# Do Consumers Distinguish Fixed Cost from Variable Cost? "Schmeduling" in Two-Part Tariffs in Energy

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## Online Appendix

## Appendix A: Handbook of residential metered heating

In this online appendix, we show the original content of the explanation of the residential metered heating that was included in the handbook delivered to all households in our sample along with its English translation.

供热计量试验收费实行两部制计费办法，即容量热费和计量热费。

用户热费=容量热费（固定热费）+计量热费（可变热费）

1.容量热费：

容量热价=现行面积热价×50%=25元/㎡×50%=12.5元/㎡。

容量热费=12.5元/㎡×供热建筑面积。

2.计量热费：

计量热价：0.091元/kwh（25.28元/GJ）。

计量热费=0.091元/kwh×当年度采暖期消耗热量。

Kwh和GJ都为热量单位，分别称为千瓦时和吉焦。

例如：某用户供热建筑面积为100平米，整个采暖期的耗热量为8000kwh，则用户的容量热费为12.5元/平米×100平米=1250元；计量热费为0.091元/kwh ×8000kwh=728元，用户热费应为容量热费和计量热费之和为1250元+728元=1978元。用户按照面积收费原为100平米×25元/平米=2500元。所以，实施供热计量收费后，应向用户退费2500-1978=522元。

[English translation by the authors]: We will implement a two-part tariff for metered heating charges: a fixed charge and a charge for metered heating usage.

Heating bill = Fixed cost + variable cost (depending on metered heating usage)

- Fixed cost = 12.5 RMB/$m^2$ * home size (in square meter)

- Variable cost = 0.091 RMB/kWh * total heating usage of a heating season

Here is one example on how a user's heating bill changes after switching to the two-part tariff. Suppose a user's home has 100 $m^2$, and the heating usage of a heating season is 8000 kWh. The fixed cost is 12.5 RMB/$m^2$ * 100 $m^2$ = 1250 RMB; the variable cost is 0.091 RMB/kWh * 8000 kWh = 728 RMB. The total heating cost is the sum of fixed cost and variable cost: 1250 RMB + 728 RMB = 1978 RMB. Previously, when the heating cost was fixed, the user's heating bill was 100 $m^2$ * 25 RMB / $m^2$ = 2500 RMB. Therefore, after the implementation of the two-part tariff, the user can save 2500-1978 = 522 RMB.

## Appendix B: Results using the OLS with Two-Way Fixed Effects

Recent developments in the econometrics literature highlight that the OLS could produce biased estimates for two-way fixed effects models such as equation (1) if treatment effects are heterogeneous across households and/or time (de Chaisemartin and D'Haultfœuille, 2020; Callaway and Sant'Anna, 2021). To address this problem, in our main analysis in the paper, we use a method developed by de Chaisemartin and D'Haultfœuille (2020) to estimate equation (1) so that we do not impose the assumption of homogeneity in the treatment effects.

In this appendix, we compare our estimation results based on the method developed by de Chaisemartin and D'Haultfœuille (2020), which we report in Table 3, and our estimation results based on the conventional OLS with two-way fixed effects, which we report in Table A.7 in this appendix. We also would like to note that an earlier version of our working paper also used the conventional OLS with two-way fixed effects.

We find that the results are indeed different between the two estimation methods. de Chaisemartin and D'Haultfœuille (2020) show that the conventional OLS does not produce the correct average treatment effects when the treatment effects are heterogeneous across individuals and/or time. This is because the conventional OLS produces an incorrect weighted average of treatment effects across cohorts and time. In addition, some of these wrong weights can be negative.

To be more precise, de Chaisemartin and D'Haultfœuille (2020) define cohort $g$ and time $t$ for a staggered difference-in-differences method. Cohort $g$ is the group of units who share the timing of the start of treatment. $t$ is the time period of the data. de Chaisemartin and D'Haultfœuille (2020) show that $E\left[\hat{\beta}_{OLS}\right] = E\left[\sum_{g,t} W_{g,t}\Delta_{g,t}\right]$, where $\hat{\beta}_{OLS}$ to be an estimate from the OLS with two-way fixed effects, $\Delta_{g,t}$ is the ATE for group $g$ and time $t$, and $W_{g,t}$ is weights summing to one.

If $W_{g,t}$ are the relative sample size in $(g,t)$, $E\left[\hat{\beta}_{OLS}\right]$ is equal to the ATE across $(g,t)$. However, de Chaisemartin and D'Haultfœuille (2020) shows that $W_{g,t}$ in the OLS are not necessarily equal to the relative sample size in $(g,t)$ when the treatment effects are heterogeneous across $g$ and/or $t$. Moreover, many of $W_{g,t}$ can be negative. If many of $W_{g,t}$ are negative, $E\left[\hat{\beta}_{OLS}\right]$ could have an opposite sign of the correct ATE over $(g,t)$.

To explore this point in our data, we use the approach developed by de Chaisemartin and D'Haultfœuille (2020) to compute the weights $W_{g,t}$ in the conventional OLS with two-way fixed effects. In our application, the cohorts ($g$) are defined by the staggered timings of the introduction of the CBB, and the time ($t$) is year-by-month.

In Figure A.4, we show $W_{g,t}$ against the "correct" cohort-by-time weights, which are the relative sample size across the cohort-by-time cells. If the OLS uses weights that are equivalent to the correct weights (i.e., the OLS weights and correct weights line up at the 45-degree line in the figure), we can obtain the correct average treatment effect using the OLS.

However, the figure shows that many weights are not on the 45-degree line. Furthermore, 46% of the weights used by the OLS are negative. These results imply that the OLS estimates could be substantially different from the ATE and even could have a wrong sign. Indeed, we find that the sign of the estimates are different between the two methods for the quartile group 1 (column 1 in each table).

de Chaisemartin and D'Haultfœuille (2020) and Callaway and Sant'Anna (2021) describe that the OLS with two-way fixed effects could produce biased estimates because it effectively uses all units, including already-treated units, as control units. The estimation methods developed by de Chaisemartin and D'Haultfœuille (2020), which we use in our main analysis, address this problem. Another alternative approach is to use OLS to estimate a cohort-specific treatment effect. We divide our sample into cohorts based on the staggered timing of the introduction of the CBB. For each cohort, we use households who were not-yet-treated as a clean control group, which allows the cohort-specific OLS estimation to be a standard difference-in-differences without a staggered roll-out. To check the robustness of our main approach, we also estimate this cohort-specific OLS regression and take the weighted average of these estimates using the relative sample size as weight. We estimate that this approach produces results consistent with our main results.[28]

[28] Among available methods in this literature, we use de Chaisemartin and D'Haultfœuille (2020) for our analysis for a few reasons. First, their estimation method allows us to use ever-treated groups as the control groups. Second, the paper provides a readily available code to compute the weights $W_{g,t}$ in the conventional OLS with two-way fixed effects to investigate the source of bias as we present in Figure A.4.

## Appendix C: Calculation of the Externalities from Air Pollution

To calculate the additional welfare gain from reduced environmental externalities, we need to understand how household energy conservation affects local ambient pollution. First, we examine whether pollution emissions of the heating plant correlate with household heating usage. We use emission concentration data from the CEMS (Continuous Emission Monitoring System) monitor placed at the heating plant. Figure A.5a shows that as the daily total heating usage of households in this district increases, daily average $SO_2$ concentration also increases. This positive association is also observed for $NO_x$ and $PM$ in Figure A.5b and Figure A.5c. As a major polluting source in winter, the heating plant's emissions likely affect the local ambient air quality.

Second, we estimate the correlation between household heating usage and ambient air pollution, using air pollution data from a pollution monitor located in the residential area. In Table A.8, the ambient pollution data and the total heating usage of all households are both at the daily level, and we control for weather conditions, year-by-week fixed effects, and day of week fixed effects. We find that 1 percent increase in heating consumption is associated with 0.88 percent increase in ambient $\text{PM}_{10}$ concentrations, where the baseline $\text{PM}_{10}$ concentrations before the reform was 131. For each of the decile groups, we combine these estimates with the ITT estimate on heating usage to calculate the amount of reductions in $\text{PM}_{10}$ concentrations following the reform. Ito and Zhang (2020) and the average household income in Tianjin suggests that a Tianjin household's marginal willingness to pay for a reduction in $\text{PM}_{10}$ is 1.43 dollars per ug/m$^3$ of $\text{PM}_{10}$ per year. We then multiply these two estimates to measure the WTP for the policy-induced reduction in $\text{PM}_{10}$. We find that the marginal cost of the environmental externality is 0.0153 USD per kWh of heating usage.[29]

[29] Note that this estimate is likely to be a lower bound estimate for environmental externalities because this calculation does not include other potential environmental externalities than $\text{PM}_{10}$ and the MWTP for reductions in $\text{PM}_{10}$ in Ito and Zhang (2020) is a lower bound estimate for reasons described in that study.

# Appendix C: Additional Tables

Table A.1: Timing of the CBB policy

| Dependent variable: Rollout year of usage-based pricing | |
|---|---|
| Year of build | 0.051 |
| | (0.036) |
| Average condo size (square meter) | -0.005 |
| | (0.008) |
| Average home price per square meter (1,000 dollars) | 0.018 |
| | (0.016) |
| Annual heating usage prior to CBB (1,000 kWh) | -0.041 |
| | (0.034) |
| Number of Buildings | 484 |
| $R^2$ | 0.89 |

Notes: In this table, we test if observed building characteristics are associated with the staggered rollout timings of policy implementation. The observations are at the building level. The dependent variable is the rollout year of consumption-based billing. The estimation includes the meter installation year fixed effects.

Table A.2: Robustness of the Impacts of the CBB by the Quartiles of the Predicted Changes in Average Price (non-parametric controls of cohort trends are included)

Dependent variable: Log of daily heating usage

| | ITT | | | |
|---|---|---|---|---|
| | Quartile 1 | Quartile 2 | Quartile 3 | Quartile 4 |
| CBB | 0.216 | 0.019 | -0.159 | -0.154 |
| | (0.060) | (0.052) | (0.061) | (0.028) |
| Observations | 44,384 | 57,106 | 31,602 | 44,362 |

Notes: We divide customers by quartile based on their policy-induced changes in average price and estimate equation (1) for each quartile group separately. The estimation includes household fixed effects and year-by-month fixed effects. Non-parametric controls of cohort trends are included. Standard errors in parentheses are clustered at the building level.

Table A.3: Does Heating Usage Depend on Neighbors' Compliance Status?

| | ln(daily heating usage) |
|---|---|
| CBB*complied | -0.088 |
| | (0.016) |
| CBB*next door neighbor complied | -0.006 |
| | (0.014) |
| CBB*upper or lower level neighbor complied | -0.021 |
| | (0.014) |
| Observations | 201,338 |
| $R^2$ | 0.67 |

Notes: In this table, we test if changes in heating usage are correlated with neighbors' compliance status. The regression includes household fixed effects and year-by-month fixed effects. The first coefficient implies that changes in heating usage are negatively correlated with households own compliance status, which is consistent with our main findings on the policy's treatment effects. The rest of the coefficients indicate that there is little statistical evidence that changes in heating usage are correlated with neighbors' compliance status.

Table A.4: ATET: Impacts of the CBB by the Quartiles of the Predicted Changes in Average Price

Dependent variable: Log of daily heating usage

| | ATET | | | |
|---|---|---|---|---|
| | Quartile 1 | Quartile 2 | Quartile 3 | Quartile 4 |
| CBB | 0.312 | 0.022 | -0.221 | -0.224 |
| | (0.062) | (0.082) | (0.088) | (0.030) |
| Observations | 44,384 | 57,106 | 31,602 | 44,362 |
| Change in Marginal Price | 0.014 | 0.014 | 0.014 | 0.014 |
| ATET on ln(Average Price) | -0.321 | 0.071 | 0.267 | 0.396 |
| ATET on ln(Predicted Average Price) | -0.170 | 0.081 | 0.084 | 0.339 |

Notes: The regression includes household fixed effects and year-by-month fixed effects. This table reports the DID estimates (ATET) of the overall reform effect by quartile group of predicted average price.

Table A.5: ATET: Testing for Schmeduling

| | ATET | | | | $H_0$: $\beta \leq 0$ |
|---|---|---|---|---|---|
| | Marginal price | ln(Predicted average price) | ln(Actual average price) | ln(Usage) | (p-value) |
| Full sample | 0.014 | -0.170<br>(0.008) | -0.321<br>(0.054) | 0.312<br>(0.062) | 0.000 |
| Households with home value > median | 0.014 | -0.166<br>(0.012) | -0.280<br>(0.065) | 0.237<br>(0.076) | 0.001 |
| Households with home value <= median | 0.014 | -0.172<br>(0.009) | -0.274<br>(0.077) | 0.246<br>(0.085) | 0.002 |
| Households with home size > median | 0.014 | -0.170<br>(0.012) | -0.337<br>(0.076) | 0.287<br>(0.087) | 0.000 |
| Households with home size <= median | 0.014 | -0.168<br>(0.009) | -0.211<br>(0.060) | 0.225<br>(0.090) | 0.006 |

Notes: This table reports the DID estimates (ATET) of the reform effect in quartile 1 of predicted average price.

Table A.6: Middle vs. Top and bottom floors, and Corner vs. Non-corner unites

| | ln(daily heating usage) | |
|---|---|---|
| | Panel A: Middle vs. Top and bottom floors | |
| | (1)<br>Middle floors | (2)<br>Top and bottom floors |
| CBB | -0.083<br>(0.025) | -0.062<br>(0.026) |
| Observations | 205,432 | 41,100 |
| | Panel B: Non-corner vs. Corner units | |
| | (1)<br>Non-corner units | (2)<br>Corner units |
| CBB | -0.081<br>(0.027) | -0.043<br>(0.019) |
| Observations | 54,971 | 78,746 |

Notes: The regression includes household fixed effects and year-by-month fixed effects. In Panel B, we use a subsample of buildings where we can identify corner vs. non-corner units: buildings with three, four or eight households on the same floor.

Table A.7: Results Based on the Conventional OLS with Two-way Fixed Effects

| | ln(daily heating usage) | | | |
|---|---|---|---|---|
| | (1) Quartile 1 | (2) Quartile 2 | (3) Quartile 3 | (4) Quartile 4 |
| First year of CBB | -0.056 | -0.111 | -0.055 | -0.048 |
| | (0.036) | (0.023) | (0.022) | (0.023) |
| Second year of CBB | -0.074 | -0.139 | -0.114 | -0.052 |
| | (0.055) | (0.036) | (0.040) | (0.047) |
| Third year of CBB | -0.146 | -0.234 | -0.229 | -0.152 |
| | (0.072) | (0.049) | (0.051) | (0.065) |
| Observations | 46,581 | 46,579 | 46,583 | 46,575 |
| $R^2$ | 0.53 | 0.64 | 0.67 | 0.69 |
| Month*First data year FE | Y | Y | Y | Y |
| Household FE | Y | Y | Y | Y |

Notes: This table shows the ITT estimates using the conventional OLS with two-way fixed effects. The estimation includes household fixed effects and year-by-month fixed effects. Standard errors in parentheses are clustered at the building level.

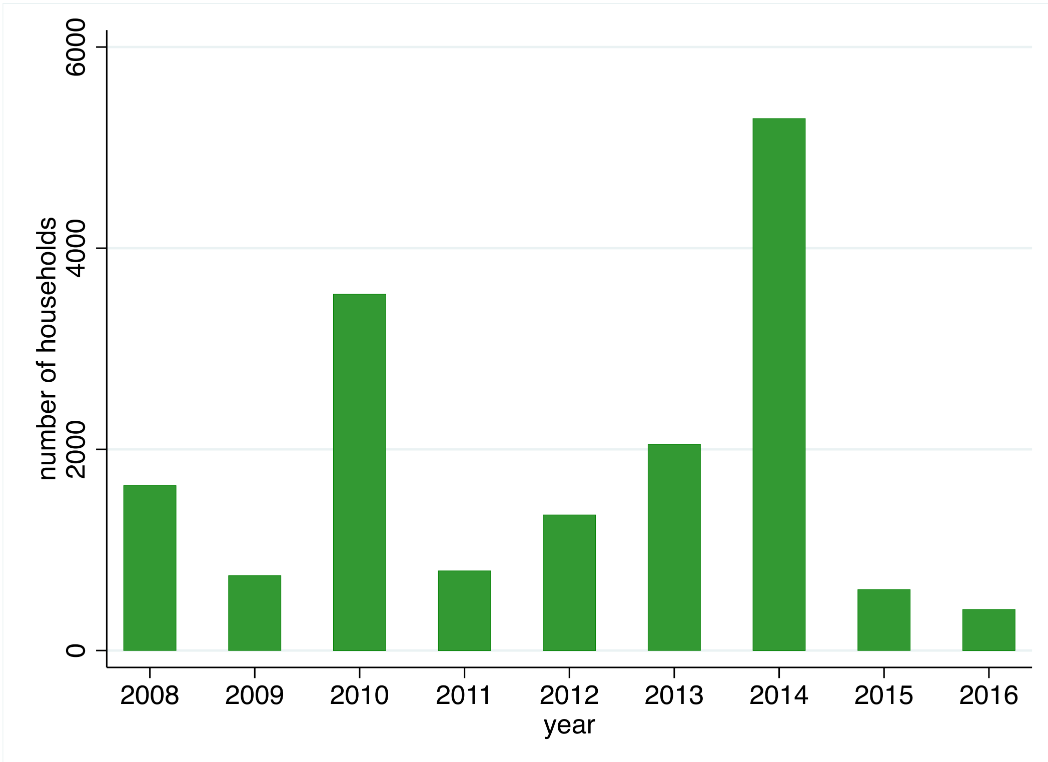
Table A.8: Household Heating Usage and Ambient Pollution

| | (1) lnSO2 | (2) lnPM2.5 | (3) lnPM10 |
|---|---|---|---|
| ln(Daily total heating usage) | 1.562 | 1.414 | 0.877 |
| | (0.434) | (0.476) | (0.414) |
| Observations | 461 | 459 | 444 |
| $R^2$ | 0.74 | 0.65 | 0.58 |
| Weather controls | Y | Y | Y |
| Year-week FE | Y | Y | Y |
| Day-of-week FE | Y | Y | Y |

Notes: In this table, we estimate the relationship between heating usage and ambient pollution. Ambient pollution data on the concentration of $SO_2$, $PM_{2.5}$ and $PM_{10}$ are from a pollution monitor located in the district of Tianjin where this study is conducted. This pollution monitor is the only one located in the district of our study, and this district is relatively isolated from other districts of Tianjin, with a road distance of about 55 kilometers from Tianjin's city center. Weather controls include temperature, precipitation and wind speed.

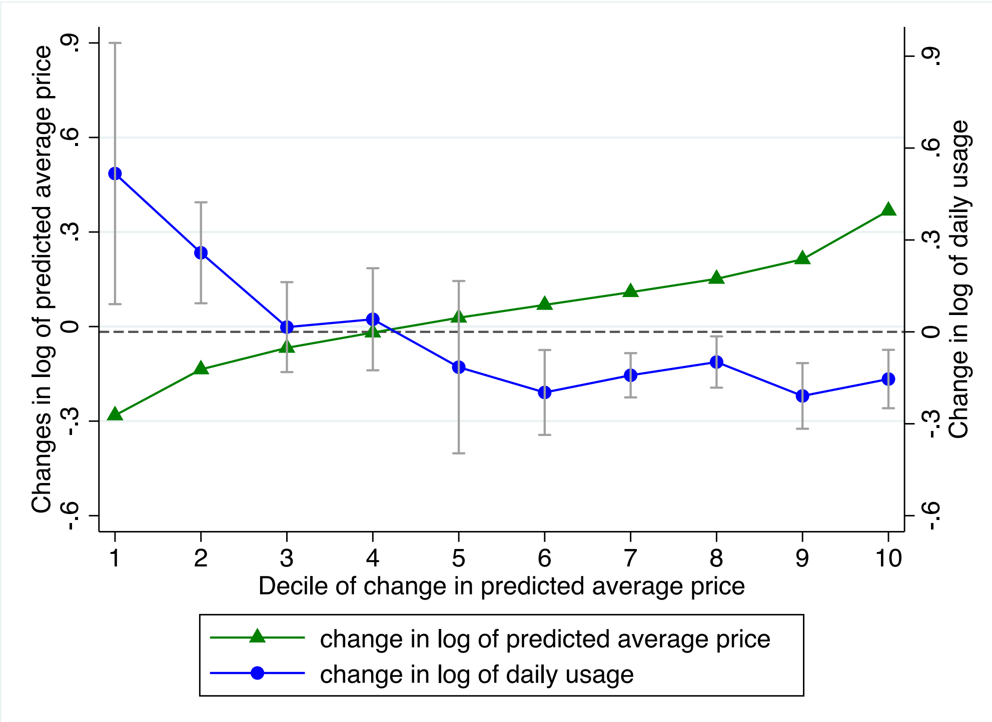
## Appendix D: Additional Figures

Figure A.1: Rollout of the reform



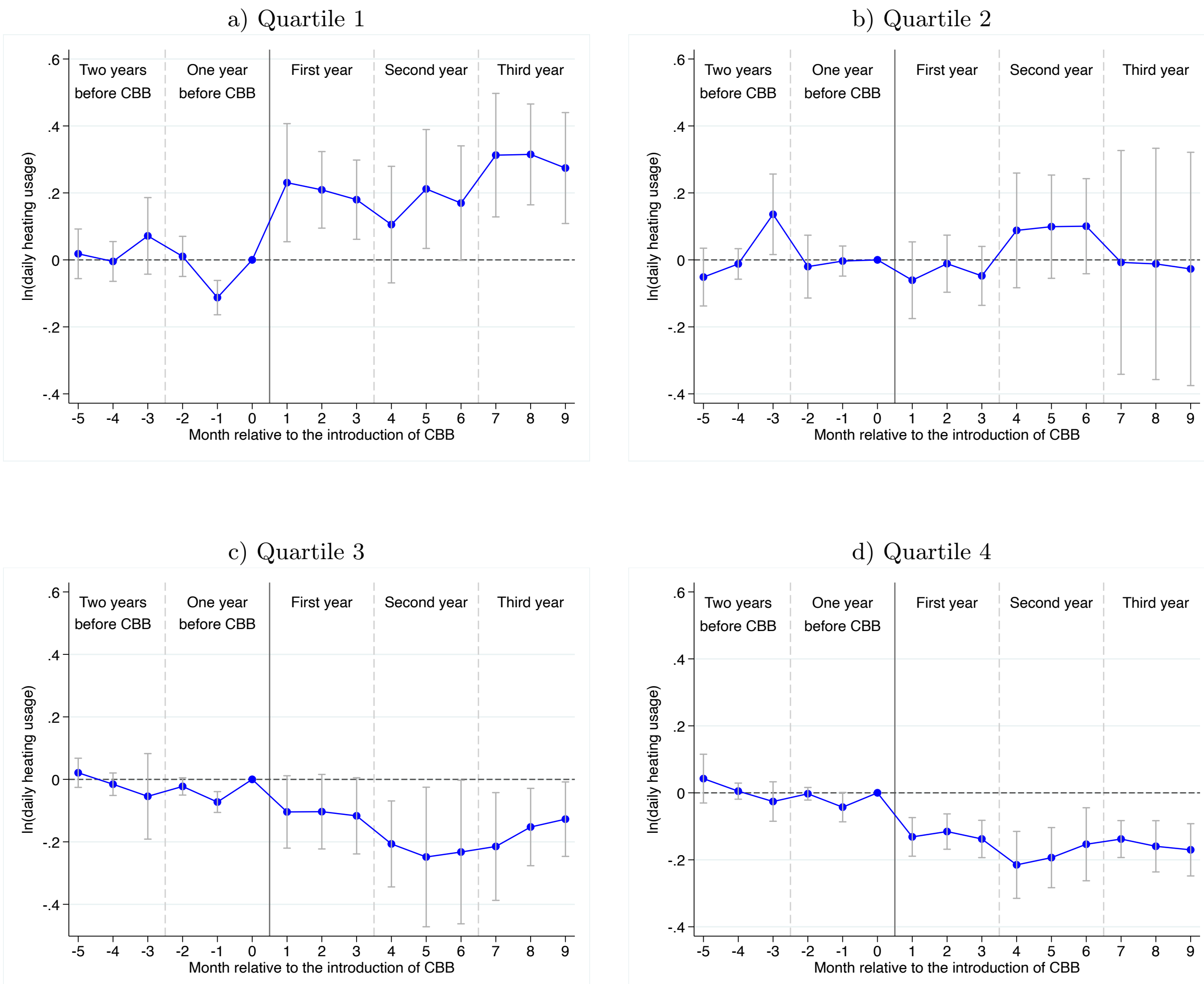

Notes: This figure shows the rollout of the consumption-based billing policy.

Figure A.2: Robustness of Policy-Induced Changes in Average Price and Usage (non-parametric controls of cohort trends are included)



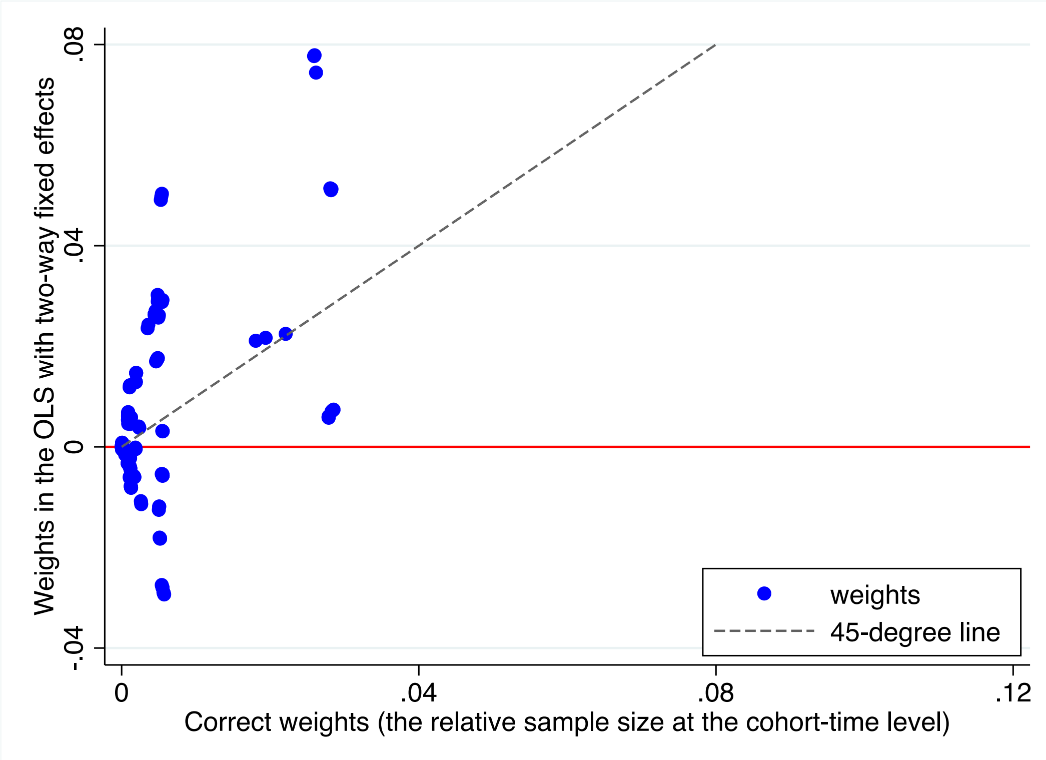

Notes: We divide customers by decile based on their policy-induced changes in average price. For each decile, we estimate the ITT of the CBB on the log of heating usage based on the difference-in-differences estimation method developed by de Chaisemartin and D'Haultfœuille (2020). We also apply the same method to estimate the ITT on the log of the policy-induced change in average price. Non-parametric controls of cohort trends are included. The bars indicate the 95 percent confidence intervals. Standard errors are clustered at the building level.

Figure A.3: Robustness of the Event-Study by Quartile (non-parametric controls of cohort trends are included)




Notes: This figure shows the ITT estimates of the staggered difference-in-differences analysis described in equation (1) based on the estimation method developed by de Chaisemartin and D'Haultfœuille (2020). There are three heating months in each year because the heating season is December, January, and February. The bars indicate the 95 percent confidence intervals. Standard errors are clustered at the building level. We divide customers by quartile based on their policy-induced changes in average price. We then estimate equation (1) for each quartile group separately to make these event study figures. In this analysis, we interact time fixed effects with cohorts.

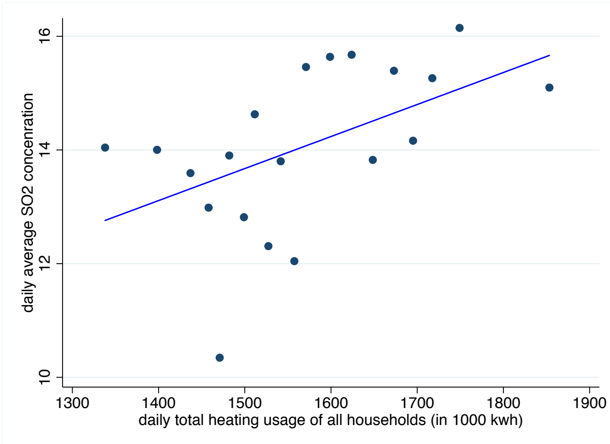
Figure A.4: Cohort-by-Time Weights Imposed by the OLS with Two-Way Fixed Effects



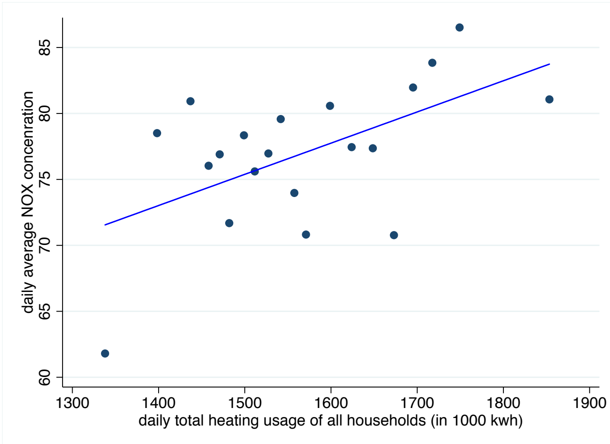

Notes: We compute the cohort-by-time weights that are imposed by the conventional OLS using the method developed by de Chaisemartin and D'Haultfœuille (2020). We then plot them against the "correct" cohort-by-time weights, which are the relative sample size across the cohort-by-time cells. If the OLS uses weights that are equivalent to the correct weights (i.e., the OLS weights and correct weights line up at the 45-degree line in the figure), we can obtain the correct average treatment effect using the OLS. However, the figure shows that many weights are not on the 45-degree line. Furthermore, 46% of the weights imposed by the OLS are negative.

Figure A.5: Household Heating Usage and Pollution Emissions of the Heating Plant

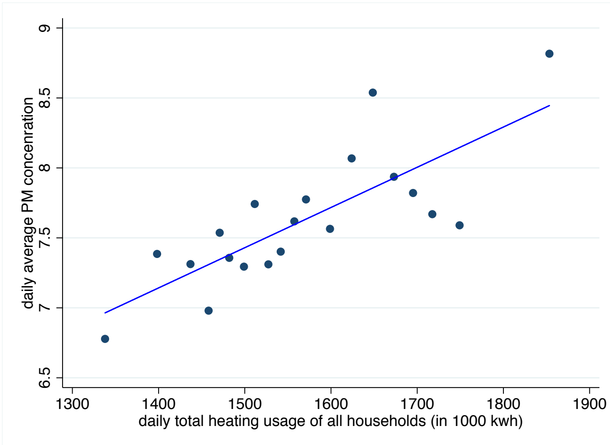
(a) $SO_2$ concentration ($mg/m^3$)




(b) $NO_x$ concentration ($mg/m^3$)




(c) PM concentration ($mg/m^3$)




Notes: Data on emission concentrations are from the CEMS monitor placed at the heating plant.