian households. Particularly, I demonstrate that in the case of Russia the negative effects (in the form of increased propensity to purchase dirty fuels) of demand-side stimuli like IBT are more pronounced among the population with higher base energy consumption, households receiving utility subsidies, and those in a vulnerable social position where the household head's primary occupation is childcare or housekeeping. Additionally, the paper finds that households headed by females are actually 20% less likely to purchase dirty fuels due to the introduction of IBT.

These findings show that the introduction of the IBT for residential electricity has a disproportional impact on certain types of households, even though in the case of Russia the design of the IBT is based on the prescribed social norms and takes into account various household and dwelling characteristics, which should have minimized the negative social implications of the IBT on the vulnerable parts of the population. Thus, my findings show that there is further room for the calculation of the social norms to be fine-tuned by the policymakers to take into account the heterogeneous impacts of the IBT discussed in this paper in order to minimize the negative social and environmental aspects of this policy.

Moreover, the findings of this study can be applicable and beneficial for other developing and transition economies looking to implement energy reforms. In particular, the results can be useful for policymakers seeking to design effective policies to reduce carbon emissions and increase energy efficiency through the implementation of pricing mechanisms such as IBT. This study highlights the importance of considering the heterogenous effects of such policies across different socio-economic and household characteristics to ensure that vulnerable households are not disproportionately affected. As such, the insights from this research can assist policymakers in developing tailored policy interventions that balance environmental and social objectives.

The rest of the paper is structured as follows. The next section provides a brief background of the natural experiment introduced in Russia in September 2013. Section 3 describes the data that is used for the analysis. Section 4 specifies the empirical methodology. Section 5 summarizes the results, and Section 6 concludes.

## 2. Natural Experiment

In September 2013 Russia has implemented the experimental introduction of the social norms for residential electricity consumption in seven pilot regions of Russia (see, the "Decree of the Government of the Russian Federation of July 22, 2013 No. 614" [1]; Veretennikova, 2014). The plan was to then introduce the social norms for residential electricity consumption countrywide in the summer of 2014.

[1] The "Decree of the Government of the Russian Federation of July 22, 2013 No. 614" was updated on 25th February of 2014 to exclude the Samara oblast from the list of pilot regions. This decreases the total number of experimental regions from seven to six. However, since the oblast of Samara is not covered by RLMS-HSE this update does not affect my estimations.

The results of the experimental introduction of social norms in pilot regions were mixed, and due to various reasons, the countrywide implementation was postponed indefinitely (see, Turdaliev, 2023 for details). However, even though the countrywide implementation was postponed indefinitely the households in the pilot regions still remained on an experimental tariff for electricity based on the prescribed social norms for electricity consumption.

In particular, the social norms are prescribed based on the household and dwelling characteristics, and vary considerably across the experimental regions both with regards to the characteristics of household and dwelling according to which the social norms are calculated, and also with respect to the actual amount of prescribed social norm for electricity consumption (kWh a month).

Unfortunately, RLMS-HSE is conducted only in three out of the seven regions where the experimental tariff schemes were introduced. In particular, RLMS-HSE is conducted in Rostov Oblast, Krasnoyarsk Krai, and Nizhny Novgorod Oblast.[2] Table 1 (adapted from Turdaliev ,2023) details the calculation of the prescribed social norms in these three pilot regions.

**Table 1: Prescribed social norms for residential electricity consumption (kWh/month)**

[2] The other experimental regions are Zabaykalsky Krai, Vladimir Oblast, Orlov Oblast, and Samara Oblast.

| Region | HH type | Urban | Rural | Urban + electric stove | Rural + electric stove | Receiving social benefits |
|---|---|---|---|---|---|---|
| ***Krasnoyarsk Krai*** | n=1 | 110 | | 220 | | ×1.0 |
| | n=2 | 150 | | 300 | | ×1.0 |
| | n=3+ | 75×n | | 150×n | | ×1.0 |
| ***Nizhny Novgorod Oblast*** | n=1 | 85 | | 85 | | 85 |
| | n=2 | 100 | | 100 | | ×1.5 |
| | n=3+ | 100+50× (n-2) | | 100+50× (n-2) | | ×1.5 |
| ***Rostov Oblast*** | n=1 | 96 | 186 | 186 | 276 | ×1.5 |
| | n=2 | 156 | 246 | 242 | 332 | ×1.5 |
| | n=3+ | 156+40×(n-2) | 246+40× (n-2) | 156+40×(n-2) +43×n | 246+40×(n-2) +43×n | ×1.5 |

Note: “*n*” denotes the household size. Reprinted from “Household-Specific Social Norms, the Elasticity of Electricity Demand, and Carbon Emissions Reductions in the Residential Sector: Evidence from a Natural Experiment in Russia” by Turdaliev S. (2023). *Climate Change Economics*, forthcoming.

Even though the concept of the social norms for energy consumption may seem unusual for the pricing of residential electricity, it is basically identical to some other countries’ “increasing-block tariffs” (IBT) where the consumption until some designated level is priced at a lower cost per unit, whereas the consumption above the designated cut-off value is priced at a higher price per unit. Therefore, in our case, the experimental regions of Russia effectively implemented a two-block increasing tariff scheme where the second block is determined according to the characteristics of the household and the dwelling.

As can be seen from Table 1 there is a considerable variation in the calculation of the social norms across the selected experimental regions both across the household and dwelling characteristics that are taken into account and in terms of the actual prescribed monthly kWh. The considerable differences in the calculation of the social norms between the experimental regions are also noted in Veretennikova (2014), where the author also notes that these considerable differences and the actual methodology (or its absence for that matter, see Turdaliev, 2023 for more details) for the calculation of the social norms within each experimental region were a subject of strong debates, and some of the regions that were originally included to the list of the pilot regions requested to be excluded from this experimental implementation of social norms (IBT schemes) for the residential electricity consumption.[3]

From the above one can conclude that the design of the methodology for the calculation of the social norms, and their assignment was accomplished in a more or less ad-hock manner, which in turn favors our econometric estimations procedure.

Besides a substantial variation in the calculation of the social norms between the experimental regions, we can also observe a considerable variation in the actual tariff charged per kWh for residential electricity across all the regions under the study. Figures 1-4 (available in Appendix) depict the tariff schemes for residential electricity for the three experimental regions under the study and the average tariff schedule for the remaining 35 regions serving as controls.[4]

*[Figure-1]*

*[Figure-2]*

*[Figure-3]*

*[Figure-4]*

We can see that before September 2013 we can observe two types of tariffs across all the regions under the study-a flat tariff for the dwellings that have an electric stove, and another flat tariff for the households that do not have an electric stove. The logic behind this differentiation is that households that have an installed electric stove in their dwellings usually do not have an access to the district supply of gas (piped gas supply), and therefore are forced to use the electric stove for cooking purposes. The electric tariffs thus try to take into account the higher base consumption of the households with electric stoves and price the electricity at a discounted rate for those households.

[3] More specifically Primorsky Krai, and Lipetsk Oblast requested to be excluded from the pilot program prior to September 2013. See Turdaliev (2023) for more details.
[4] Residential electricity tariffs were obtained from the Federal State Statistics Service of Russia (Rosstat).

After the introduction of the IBT in the experimental regions (September of 2013) we can observe four different tariffs in each of the experimental regions-two tariffs for the first-block consumption (one for households with electric stoves, and another one for households without), and two tariffs for the second block consumption (again, one tariff for households with electric stoves, and another one for households without). The control regions, as expected, remain on a flat tariff scheme.

**3. Data**

The paper exploits the Russian Longitudinal Monitoring Survey – Higher School of Economics (RLMS-HSE), a panel household data conducted jointly by the National Research University "Higher School of Economics" and OOO "Demoscope" together with the Carolina Population Center, the University of North Carolina at Chapel Hill and the Institute of Sociology of the Federal Center of Theoretical and Applied Sociology of the Russian Academy of Sciences.[5]

As in Turdaliev and Janda (2023), this paper employs the data from the waves conducted from 2010 to 2019. This particular time frame was chosen to avoid any possible bias that may arise due to the 2008-2009 financial crisis, and the Covid-19 pandemic due to various income shocks, and lock-downs that may increase the use of dirty fuels considerably.

Besides, the standard questions on family's socio-economics RLMS-HSE also asks whether a household has purchased firewood, coal, peat, or kerosene within the last 30 days. These four types of dirty fuels are considered to be the most widely used household dirty fuels in the world (WHO, 2015).

RLMS-HSE surveys more than 6000 nationally representative households each year. The survey covers 38 regions across Russia, with three of these regions (Rostov Oblast, Krasnoyarsk Krai, and Nizhny Novgorod Oblast) being the regions where the experimental

[5] https://www.hse.ru/en/rlms.

IBT electricity tariff was introduced. Out of a total of 74,165 household observations for 2010-2019, I retain 58,462 observations for the analysis.

Firstly, 10,820 household observations turned out to be singleton observations, and thus are not suitable for a fixed effects panel regression. Out of the remaining non-singleton observations, 920 are the households that report both having a district supply of gas, as well having an installed electric stove within the dwelling. To avoid any ambiguity, I drop these households as well.

Finally, I also drop households reporting abnormally high or low household income levels. In particular, I drop households that report a monthly income exceeding 800,000 rubles (about 12,000 USD adjusted for 2019), and households reporting a monthly income level below 10,000 rubles (about 150 USD adjusted for 2019). These types of households account for a further reduction of 3,963 observations in our sample.

Out of a total of 58462 remaining households about 9.4% are located in the experimental IBT regions. Table 2 summarizes the descriptive statistics of the selected sample both for experimental regions (treatment regions), as well as remaining regions with flat tariff schemes (control regions).

**Table-2**

| | | Control % | Treatment % | Difference |
|---|---|---|---|---|
| **Household head's characteristics** | | | | |
| *Female* | | 0.293 | 0.276 | 0.018*** |
| *Age:* | | | | |
| <36 years | | 0.225 | 0.265 | -0.04*** |
| 36–45 years | *Ref* | 0.414 | 0.495 | -0.082*** |
| 46–55 years | | 0.181 | 0.166 | 0.016*** |
| 56–65 years | | 0.171 | 0.139 | 0.031*** |
| 65+ years | | 0.189 | 0.174 | 0.015*** |
| *Education:* | | | | |
| Primary | | 0.176 | 0.169 | 0.007 |
| Secondary | *Ref* | 0.333 | 0.292 | 0.041*** |
| Secondary-technical | | 0.240 | 0.258 | -0.018*** |
| Higher | | 0.249 | 0.277 | -0.028*** |

| | | | | |
|---|---|---|---|---|
| *Employment status:* | | | | |
| Employed | *Ref* | 0.579 | 0.622 | -0.043*** |
| Self-employed | | 0.022 | 0.023 | -0.002 |
| Unemployed | | 0.072 | 0.053 | 0.018*** |
| Pensioner | | 0.280 | 0.254 | 0.026*** |
| Housekeeper | | 0.008 | 0.005 | 0.004*** |
| Child-care | | 0.003 | 0.005 | -0.002** |
| Disabled | | 0.018 | 0.015 | 0.003 |
| Student | | 0.017 | 0.021 | -0.005** |
| **Household characteristics** | | | | |
| *Number of household members:* | | | | |
| 1 person | | 0.231 | 0.19 | 0.041*** |
| 2–3 people | *Ref* | 0.537 | 0.573 | -0.036*** |
| 4+ people | | 0.233 | 0.237 | -0.005 |
| Tenure (rented) | | 0.075 | 0.097 | -0.022*** |
| *Receiving utility benefits:* | | | | |
| Subsidies | | 0.288 | 0.275 | 0.014** |
| Discounts | | 0.170 | 0.169 | 0.001 |
| Arrears | | 0.073 | 0.067 | 0.007* |
| *Income quantiles:* | | | | |
| 0-25th quantile | | 0.260 | 0.197 | 0.063*** |
| 25th -50th quantile | | 0.242 | 0.277 | -0.035*** |
| 50th -75th quantile | *Ref* | 0.243 | 0.28 | -0.036*** |
| 75th -100th quantile | | 0.254 | 0.246 | 0.008 |
| **Dwelling characteristics** | | | | |
| *Dwelling type:* | | | | |
| Apartment | *Ref* | 0.669 | 0.72 | -0.051*** |
| Detached | | 0.255 | 0.182 | 0.073*** |
| *Number of bedrooms:* | | | | |
| 1–2 bedrooms | | 0.607 | 0.625 | -0.018** |
| 3 bedrooms | *Ref* | 0.303 | 0.302 | 0.002 |
| 4 bedrooms | | 0.069 | 0.056 | 0.013*** |
| 5+ bedrooms | | 0.021 | 0.017 | 0.004** |
| *District supply of:* | | | | |
| Heating | | 0.706 | 0.798 | -0.092*** |
| Hot water | | 0.651 | 0.776 | -0.125*** |
| Gas | | 0.695 | 0.49 | 0.204*** |
| *Cooking via electric stove* | | 0.196 | 0.393 | -0.197*** |
| *Location* | | | | |
| Urban | *Ref* | 0.666 | 0.938 | -0.272*** |
| Rural | | 0.334 | 0.062 | 0.272*** |

*Ref* is the omitted reference category. $^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

We can see that there are some noticeable differences across the households in the treatment and control regions. Firstly, the level of urbanization in the treatment regions is about 27% higher than compared to the control regions. This in turn is reflected in other variables of interest. For instance, the share of detached dwellings is naturally higher in rural areas. Thus, in the regions with flat tariff schemes (control regions), the share of detached dwellings is more than 7% higher. The share of households with a district supply of heating and hot water, on the other hand, is about 9% and 12% respectively higher in the more urbanized treatment regions.

District delivery of gas, on the contrary, is higher in the less urbanized control regions. This result seems to be counterintuitive at first, however, taking into account that one of the three experimental regions (Krasnoyarsk krai) does not have access to the district gas supply (Piterkina, 2021) this result is not surprising. As a result, the share of households having an electric stove at their households is higher in the treatment regions as well.

For the sake of studying the heterogeneous effects of the introduction of the IBT on the propensity to purchase dirty fuels besides the standard household socio-economics, I have also included the characteristics of the household head into the econometric model specification. In the context of the RLMS-HSE the head of the household is assigned as follows:

*"The head of the household is assigned according to the following demographic hierarchy: (1) the oldest working-aged male in the household, (2) if no working-aged males, then the oldest working-age female, (3) if no working-age females, then the youngest retirement-age male, (4) if no retirement-age males, then the youngest retirement-age female, and finally (5) if no retirement-age females, then the oldest child." (https://rlms-hse.cpc.unc.edu/data/faq/).*

Analyzing the characteristics of the household heads across the treatment and control regions we can also notice some minor differences. The proportion of the relatively younger (those below the age of 36, and those between the age of 36 and 45) household heads is larger in the treatment regions, while the proportion of the household heads of older age categories is larger in the control regions.

Turning to the description of the educational profiles we can see that about a quarter of the households across both types of regions are headed by people with higher education. Another quarter is headed by people with a secondary-technical education. Approximately 30% of the household heads have a secondary education, and about one-sixth have a primary education.

The employment status of the household heads is fairly identical across the households in the treatment and control regions. About 60% of the household heads are employed, and about a quarter are pensioners. More than 5% declare to be unemployed, and more than 2% report to be self-employed. The remaining households are headed by housekeepers, people in childcare (about 1% in total), and students (about 2%). Approximately 1.5% of the household heads report being disabled.

The households in the treatment regions also tend to be larger. The share of households with two or three members, and four and more members is slightly larger in the treatment regions, while the share of households with a single member is about 20% larger in the control regions.

Most likely due to the differences in the levels of urbanization, the households' income profiles tend to be a little different across the control and the treatment regions. The share of the households in the $25^{th}$-$50^{th}$ percentiles, and the $50^{th}$-$75^{th}$ percentiles is about 3 percentage points higher in the treatment regions, while the share of the households in the lower $0^{th}$-$25^{th}$ income percentile is higher (about 6 percentage points) in the control regions. There are, however, no statistically significant differences across the share of the households in the $75^{th}$-$100^{th}$ percentiles of income.

The share of renters is larger in the treatment regions (9.7% vs 7.5%). The share of households receiving various subsidies and discounts for utilities is approximately identical across the two types of regions with about 28% receiving subsidies, and about 17% receiving discounts. The share of households with various arrears for utilities is about 7% both in treatment and control regions.

The size of the dwelling is also approximately identical across the regions with about 60% of all dwellings having one to two rooms, and 30% of the households having three rooms.

The share of female-headed households is also identical across the regions with almost 30% of all households being female-headed both in the treatment and control regions.

As can be seen, there are some statistically significant differences in the households' characteristics across treatment and control regions. I am addressing this issue by employing "coarsened exact matching" (cem) procedures outlined in the next section.

## 4. Empirical Methodology

To estimate the heterogeneous effects of the introduction of the IBP in the three experimental regions of Russia I use an empirical framework similar to the one applied by Harold et al., (2018). However, unlike Harold et al., (2018), who use a random effects estimator, I employ a fixed effects estimator to avoid the imposition of the additional assumption that the independent variables in the model are uncorrelated with the unobserved household-level heterogeneity invariant over time. Equation 1 demonstrates our empirical specification.

$$Y_{it} = a_i + \tau_t + \beta DD_{rt} + \Pi ln P_{rt} + \boldsymbol{X}_{it}\theta + \boldsymbol{W}_{rt}\Gamma + \boldsymbol{H}_{it}DD_{rt}\delta + \boldsymbol{S}_{it}DD_{rt}\varphi + \boldsymbol{D}_{it}DD_{rt}\eta + \varepsilon_{it} \quad (1)$$

In this equation, $DD$ stands for the dummy variable indicating a treatment region interacted with the post-treatment years. In the context of standard difference-in-difference (DD) empirical specification the coefficient on $DD$ is of main interest to the researcher. However, in our context besides $\beta$ we also concentrate on $\delta$, $\varphi$, and $\eta$ the coefficients on the characteristics of the household head, the household's socio-economics, and the dwelling characteristics respectively interacted with $DD$. In our empirical specification, these coefficients will estimate the heterogeneous effect of the introduction of IBT for residential electricity.

Besides the main variables of interest, our empirical specification also includes time-varying controls. Specifically, vector $X$ contains such household-level variables as the logarithm of per-capita household income, household size, and the logarithm of utility discounts or subsidies (if any) received by the household in monetary amount (adjusted for 2019 roubles).

In our empirical specification, $P$ controls for the average residential electricity tariff. I accomplish this by proxying the average prices for electricity by inputting to each household the logarithm of the average price per unit of electricity by the utilities in the area (see, Alberini et al., 2011 for more details). The vector $W$ includes the logarithms of the monthly average heating degree days, wind speed, precipitation, and humidity levels to control for the regional weather variability across Russia. The $\alpha$ and $\tau$ stand for the household fixed effects and year fixed effects respectively. $\varepsilon$ stands for the idiosyncratic error term.

Our dependent variable $Y$ is a binary indicator variable that takes a value of one $(Y = 1)$ if the family has purchased any of the four types of dirty fuels listed in the questionnaire during the month preceding the interview, and zero $(Y = 0)$ otherwise.

Since the nature of our dependent variable is binary one can estimate Equation 1 via various methods like probit, logit, or linear probability model (LPM). I decided to estimate our model via LPM as in the context of panel data LPM is more convenient, computationally tractable, and has less bias than its non-linear counterparts like probit or logit (see, Fernandez-Val, 2009; Friedman and Schady, 2012).

Furthermore, just 3.4% of the households in our case report buying any kind of dirty fuel. It was demonstrated that the LPM with fixed effects produces more precise estimates and predicted probabilities than the maximum likelihood (ML) specifications used by its non-linear counterparts in the case of rare events, specifically when the dependent variable has less than 25% of ones (or more than 75% of ones) (Timoneda, 2021).

Although LPM is frequently regarded as a better alternative to its nonlinear counterparts in the context of panel data, any regression estimated by LPM may suffer from two potential LPM-specific issues. The first issue is that when estimated from a binary response variable, OLS suffers from heteroscedasticity. This problem, however, is easily solved by employing standard heteroscedasticity robust error estimates.

The second issue, which is more complicated, results from the fact that LPM estimates are not constrained to the unit interval. As a result, probabilities that are greater than one or lower than zero can be estimated. The fact that some projected values are outside the unit interval, however, may not be as significant if the primary goal is to estimate the partial effect on the likelihood of response averaged over the distribution of the independent variables (Wooldridge, 2002 (p. 455)). Additionally, if none or very few predicted probabilities lie outside the unit interval, LPM is unbiased and consistent (Horrace & Oaxaca, 2006). In Section 5, I demonstrate that a very few estimated probabilities are beyond the unit interval in our case.

In addition, to account for the relatively smaller proportion of the treatment households within our sample, as well as some structural differences in the observed characteristics between the households in the treatment and control regions I apply the coarsened exact matching (cem) procedure as described in (Iacus et al., 2012).

The cem is a relatively new development in the literature. It belongs to a new class of so-called “monotonic imbalance bounding” (MIB) matching methods. As opposed to its counterparts like “propensity score matching” (PSM), and “Mahalanobis “matching which belongs to the so-called “equal percent bias reducing” matching methods, the cem works in sample and requires no assumptions about the data generation process, except the usual “ignorability” assumptions (ibid).

Moreover, it was also shown that the cem-based causal estimates possess a large variety of powerful statistical properties, and dominate commonly used EPBR matching methods in a large variety of real and simulated data sets (Iacus et al., 2009, 2011, 2012; King and Nielsen, 2019).

Any matching method should have a clearly defined measure of imbalance if one is to identify whether the application of matching was successful and whether the imbalance was indeed reduced between the treatment and control observations. Some researchers argue that it is only necessary to make sure that the weighted means of the chosen variables are balanced across the groups.

However, as argued by Iacus et al., (2012) the purpose of matching is to reduce imbalance and thus model dependence, and therefore assuming that the analysis model is correct because of the balance in the weighted averages of the model variables is simply incorrect; for the correct inference, the goal of matching should be to match as much of the entire empirical distribution as possible.

Thus Iacus et al., (2011) introduce the multivariate measure of imbalance via an L1 distance measure defined as:

$$L_1(f, g) = \frac{1}{2}\sum_{l_1 \dots l_k} | f_{l_1 \dots l_k} - g_{l_1 \dots l_k} | \qquad (2)$$

In this equation $f_{l_1 \dots l_k}$ and $g_{l_1 \dots l_k}$ are the $k$-dimensional relative frequencies for the treatment and control observations respectively. They are calculated from the cross-tabulation of the coarsened covariates.

Unlike most imbalance measuring methods in the literature that were designed to measure the imbalance in the mean of each variable between the treatment and the control groups, an L1 multivariate measure of imbalance takes mean imbalance only as a part of the goal, and concentrates rather on a multidimensional measure of the imbalance between the groups. It does so by measuring the distance between the multivariate empirical distributions (histograms) of the chosen covariates between the treated and control units.

## 5. Results

I start by examining the matching statistics between the experimental and control regions. Tables 3 and 4 present the univariate and multivariate imbalance statistics on the chosen covariates of interest. Specifically, as outlined in Turdaliev and Janda (2023), this study also matches the two samples on such characteristics as per-capita income of the household, household size, square footage of the dwelling, whether the dwelling is located in the urban area, and whether it has access to the district delivery of heating, hot water, or gas.

As can be seen from the Table below we can observe an overall improvement in both univariate and multivariate imbalance statistics after the application of a cem procedure. The multivariate L1 distance imbalance statistics improved from about 0.75 to approximately 0.67, while the univariate L1 imbalance statistics dropped to virtually zero after the application of cem.

**Table 3**

| **Full Sample** | |
|---|---|
| **Multivariate L1 distance:** | **0.74840665** |
| **Univariate imbalance:** | |

| Variable | L1 | mean | min | 25% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|
| Household size | 0.03776 | 0.04364 | 0 | 0 | 0 | 0 | -3 |
| Dwelling size (sq.m) | 0.11443 | -3.6587 | 2 | -1.8 | -1.4 | -2.5 | -125 |
| Detached dwelling | 0.07927 | -0.07927 | 0 | 0 | 0 | -1 | 0 |
| Urban | 0.2731 | 0.2731 | 0 | 1 | 0 | 0 | 0 |
| Hot-water | 0.13001 | 0.13001 | 0 | 1 | 0 | 0 | 0 |
| Dist. Gas supply | 0.21861 | -0.21861 | 0 | 0 | -1 | 0 | 0 |
| Per capita income | 0.09338 | -638.64 | 1152.8 | 1314 | 719.29 | -219.79 | 77728 |
| Dist. heating | 0.0985 | 0.0985 | 0 | 1 | 0 | 0 | 0 |

| **Matched sample** | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Multivariate L1 distance:** | | | | **0.67404463** | | | |
| **Univariate imbalance:** | | | | | | | |
| Variable | L1 | mean | min | 25% | 50% | 75% | max |
| Household size | 0.04179 | 0.103 | 0 | 0 | 0 | 0 | -2 |
| Dwelling size (sq.m) | 0.10689 | -1.539 | 2 | 0.6 | -0.5 | -1 | . |
| Detached dwelling | 5.4e-15 | 5.7e-15 | 0 | 0 | 0 | 0 | 0 |
| Urban | 6.2e-15 | 5.4e-15 | 0 | 0 | 0 | 0 | 0 |
| Hot-water | 2.2e-14 | 3.4e-14 | 0 | 0 | 0 | 0 | 0 |
| Dist. Gas supply | 7.6e-14 | 1.4e-13 | 0 | 0 | 0 | 0 | 0 |
| Per capita income | 0.07359 | -2932.7 | 1152.8 | -40.207 | -931.53 | -2699.3 | 77728 |
| Dist. heating | 9.2e-15 | 1.1e-14 | 0 | 0 | 0 | 0 | 0 |
| **Number of strata:** | | | | **72** | | | |
| **Number of matched strata:** | | | | **36** | | | |
| | | | **Control** | | | **Treatment** | |
| **All** | | | **52948** | | | **5514** | |
| **Matched** | | | **41693** | | | **5514** | |
| **Unmatched** | | | **11255** | | | **0** | |

After improving the balance of the covariates between the experimental and control regions, we can run a standard difference-in-difference (DD) regression specification in the context of panel data with fixed effects as described by Equation 1.

**Table 4**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| *D* | 0.046** | 0.059** | 0.151*** | 0.151*** | 0.158*** |
| | (0.021) | (0.023) | (0.039) | (0.039) | (0.039) |
| lnAvPrice | -0.025 | -0.024 | -0.020 | -0.020 | -0.030* |
| | (0.017) | (0.017) | (0.017) | (0.017) | (0.016) |
| **Household head's characteristics** | | | | | |
| *Female*D* | -0.035** | -0.034** | -0.030** | -0.030** | -0.030** |
| | (0.014) | (0.014) | (0.014) | (0.014) | (0.014) |
| *Age*D* | | | | | |
| | | | | | |
| <36 years | -0.002 | -0.002 | -0.003 | -0.003 | -0.003 |
| | (0.014) | (0.014) | (0.014) | (0.014) | (0.014) |
| 36–45 years *(Ref)* | | | | | |
| | | | | | |
| 46–55 years | 0.002 | 0.002 | 0.002 | 0.002 | 0.002 |
| | (0.018) | (0.018) | (0.018) | (0.018) | (0.018) |
| 56–65 years | 0.012 | 0.011 | 0.009 | 0.009 | 0.010 |
| | (0.020) | (0.020) | (0.020) | (0.020) | (0.020) |
| 65+ years | 0.004 | 0.006 | 0.003 | 0.003 | 0.003 |
| | (0.023) | (0.023) | (0.022) | (0.022) | (0.022) |
| *Education*D* | | | | | |
| | | | | | |
| Primary | 0.002 | 0.000 | -0.004 | -0.004 | -0.004 |
| | (0.024) | (0.024) | (0.023) | (0.023) | (0.023) |
| Secondary *(Ref)* | | | | | |
| | | | | | |
| Secondary-technical | -0.012 | -0.012 | -0.010 | -0.011 | -0.010 |
| | (0.013) | (0.013) | (0.013) | (0.013) | (0.013) |
| Higher | -0.015 | -0.013 | -0.009 | -0.010 | -0.010 |
| | (0.012) | (0.012) | (0.012) | (0.012) | (0.012) |
| *Employment status*D* | | | | | |
| | | | | | |
| Employed *(Ref)* | | | | | |
| | | | | | |
| Self-employed | -0.020 | -0.017 | -0.015 | -0.015 | -0.015 |
| | (0.015) | (0.015) | (0.015) | (0.015) | (0.015) |
| Unemployed | 0.000 | -0.000 | 0.000 | 0.001 | 0.000 |
| | (0.019) | (0.019) | (0.019) | (0.019) | (0.019) |
| Pensioner | 0.014 | 0.014 | 0.012 | 0.012 | 0.012 |
| | (0.017) | (0.017) | (0.017) | (0.016) | (0.017) |
| Housekeeper | 0.128* | 0.127* | 0.129* | 0.131** | 0.130* |
| | (0.071) | (0.070) | (0.066) | (0.066) | (0.066) |
| Child-care | 0.025* | 0.026* | 0.027** | 0.029** | 0.028** |

| | | | | | |
|---|---|---|---|---|---|
| | (0.013) | (0.014) | (0.014) | (0.013) | (0.013) |
| Disabled | 0.038 | 0.039 | 0.046 | 0.046 | 0.045 |
| | (0.030) | (0.030) | (0.030) | (0.030) | (0.030) |
| Student | -0.002 | -0.003 | -0.002 | -0.002 | -0.002 |
| | (0.019) | (0.019) | (0.019) | (0.019) | (0.019) |
| **Household characteristics** | | | | | |
| *n of household members *D* | | | | | |
| | | | | | |
| 1 person | -0.011 | -0.013 | -0.012 | -0.013 | -0.013 |
| | (0.015) | (0.015) | (0.014) | (0.014) | (0.014) |
| 2-3 people *(Ref)* | | | | | |
| | | | | | |
| 4+ people | -0.004 | -0.003 | -0.005 | -0.004 | -0.004 |
| | (0.017) | (0.017) | (0.017) | (0.017) | (0.017) |
| *Tenure*D* | | | | | |
| | | | | | |
| Rented | -0.015 | -0.018 | -0.012 | -0.013 | -0.013 |
| | (0.019) | (0.019) | (0.019) | (0.019) | (0.019) |
| Owned *(Ref)* | | | | | |
| | | | | | |
| *Arrears and Benefits*D* | | | | | |
| | | | | | |
| Subsidies | 0.023** | 0.024** | 0.028*** | 0.027*** | 0.028*** |
| | (0.010) | (0.010) | (0.010) | (0.010) | (0.010) |
| Discounts | -0.001 | -0.001 | 0.004 | 0.004 | 0.004 |
| | (0.012) | (0.012) | (0.012) | (0.012) | (0.012) |
| Arrears | -0.008 | -0.010 | -0.008 | -0.008 | -0.008 |
| | (0.010) | (0.010) | (0.010) | (0.010) | (0.010) |
| *Income quantiles*D* | | | | | |
| | | | | | |
| 0-25$^{th}$ quantile | -0.015 | -0.015 | -0.019 | -0.019* | -0.019 |
| | (0.012) | (0.012) | (0.011) | (0.011) | (0.011) |
| 25$^{th}$ -50$^{th}$ quantile | 0.002 | 0.002 | 0.000 | 0.000 | 0.000 |
| | (0.009) | (0.009) | (0.009) | (0.009) | (0.009) |
| 50$^{th}$ -75$^{th}$ quantile *(Ref)* | | | | | |
| | | | | | |
| 75$^{th}$ -100$^{th}$ quantile | 0.005 | 0.004 | 0.006 | 0.007 | 0.006 |
| | (0.008) | (0.008) | (0.008) | (0.008) | (0.008) |
| **Dwelling characteristics** | | | | | |
| | | | | | |
| *Number of bedrooms*D* | | | | | |
| | | | | | |
| 1–2 bedrooms | -0.015 | -0.016 | -0.008 | -0.008 | -0.008 |
| | (0.013) | (0.013) | (0.013) | (0.013) | (0.013) |
| 3 bedrooms *(Ref)* | | | | | |
| | | | | | |
| 4 bedrooms | 0.010 | 0.008 | -0.003 | -0.003 | -0.004 |

| | | | | | |
|---|---|---|---|---|---|
| | (0.027) | (0.027) | (0.025) | (0.025) | (0.025) |
| 5+ bedrooms | 0.078 | 0.079 | 0.043 | 0.043 | 0.042 |
| | (0.057) | (0.056) | (0.054) | (0.054) | (0.054) |
| *Location * D* | | | | | |
| | | | | | |
| Rural | 0.057 | 0.044 | -0.032 | -0.031 | -0.031 |
| | (0.063) | (0.064) | (0.068) | (0.068) | (0.068) |
| Urban *(Ref)* | | | | | |
| | | | | | |
| *District supply of () *D* | | | | | |
| | | | | | |
| Gas | | $-0.027^{**}$ | $-0.026^{**}$ | $-0.027^{**}$ | $-0.026^{**}$ |
| | | (0.012) | (0.012) | (0.012) | (0.012) |
| | | | | | |
| Heating | | | $-0.112^{***}$ | $-0.111^{***}$ | $-0.111^{***}$ |
| | | | (0.030) | (0.030) | (0.030) |
| | | | | | |
| _cons | 0.144 | 0.141 | 0.120 | 0.158 | $0.239^{**}$ |
| | (0.109) | (0.109) | (0.110) | (0.102) | (0.105) |
| *Weather variables* | *yes* | *yes* | *yes* | *no* | *yes* |
| *Year fixed effects* | *yes* | *yes* | *yes* | *yes* | *yes* |
| *Household fixed effects* | *yes* | *yes* | *yes* | *yes* | *yes* |
| *CEM* | *yes* | *yes* | *yes* | *yes* | *no* |
| *N* | 47182 | 47182 | 47182 | 47182 | 58432 |
| *n of predicted values* $\notin [0,1]$ | 67 | 106 | 140 | 152 | 153 |

Standard errors are clustered at the household level: $^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$
*Ref* is omitted reference category

The results of the regression are reported in Table 4. Generally, we can observe that the introduction of IBT for residential electricity in the experimental regions of Russia resulted in the increased propensity to purchase dirty fuels among the population in these regions as evidenced by the positive and statistically significant coefficient on the DD estimator in all regression specifications.

I first start by running a regression (Column 1) without major dwelling characteristics that impact energy consumption. Thus Column 1 reports the DD regression output excluding such dwelling characteristics as a connection to district heating, how-water, and piped gas.

The impact of IBT averaged out over the households without controlling for the major energy characteristics of the dwelling is equal to 4.6 percentage points. This indicates that without controlling for dwelling's energy characteristics, on average, the households residing in the experimental regions have a 4.6 percentage points, or about 83%, higher propensity to purchase dirty fuels due to the introduction of IBT compared to their counterparts in the control regions.

The effect growth in size after we start including interactions for the major dwelling energy controls. Particularly, after we interact the main treatment indicator (*D*) with a dummy on whether the household has access to the district gas supply the estimated parameter on the main treatment variable increases to 5.9 percentage points, or about 60% higher propensity to purchase dirty fuels compared to similar households (households with no district gas supply) in the control regions. The effect of the main treatment indicator continues to grow to 15.1 percentage points once we also interact the main treatment indicator with a dummy variable on whether the dwelling has an access to the district heating.[6] These types of households (households with no district gas supply and district heating supply) increase their propensity to purchase dirty fuels by about 32% compared to their counterparts (households with no district gas supply and district heating supply) in control regions.

The significant heterogeneity of the IBT treatment with respect to the household's energy characteristics is not surprising, especially in the context of Russia where over 70% of the households are heated, and receive hot water via district supply (Rosstat, 2021) at a subsidized below the market prices. Thus, these types of households are less sensitive to various price fluctuations of electricity, as opposed to the households that do not have such privileges. In our sample, the households that are heated via district are, on average, 11.2 percentage points (or 74%) less prone to purchase dirty fuels, and households that receive

[6] I do not estimate the heterogenous effects of the IBT with respect to such dwelling characteristics as whether the dwelling is connected to the district hot-water supply, whether it is a detached single-family building, and whether the household has an electric stove. Upon the inspection these variables were found to be highly correlated with some other variables present in our specification. More specifically, there is a high pairwise correlations between connection to the district heating and whether the dwelling is a single-family detached building (-0.83), connection to the piped district gas delivery and whether there is an electric stove (-075) and connection to the district hot-water delivery and district heating (0.76).

piped gas are 2.7 percentage points (or 18%) less prone to purchase dirty fuels due to the introduction of IBT.

These findings are in line with Harold et al., (2018) who conclude that households with higher base energy consumption are more sensitive to demand-side energy stimuli, and with Will (1981) and Reiss and White (2005) who conclude that the dwelling's energy characteristic are important determinants of the energy demand.

Researchers are also often interested in whether households respond to changes in the rate structure, or changes in price (Zhang et al., 2017). In our particular case, we can see that the households in Russia do not seem to respond to the variation in price. The coefficient on the average regional price (as opposed to the coefficient on the rate structure) of residential electricity is statistically insignificant in all specifications.

Turning to other dwelling and household characteristics, I document no evidence that the purchase of dirty fuels due to the introduction of IBT is heterogeneous with respect to the age of the household's head. This is in contrast to Harold et al., (2018) who find that the demand side stimuli are more effective in households where the household head is above 46 years old, and Mills and Schleich (2012), who conclude that the households with older residents are less likely to adopt energy conservation practices in the home, and Lin and Zhu (2021) who conclude that the energy-saving effect is more pronounced among residents over 50 years old.

Also, in contrast to Harold et al., (2018) and Mills and Schleich (2012) I find no evidence that the stimuli vary among the households that are less educated. In the case of Russia, the educational profile of the household head proved to be statistically insignificant.

In addition, in contrast to Liu and Lin (2020), and Harold et al., (2018), I do not document that the number of people residing in the dwelling affects the strength of the demand side stimuli. I also do not find that the tenure (rented vs owned) affects the purchase of dirty fuels in the case of Russia.

The size of the house (proxied by the number of rooms) also proved to be a statistically insignificant determinant of the ATE. This is, again, in contrast to Harold et al (2018) who find that larger dwellings are more responsive to stimuli, and to Dolan and Metcalfe (2015) who reports that the effect of ATE is smaller for larger dwellings.

I also find little evidence that the purchase of dirty fuels is sensitive to a household's income. This is in sharp contrast to papers that studied the impacts of the implementation of the IBT in China (see, Sun and Lin, 2013; Sun, 2015; Lin and Zhu, 2021) that conclude that the household's income is, in general, a statistically significant determinant of the household's energy behavior towards the introduction of IBT.

We can observe, however, that in the case of Russia, the effect of the treatment varies with respect to the gender of the household head. In particular, those households which are headed by females are about 3 percentage points (or about 20%) less prone to purchase dirty fuels due to the introduction of IBT.[7] This is in contrast to Harold et al., (2018) who show that in the case of Ireland, the gender of the household head is an insignificant determinant of the ATE.

The employment status of the household head also proved to be a statistically significant determinant of the ATE. In our case, the households where the household head's primary role is housekeeping are about 12.9 percentage points (or about 85%) more prone to purchase dirty fuels due to the introduction of IBT, whereas the households where the household head's primary role is child-care are about 2.7 percentage points (or about 18%) more prone to purchase dirty fuels due to the IBT. In contrast to Harold et al., (2018) I do not

[7] Since these are the primary regression estimates that include the entire set of covariates and have previously undergone a matching procedure, we concentrate on Column 3 when interpreting the heterogenous effects in our regression.

find any evidence that households headed by the self-employed are more sensitive to the treatment.

The strong heterogeneity of the treatment with respect to the employment status of the household head can mainly be explained by the income effect. As explained previously in the context of RLMS-HSE the oldest individual in the household with an active income stream is selected as the household head. This means that the households headed by people who are on child-care or whose primary role is housekeeping simply may be in a disadvantaged financial situation, and therefore are forced to substitute their energy needs by purchasing cheaper dirty alternatives due to the introduction of IBT.

The results also do not indicate that rural households are more (or less) sensitive to the introduction of the IBT. The coefficient on the interaction of the main treatment dummy with the dummy indicating whether the dwelling is located in a rural area is statistically insignificant.

I also find that the households that receive subsidies (cashback) are more sensitive toward the introduction of the IBT. This result is in accord with Turdaliev and Janda (2023) who find a positive association between receiving subsidies by the household and the propensity purchase of dirty fuels. The results show that these households are about 2.8 percentage points (or about 18.5%) more prone to purchase dirty fuels due to the introduction of IBT. The positive and statistically significant effect of the subsidies indicator can be explained by the fact that, unlike discounts (which are statistically insignificant), the receipt of the subsidies is conditional on the ratio of overall spending of the household on the utilities and its total income. Thus, the households that receive subsidies are usually spending a higher share of their income on utilities and, therefore, are more sensitive towards the demand side stimuli.

## 6. Conclusion and policy implications

In this paper, I analyze the heterogenous effects of the experimental introduction of IBT for residential electricity on the propensity to purchase dirty fuels in a number of regions of Russia. While previous research has investigated the impact of this experimental introduction of IBT on such factors as electricity consumption, propensity to invest in major electrical appliances, and the propensity to purchase dirty fuels (Turdaliev, 2023; Turdaliev, 2021; Turdaliev and Janda, 2023), none have explored the differential impact with respect to dwelling and household characteristics. However, the examination of these heterogeneous effects is essential for a proper understanding of the impacts of IBT and proper policy targeting and implementation.

I document the presence of heterogeneous effects of the introduction of IBT for residential electricity in three experimental regions of Russia. The results indicate that dwelling energy characteristics play a crucial role in determining the impact of the demand side stimuli. Specifically, households connected to district heating networks and piped gas are less likely to purchase dirty fuels due to the introduction of IBT (74% and 18% respectively). In contrast to some previous studies on energy reforms conducted in other developing, as well as developed countries, no heterogeneous effects were found with respect to house size, number of residents, age of household head, education of household head, or tenure status.

However, the gender of the household head and employment status were found to play a crucial role in determining the effectiveness of the treatment. Households headed by females were 20% less likely to purchase dirty fuels due to the introduction of IBT, while households with a household head in child-care were 18% more likely to purchase dirty fuels. Households where the household head identifies as a housekeeper were also more sensitive to the introduction of IBT, with an 85% increase in their propensity to purchase dirty fuels.

Additionally, households receiving subsidies in the form of cashbacks were found to be more sensitive to the implementation of IBT, consistent with Turdaliev and Janda's (2023) finding that subsidies are positively correlated with the propensity to purchase dirty fuels. The implementation of IBT increased the propensity of these households to purchase dirty fuels by 18.5%.

The results of this study demonstrate that the introduction of IBT for residential electricity has a disproportionately high impact on certain types of households, despite household and dwelling specific cut-offs for second block consumption intended to minimize negative social implications. These findings suggest that there is room for refinement of the calculation of social norms by policymakers to take into account the heterogeneous impacts of IBT and minimize its negative aspects.

Moreover, policymakers can benefit from knowing which parts of the population are particularly vulnerable to negative aspects of energy demand-side stimuli programs and adapt energy policies to target these vulnerable populations through appropriate tariffs, social norms, and energy subsidy programs.

The results of this study have important implications beyond the context of Russia as well. The findings are relevant to other developing and transition economies seeking to implement energy reforms, including pricing mechanisms like IBT. The research demonstrates the importance of accounting for heterogenous effects across socio-economic and household characteristics when designing and implementing such policies, to avoid adverse effects on vulnerable households. The insights gained from this study can guide policymakers in developing tailored policy interventions that balance environmental and social objectives, which can ultimately support the transition to a sustainable energy future. Therefore, the results of this study can serve as a useful reference point for policymakers seeking to design effective energy policies that benefit both the environment and society.

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**Appendix**

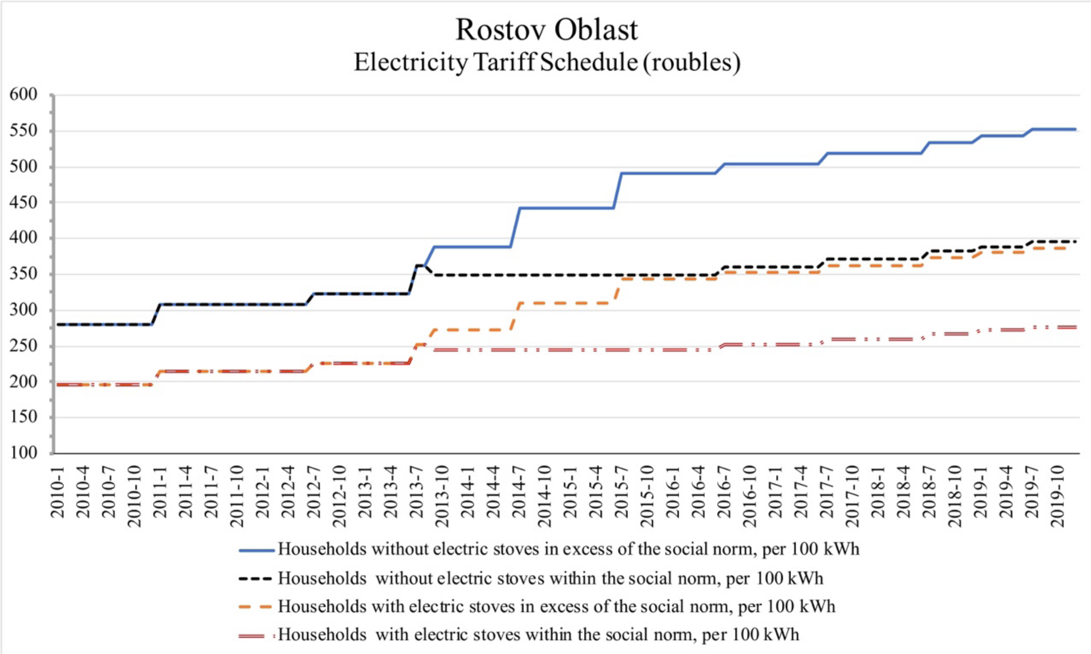


**Figure 1.** Electricity tariff schedule for Rostov Oblast.

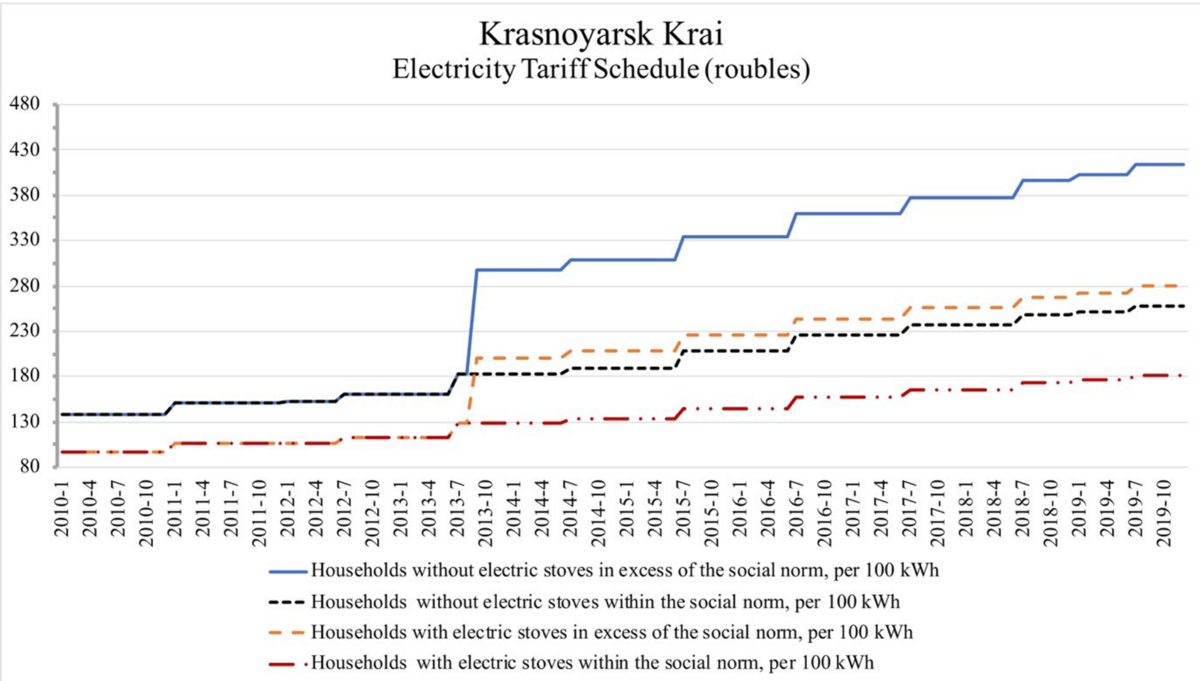


**Figure 2.** Electricity tariff schedule for Krasnoyarsk Krai.

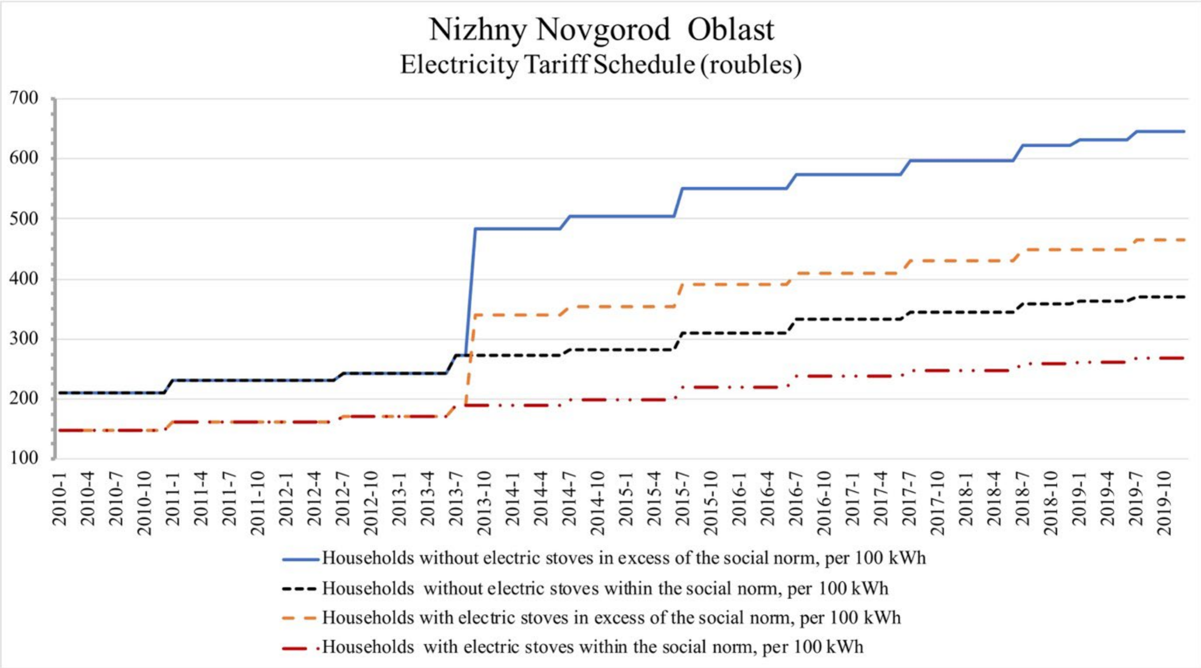


**Figure 3.** Electricity tariff schedule for Nizhny Novgorod Oblast.

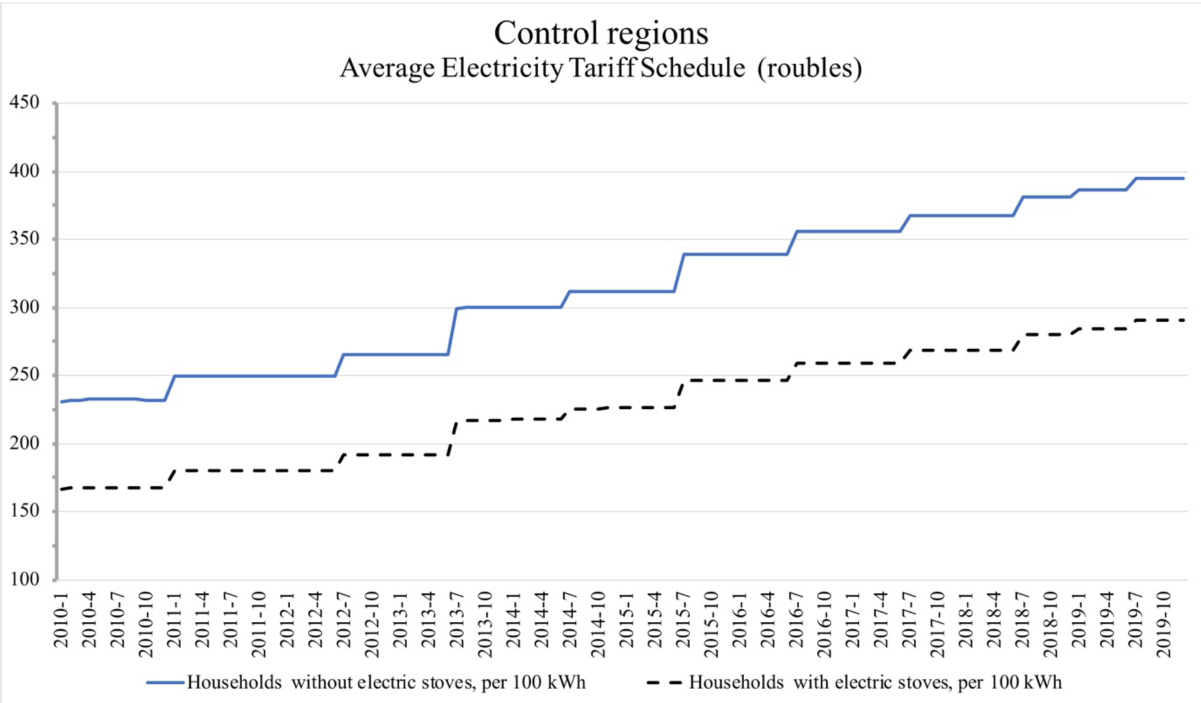


**Figure 4.** Average electricity tariff schedule for control regions.

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