Hourly Price Elasticities of Household Electricity Demand using Smart-Meter and Survey Data

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Motivation

- Failure in electricity pricing
  - Imbalance between time-varying generation costs and time-invariant retail price
  - Dynamic pricing as a promising solution
- Estimating hour-level demand under “existing” tariffs
  - More temporally detailed elasticity estimates for tariff design
  - Limitations of small-scale pricing pilots (Ham et al., 1997; Barnow et al., 1980; Vine et al., 2014)

  → Selection bias and external validity might be into question
- Necessity of novel identification strategy for electricity price
  - Possible issue of price endogeneity under increasing block tariffs (IBT)

Literature

- Scant literature on the identification of *hourly* electricity demand
  - Price or income elasticities using *annual* electricity data (Halicioglu, 2007; Ziramba, 2008; Paul et al.,2009; Alberini and Filippini, 2011)
  - Price elasticity of *monthly* electricity demand (Archibald et al., 1982; Branch, 1993; Labandeira et al., 2012; Hung and Huang, 2015)

- No studies on the *hourly* price response of households facing block tariffs
  - Hourly electricity demand of industrial customers under real-time pricing (RTP) (Taylor et al., 2005)
  - Hourly demand response of households under RTP experiment (Allcott, 2011)
  - Responses to price changes under experimental settings (Wolak, 2011; Jessoe and Rapson, 2014)

Literature

- Monthly demand studies based on a *perceived* electricity price under the IBT
  - Empirical support for consumer response to *average price* (Shin, 1985; Ito, 2014)
  - Expected marginal price capturing exogenous factors (Borenstein, 2009; Mansur and Olmstead, 2012)
- Understanding of heterogeneity in electricity demand response
  - To provide concrete insights into customized service plans (Braithwait et al., 2007)
  - Price responsiveness across different income and usage groups (Reiss and White, 2005; Silva, 2017)

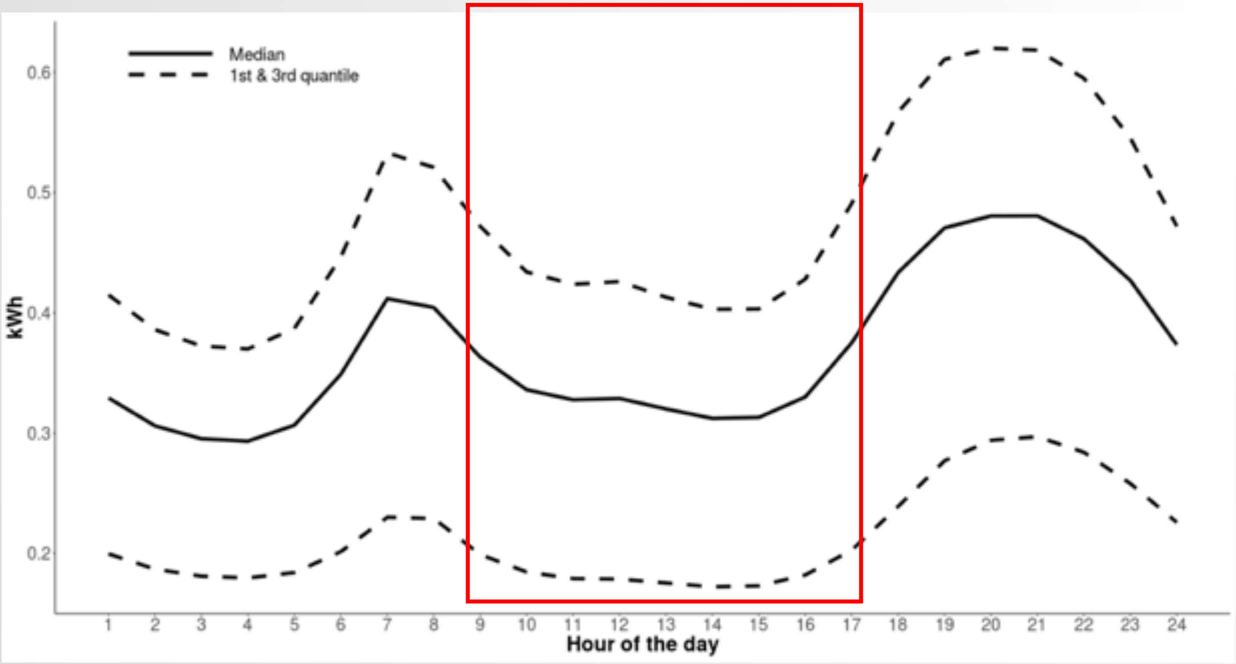
Research Question

1) How would the price elasticity of electricity demand vary within a day for households under increasing block tariffs?

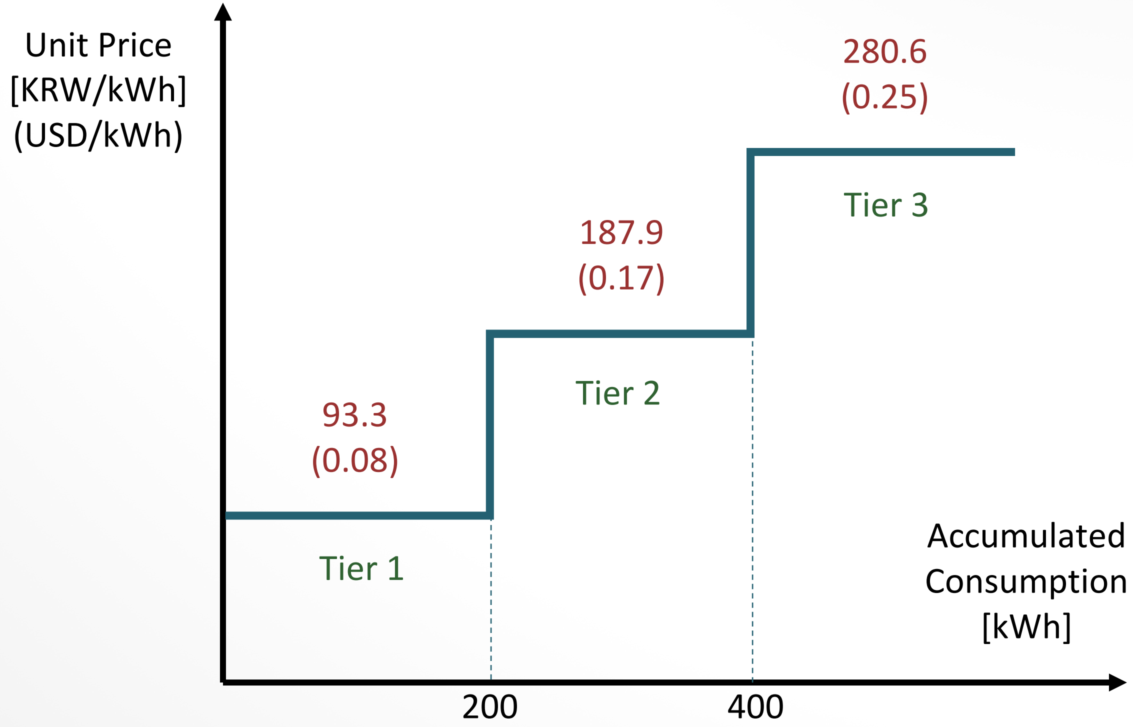
2) How would hourly price elasticities differ across households?

Data

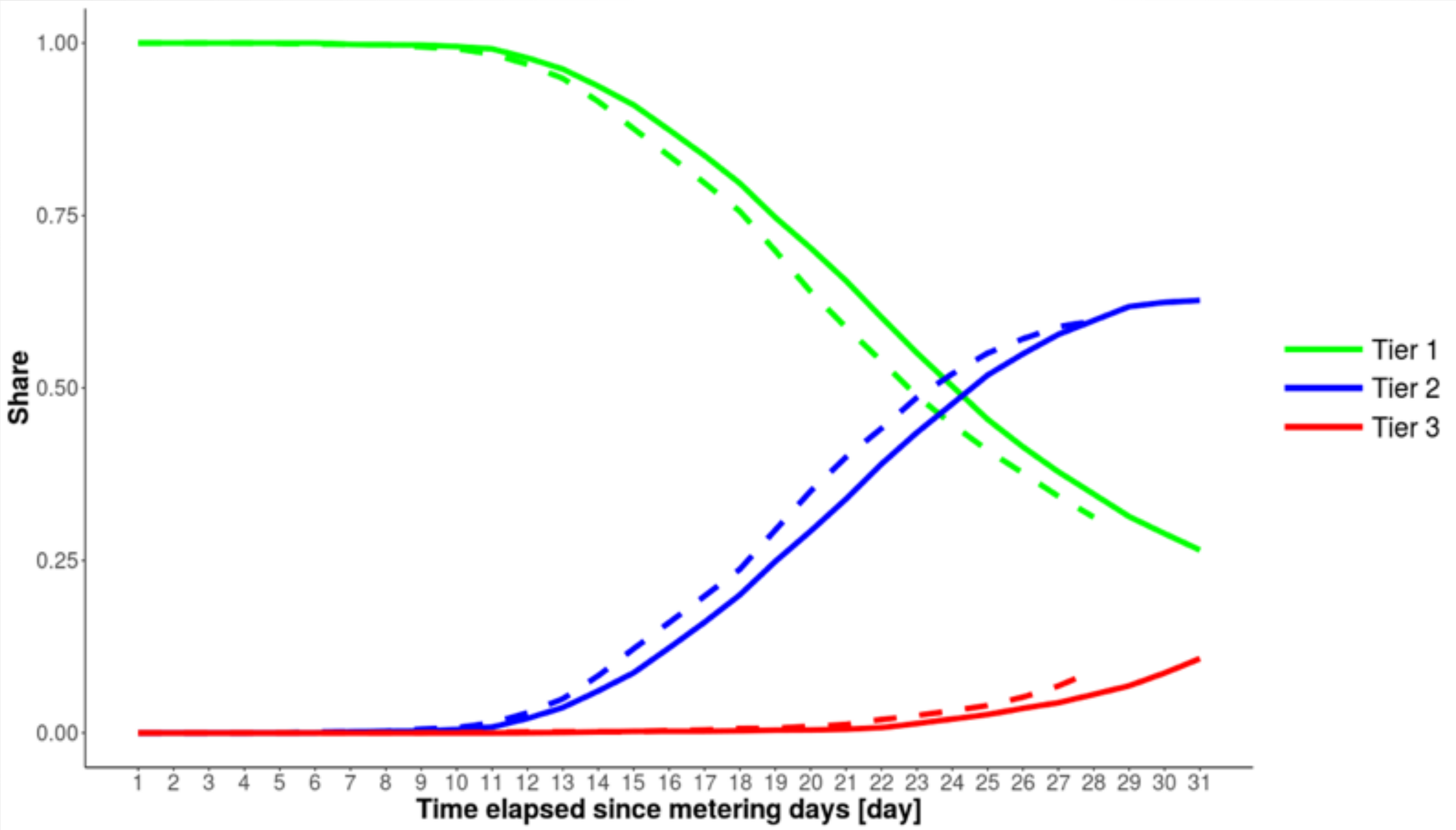
- Hourly-metering data of 1,176 households spanning two consecutive billing months
  - Usage peaking immediately before and after working hours
  - Three-tiered increasing block rates



Households' hourly load profile on weekdays



Data



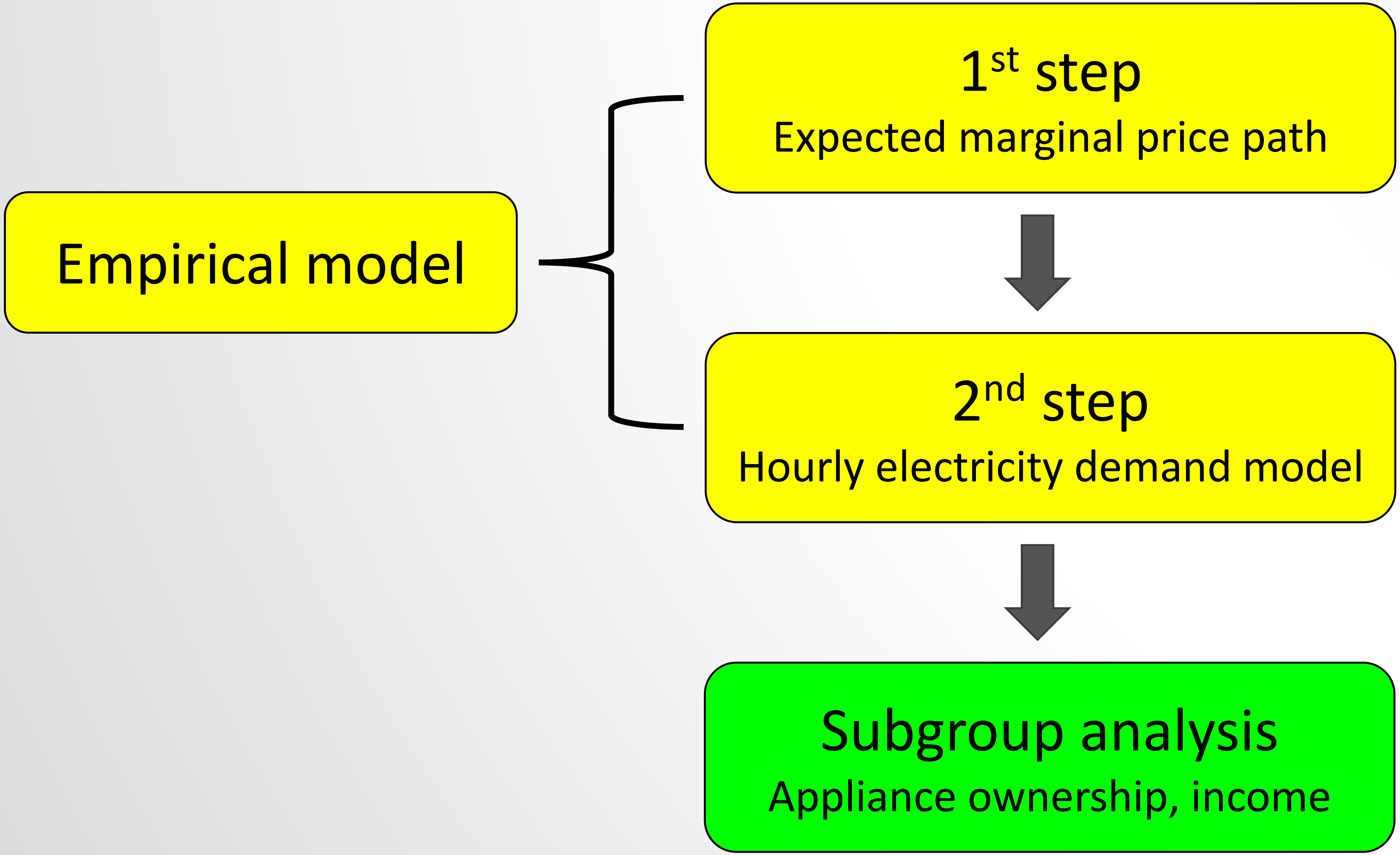
Shares of the sample households placed in each of the three block tiers during February (dashed) and March (solid)

Data: Survey

Variable	Description	Unit	Mean	Std. Dev.	Min	Max
use	Hourly electricity usage	kWh	0.37	0.24	0.01	4.59
hdh	Heating degree hours (reference: 18°C)	°C	12.07	5.52	0	24.3
humidity	Outdoor humidity	%	49.77	17.94	17	95
income	Households' monthly income	KRW	330.53	193.18	40	1050
area	Floor area of the building	m^2	66.77	26.45	3.3	198
household	Number of households	-	2.84	1.23	1	7

	Percentage		Percentage
HOUSING TYPE		***BUILDING YEAR***	
Detached	6.3	1970s	1.4
Multi-family	34.7	1980s	15.9
Multiplex	26.8	1990s	42.4
Rowhouse	24.7	2000s	34.2
Apartment	7.5	2010s	6.1
ELECTRIC APPLIANCES			
Refrigerator	99.3	Set-top box	70.2
Washing machine	98.1	Computer	64.8
Fan	97.7	Router	61.7
TV	95.9	Blender	59.1
Electric rice cooker	93.9	Electric pot	42.8
Hair dryer	89.0	LED lamp	35.4
Air conditioner	83.9	Incandescent lamp	30.5
Vacuum cleaner	82.6	Desk lamp	15.1
Microwave	82.1	Indoor environment devices	27.8
Kimchi refrigerator	80.9	Cooking machines	23.4
Iron	80.0	Audiovisual	13.8
Electric pad	77.1	Electric heaters	6.0
Fluorescent lamp	75.3	Dish cleaning	4.3

Analysis Overview



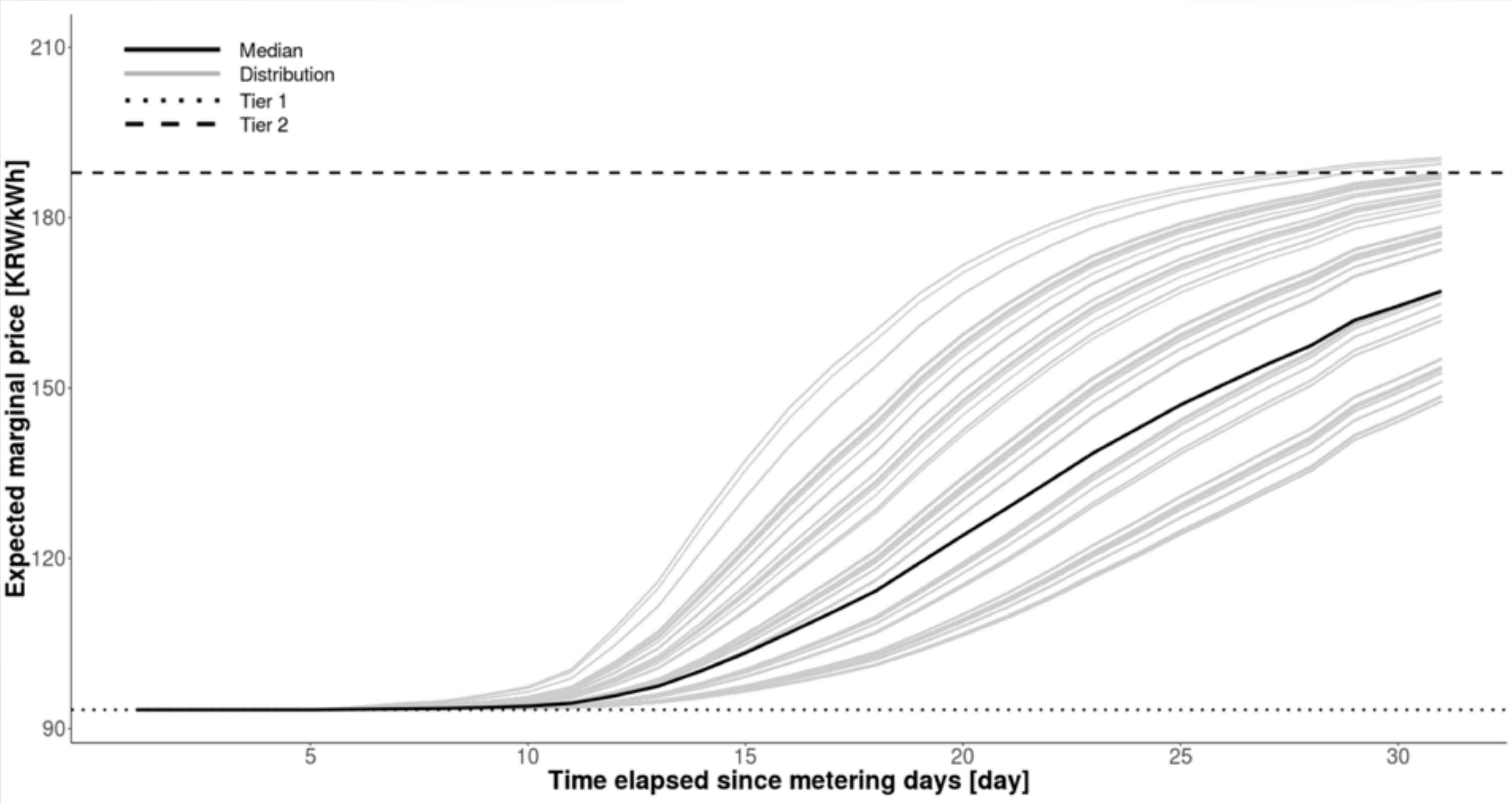
Estimation

- **First step:** marginal expected price path over the billing cycle
  - Multinomial logit (MNL) model to predict the likelihood of being placed on each block (Matsukawa, 2004)
    - Independence of irrelevant alternatives (IIA) property holds
  - Expected value of marginal prices based on:
    - The present time during a billing month (metering-date fixed effects)
    - Scale factors (e.g., demographic characteristics)

$$Pr(Y_{id} = 1) = \frac{1}{1 + \sum_{k=2}^{3} e^{X'_{ikd}\beta_k}}$$

$$Pr(Y_{id} = j) = \frac{e^{X'_{ikd}\beta_j}}{1 + \sum_{k=2}^{3} e^{X'_{ikd}\beta_k}} \quad (j = 2, 3)$$

Estimation



Expected marginal price path in March

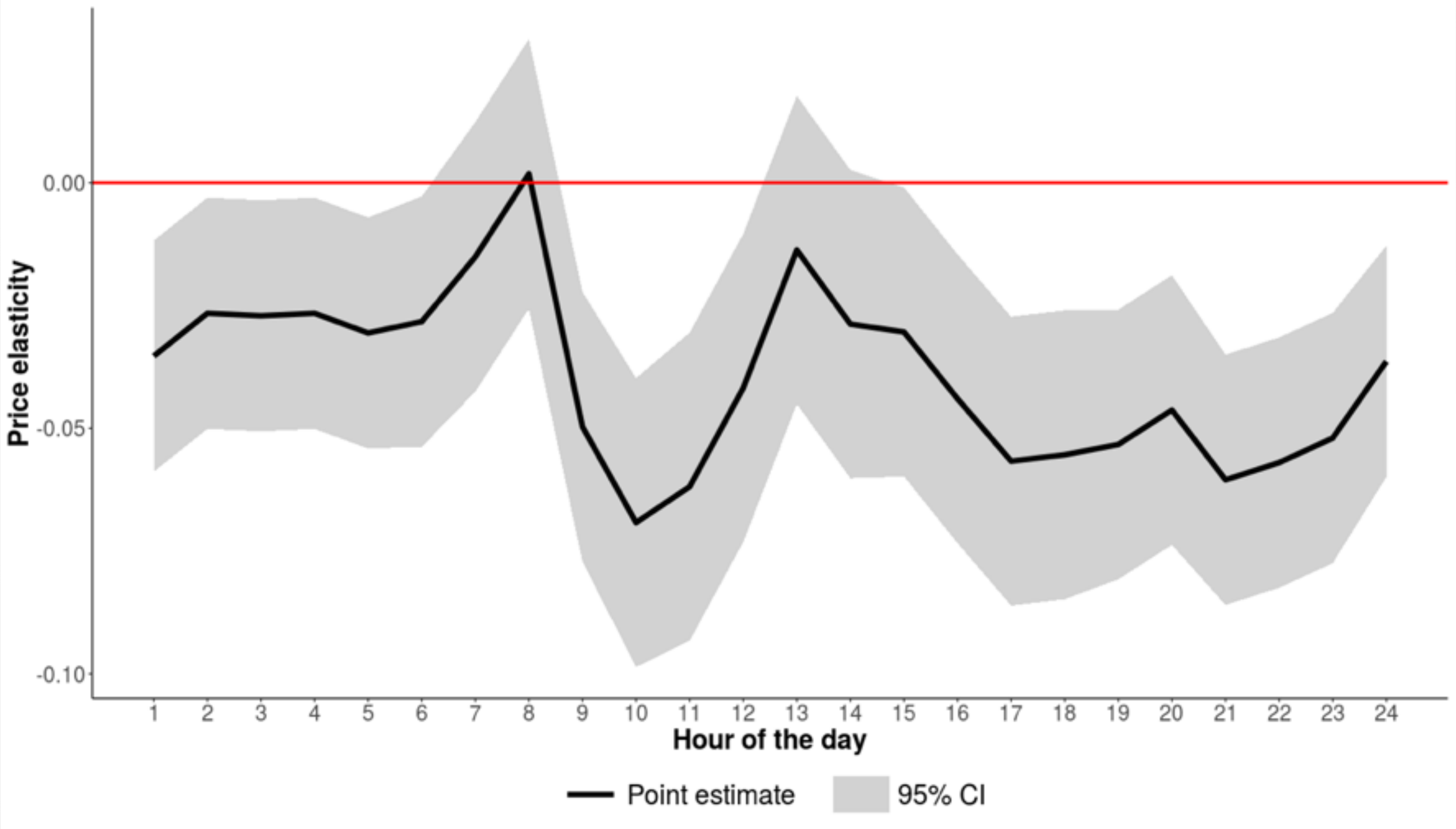
Estimation

- **Second step:** estimation of hourly electricity demands
  - A system of equations of 24 hourly electricity demands
  - Double-log functional form (Hirst et al., 1982; Alberini and Filippini, 2011)
  - Seemingly unrelated regression (SUR) to consider contemporaneous errors

$$log(q_{imdh})$$
$$= \alpha_h + \delta_{mdh} + \beta_h log(\bar{p}_{imdh}) + \gamma_{1h} hdh6_{imdh} + \gamma_{2h} humid_{imdh} + \zeta_h I_i + \theta_h Z_i + \varepsilon_{imdh} \ (h = 1, 2, \dots, 24)$$

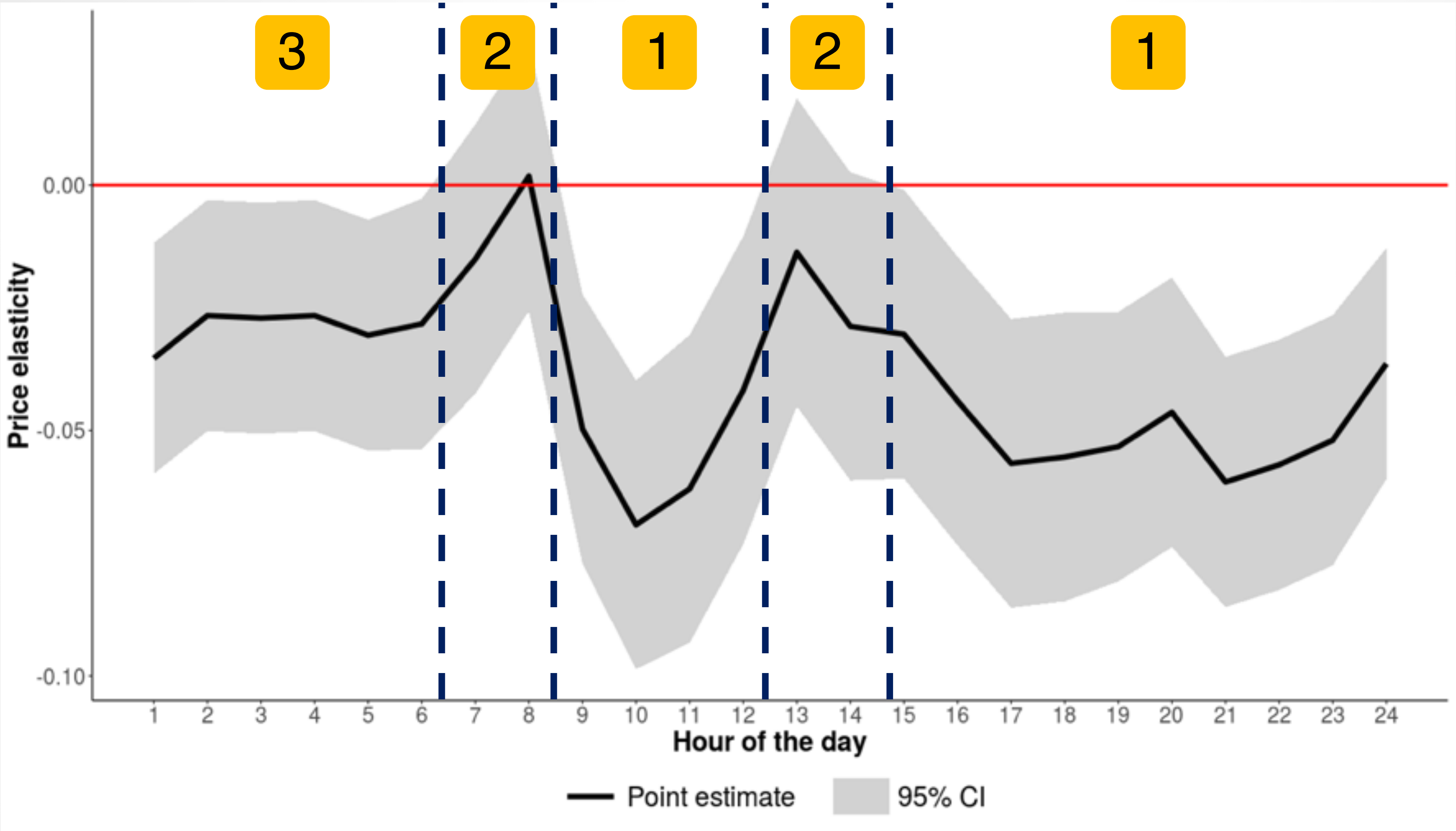
- Subgroup analysis to examine the heterogeneity of hourly price elasticities
  - Ownership of appliances
  - Income quartiles

Results: Hourly price elasticities



- The own-price elasticities between -0.02 and -0.07
- Simultaneous exclusion test and equality test for 24 coefficients all rejected

Results: Hourly price elasticities



- Household's daily lifestyles provide possible explanations

Results: Subgroups by appliance ownership

- ***K-modes clustering*** algorithm

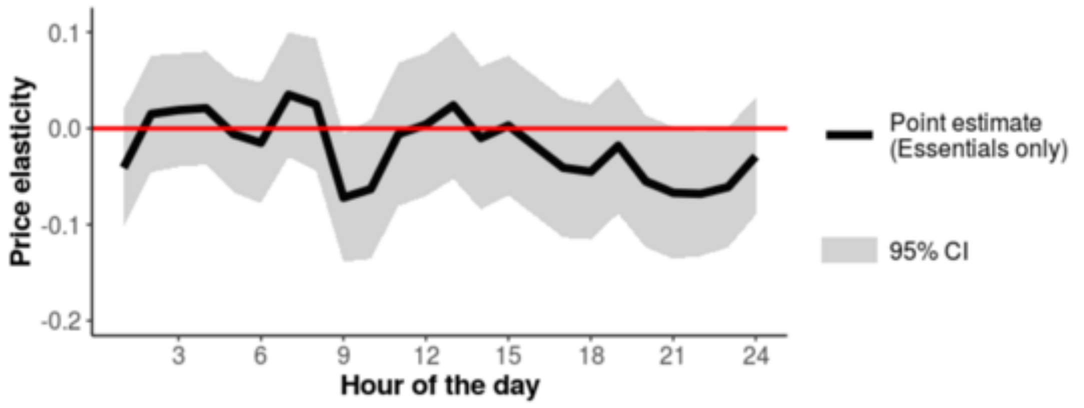
1) "Essentials only" group: only basic home appliances
2) "Urban life" group: typical household appliances
3) "Wellness" group: typical appliances plus some other discretionary items

Group 1: Essentials only
Group 2: Urban life
Group 3: Wellness

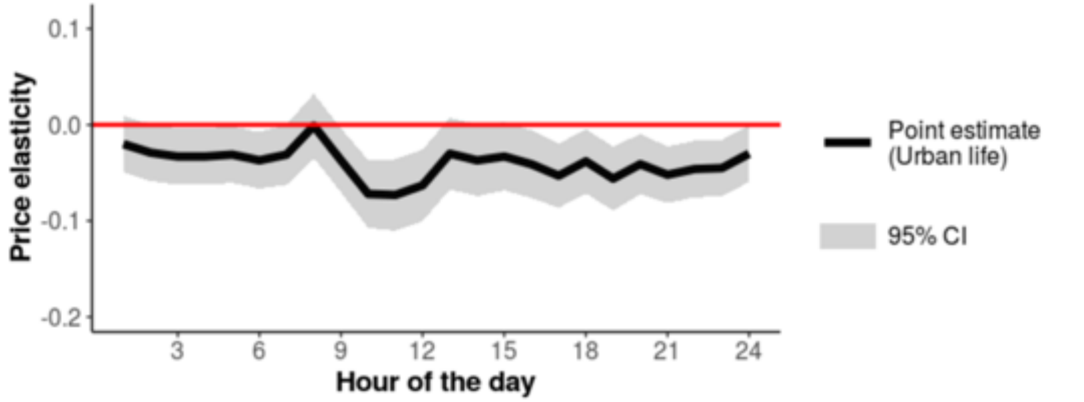
	1	*2*	*3*		*1*	*2*	*3*		*1*	*2*	*3*
Washing machine	1	1	1	Vacuum	0	1	1	Electric pot	0	0	1
TV	1	1	1	Microwave	0	1	1	LED lamp	0	0	1
Electric rice cooker	1	1	1	Iron	0	1	1	Indoor environment	0	0	1
Hairdryer	1	1	1	Set-top box	0	1	1	Cooking machines	0	0	1
Air conditioner	1	1	1	Computer	0	1	1	Audiovisual	0	0	0
Kimchi refrigerator	1	1	1	Router	0	1	1	Heating machines	0	0	0
Electric pad	1	1	1	Blender	0	1	1	Dish cleaning	0	0	0

Results: Subgroups by appliance ownership

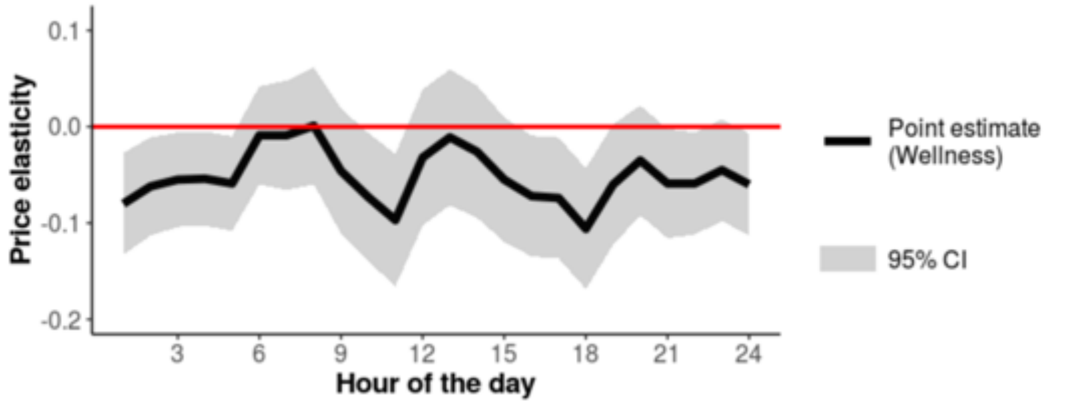
Essentials only:



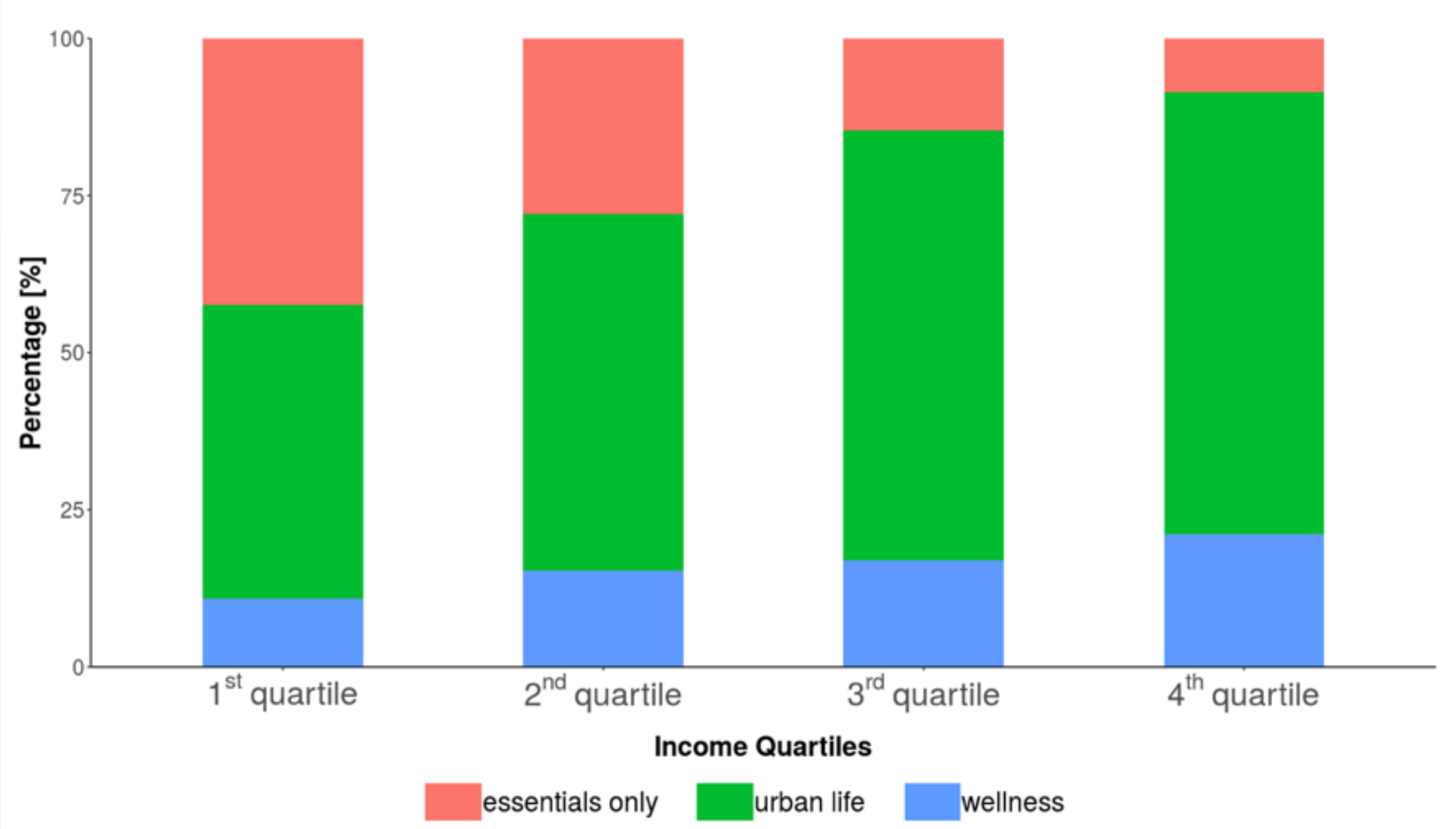
Urban life:



Wellness:

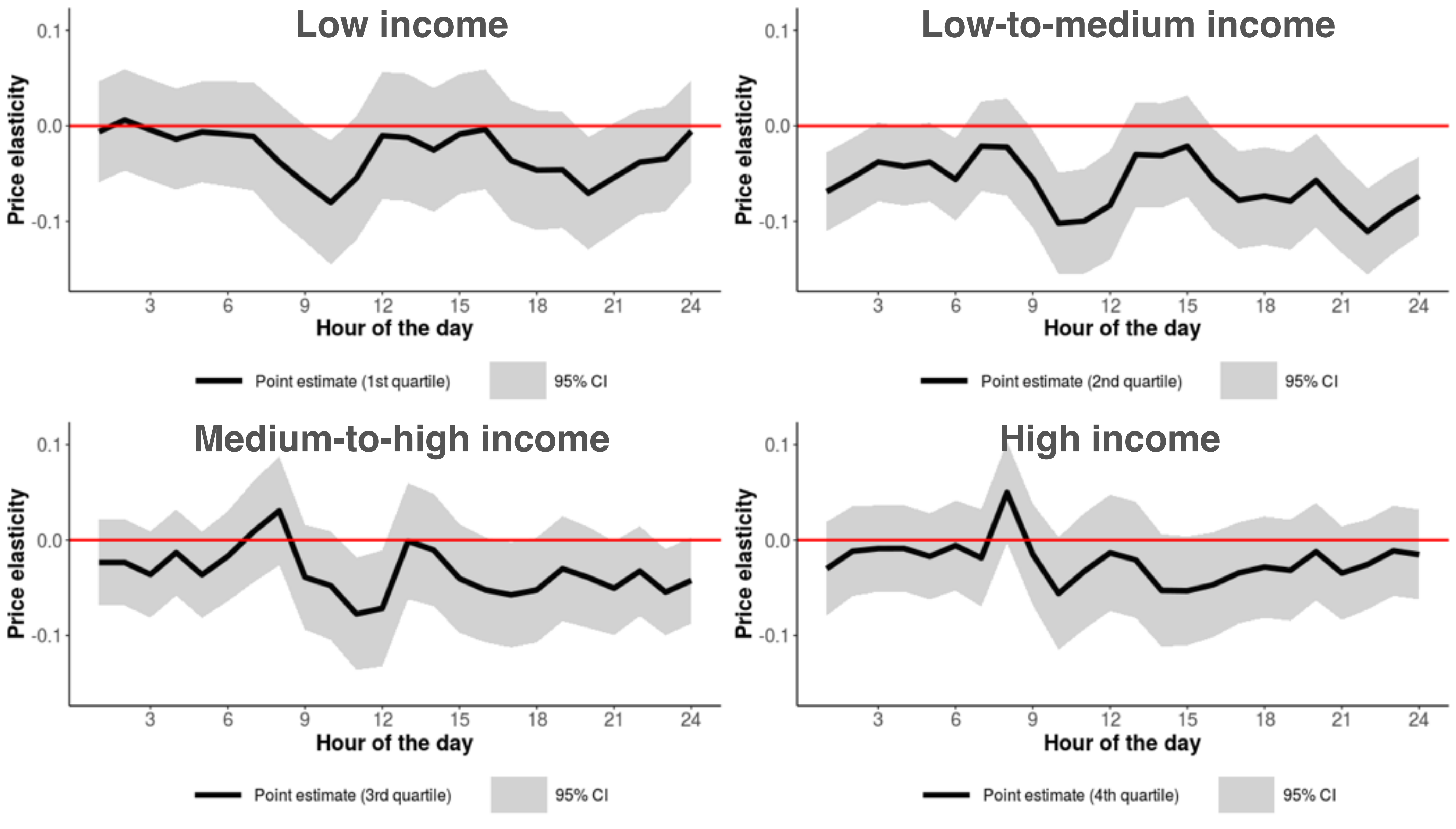


Results: Subgroups by income quartile



- No particular appliance ownership type dominates each income quartile.
- The general trend serves our intuition though.

Results: Subgroups by income quartile



Summary

✓ **Findings**

1) Hourly own-price elasticities change within a day, ranging from -0.07 to -0.02
2) Low-middle-income families and those equipped with discretionary appliances exhibit the most pronounced price responsiveness → Larger losses expected for low- and high-income households with the introduction of dynamic pricing

✓ **Contribution**

1) Novel approach to identifying hourly price elasticities (expected marginal price "path")
2) Applicable to utility service territories that intend to introduce dynamic-pricing scheme

Discussion

✓ **Implications**

1) Useful in determining the location of peak hours and their price levels for dynamic pricing plans
2) Targeted marketing and customized pricing plans to improve political feasibility and adoption
3) Appliance-level DR program (TOU plans w/ smart appliances)

✓ **Future work**

1) More detailed individual-level measure of electricity price
2) Policy simulation and welfare analysis

Thank you ☺

Acknowledgments

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Appendix: MNL estimates

- Estimated MNL model in the first step conforms to our expectation
  1) The customers tend to avoid placing on the 2nd and 3rd block due to high price levels
  2) The households believe that they are not under the 1st block any longer in the billing month when they have used much electricity needed for heating
  3) The households with large number of members are expected to choose high block tiers
  4) No monotonicity between the block choice and the level of income

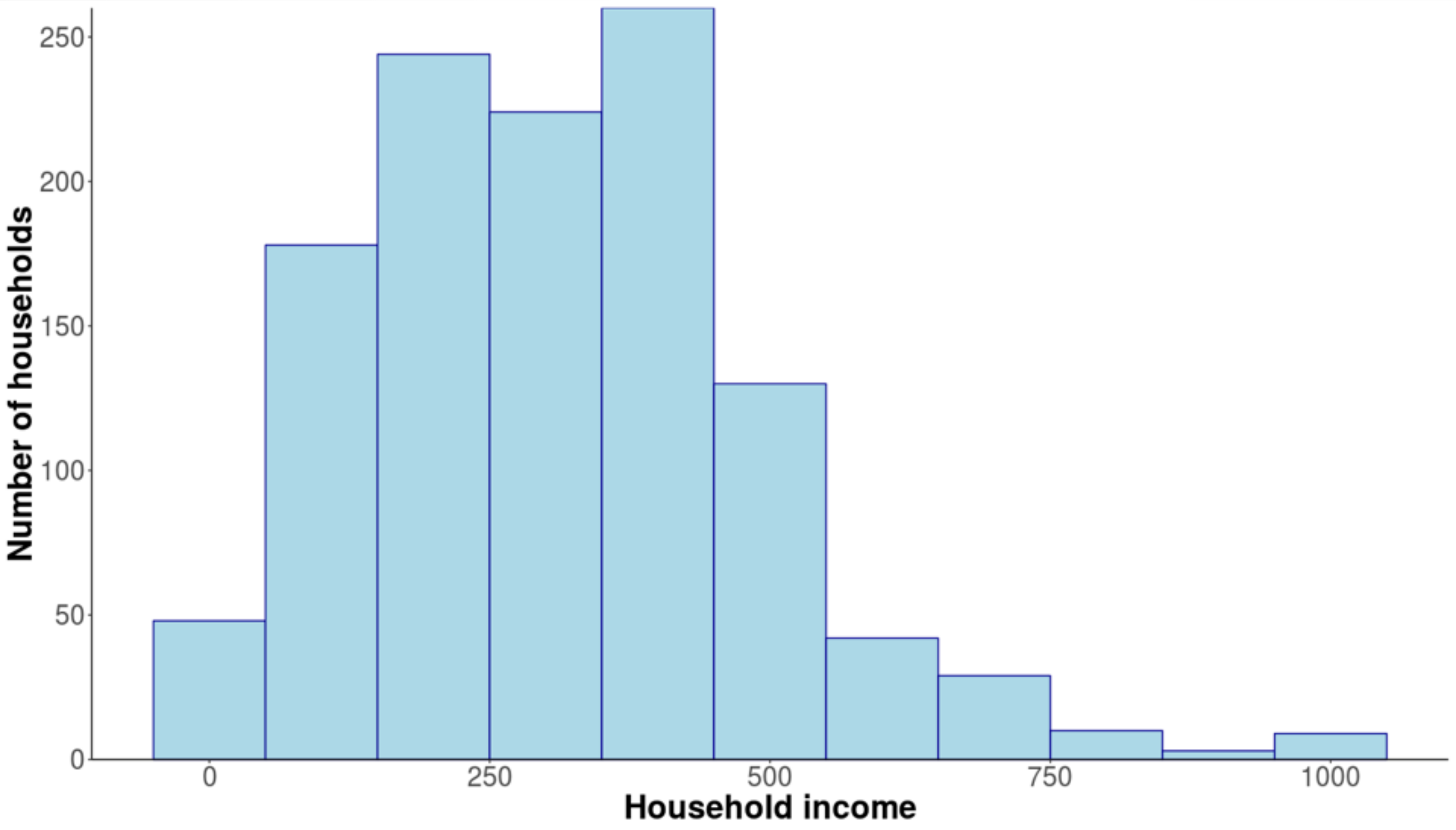
	Block	Coefficient	Standard error
Price divided by income	(1, 2, 3)	-0.066***	0.007
Cumulative HDD	(2, 3)	0.002***	0.00014
Low-income assistance	(2, 3)	0.585***	0.012
Income (second quantile)	(2, 3)	-0.014*	0.008
Income (third quantile)	(2, 3)	-0.230***	0.009
Income (fourth quantile)	(2, 3)	0.048***	0.010
Household size (second level)	(2, 3)	1.127***	0.006
Household size (third level)	(2, 3)	2.240***	0.010
Intercept (second block)		-11.230***	0.289
Intercept (third block)		-13.882***	0.289
R^2		0.388	
Log-likelihood		-602,807.7	
Likelihood-ratio Test		764,618.1*** (df = 36)	
N		1,653,721	

Appendix: Linear hypothesis tests

	Equality of coefficients	All zero coefficients
All	0.003	0.000
Income (first quartile)	0.588	0.573
Income (second quartile)	0.025	0.000
Income (third quartile)	0.069	0.025
Income (fourth quartile)	0.266	0.268
Essentials only	0.004	0.004
Urban life	0.109	0.007
Wellness	0.092	0.017

Notes: p-values of the tests for the model (Eq. (3)) for all customers in our sample (first row) and customer groups by income quartiles and appliance holdings are shown in the table. As described in Section 5.1, “Equality of coefficients” indicates the test for the hypothesis that the estimated elasticities are identical for all hours. “All zero coefficients” refers to the test for the hypothesis that the coefficients of the price variable in all equations are zero.

Appendix: Distribution of income

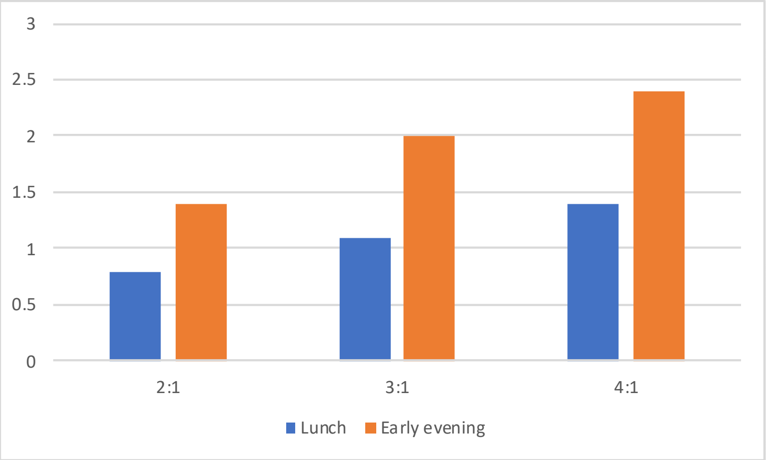


Results: Simulation of TOU pricing policies

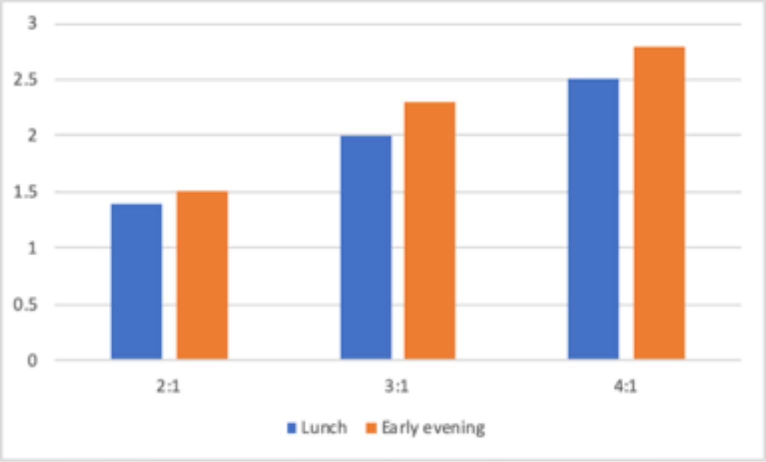
1) Load Reduction [kWh]

Demand function: $q_h = A_h \cdot \bar{p}^{\varepsilon_h}$ (Borenstein, 2005)

Hourly elasticities



Constant elasticity [-0.06] (Ito, 2014)



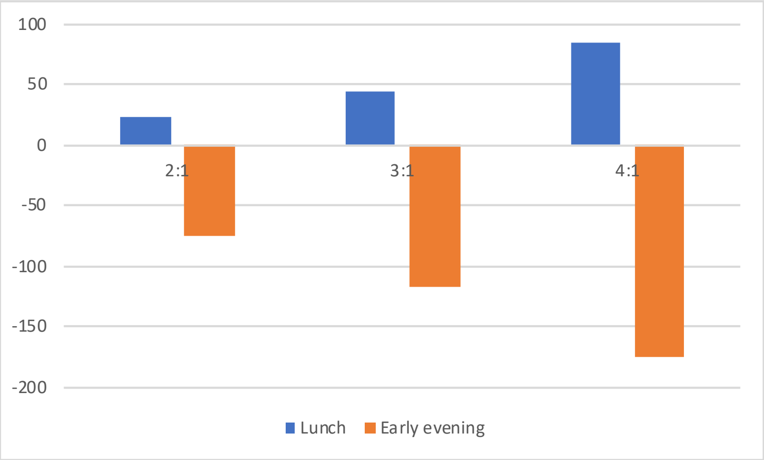
- Highly contingent on a couple of factors:
  1) Which hours of the day the peak hours are placed
  2) Magnitude of the hourly price elasticities

Results: Simulation of TOU pricing policies

2) Consumer Surplus (CS) [KRW]

Aggregate change in CS: $\Delta CS = \sum_{h=1}^{24} \frac{A_h}{\varepsilon_h+1}\left(\bar{p}^{\varepsilon_h+1} - p_{TOU}^{\varepsilon_h+1}\right)$

Hourly elasticities



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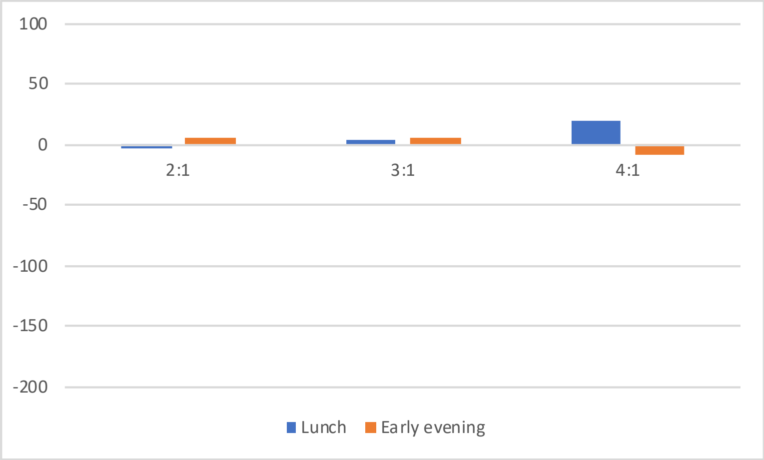

- In case of hourly-varying price elasticities:
    1) Large differences in the CS changes depending on the peak time zones and price ratios
    2) Exaggerate the effect of the load variation, resulting in substantial household surplus changes