We Can Do Better: Effects of Government Incentives on EV Adoption

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DSE CONFERENCE

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Substantive Research Questions

- Does an EV Tax Credit Lead to More EVs?
  - *He et al.* 2022 "Consumer Tax Credits for EVs" and *Beresteanu and Li* 2011 "Gasoline Prices, Government Support" says yes
  - More importantly, do the policy makers have it right? Is a policy focused on battery capacity rather than efficiency better for reducing CO2 emissions?
  - Are tax credits for purchases, the most effective incentive for EV adoption?

Empirical Setting: Electric Vehicles Sales in WA

- Sales of Battery (BEV) and Plug-in Hybrid (PHEV)
- Sales of BEVs and PHEVs by County (King, Snohomish and Pierce) = 77% of all EVs sold in Washington
- Sales by Make and Model (29 models from 17 makes)
- Data from Q1 2016-Q4 2019 by make, model, county
- Rebates for each model car and the amount of CO_2 emission per model car in tons per year

Data

- Aggregated Quarterly EV sales by make, model, county AND *income level* in WA
- Data for **Three** Groups:
  - Quarterly Sales data from consumers with income above the 90th percentile
  - Quarterly Sales data from consumers with income between 90th and 75th percentiles
  - Quarterly Sales data from consumers with income below the 75th percentile

Innovations

Substantive:

- Illustrate infrastructure incentives are preferred over consumer tax credits to increase adoption of EVs and reduce CO2

Methodological:

- Present new structural estimation methodology for *dynamic discrete choice* models with group-level aggregate sales data
  - Two steps: NLS and 2SLS
  - Incorporates continuous unobserved consumer heterogeneity
  - Agnostic about consumer beliefs for state transition (e.g. $\Pr(P_{t+1} | P_t)$)

Stylized Dynamic Discrete Choice Model with Aggregate Group Level Data

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Stylized Model: Consumer Demand

- Consider consumer *i* who is of type (g, U), $g \in (1,2,3)$.

$$u_{ijt} = f\left(X_{jt}, \xi_{jt}\right) - \alpha_i P_{jt} + \varepsilon_{ijt}$$

$$f\left(X_{jt}, \xi_{jt}\right) = \overbrace{\delta_j}^{\text{Product Fixed Effect}} + \overbrace{\gamma' X_{jt}}^{\text{Observable Characteristics}} + \overbrace{\xi_{jt}}^{\text{Unobservable Characteristics}}$$

$$\alpha_i = \alpha^{(1)} + \tau^{(2)} D_i^{(2)} + \cdots + \tau^{(g)} D_i^{(g)} + \omega U_i$$

- f(X_{jt}, ξ_{jt})= flow utility a consumer receives in each period post purchase
- α_i captures observed price heterogeneity across groups and <u>unobserved</u> heterogeneity within groups
- $\boldsymbol{U_i \sim \mathrm{N}(0,1)}$ ω = controls the size of within group variation
- $\mathrm{E}[\xi_{jt}] = 0$ ε_{ijt}=iid logit error term

Consumer Choice Probability

- Given a consumer EXITS after purchase, we can specify the choice specific value functions and recover the likelihood of purchasing for a (g,U) consumer

$$v_{\mathrm{jt}}^{(g)}(U) = \frac{f\left(X_{jt}, \xi_{jt}\right)}{1-\beta} - \left(\alpha^{(1)} + \tau^{(g)} + \omega U\right) P_{jt} \qquad j=1, \dots, J$$

$$v_{0t}^{(g)}(U) = \beta E\left[V_{t+1}^{(g)}\left(\Omega_{i,t+1}, U \mid \Omega_{i,t}\right)\right] = \beta E\left[\bar{V}_{t+1}^{(g)}\left(X_{i,t+1}, P_{i,t+1}, \xi_{i,t+1}, U \mid X_t, P, \xi_t\right)\right]$$

- With the choice specific value functions specified, the likelihood of purchasing product *j* in period *t* for consumer of type *(g,U)* is:

$$\sigma_{jt}^{(g)}(U) = \frac{\exp\left(v_{jt}^{(g)}(U)\right)}{\exp\left(v_{0t}^{(g)}(U)\right) + \sum_{k=1}^{J} \exp\left(v_{kt}^{(g)}(U)\right)}$$

Estimation Challenge

- Leverage Hotz & Miller, 1993 inversion
- This means that for any (g,U) consumer, the difference in choice specific value functions is equal to the log odds ratio (assuming product 1 acts as the reference product)

$$\ln\left[\frac{\sigma_{jt}^{(g)}(U)}{\sigma_{1t}^{(g)}(U)}\right] = v_{jt}^{(g)} - v_{1t}^{(g)} = \frac{\delta_j - \delta_1}{1-\beta} + (X_{jt} - X_{1t})'\frac{\gamma}{1-\beta} - \alpha^{(1)}(P_{jt} - P_{1t}) + \frac{\xi_{jt} - \xi_{1t}}{1-\beta} \; - \omega U(P_{jt} - P_{1t})$$

- But our model includes unobserved consumer heterogeneity, so we must integrate over U wrt its distribution function in period t, we also don't observe $\sigma_{jt}^{(g)}(U)$

$$\int ln\left[\frac{\sigma_{jt}^{(1)}(U)}{\sigma_{1t}^{(1)}(U)}\right] \mathrm{d}F_t^{(1)}(U) + \omega(P_{jt} - P_{1t})\int U\,\mathrm{d}F_t^{(1)}(U) = \frac{\delta_j - \delta_1}{1-\beta} + (X_{jt} - X_{1t})'\frac{\gamma}{1-\beta} - \alpha^{(1)}(P_{jt} - P_{1t}) + \frac{\xi_{jt} - \xi_{1t}}{1-\beta}$$

Estimation Challenge

- Difficulty in recovering

$$Y_{jt}^{dynamic} \equiv \int ln\left[\frac{\sigma_{jt}^{(1)}(U)}{\sigma_{1t}^{(1)}(U)}\right] \mathrm{d}F_t^{(1)}(U) + \omega\left(P_{jt} - P_{1t}\right) \int U \, \mathrm{d}F_t^{(1)}(U)$$

- But note, if $Y_{jt}^{dynamic}$ is known, $\gamma, \alpha, \delta_j, \xi_{jt} - \xi_{1t}$ can be estimated
- **Our methodological innovation is to illustrate how to recover $\mathbf{Y_{jt}^{dynamic}}$ simply without requiring strong assumptions about the size of the state space or beliefs about the state transitions** (to eliminate the curse of dimensionality in simulating the option value of waiting as has been done in previous research and with unobserved heterogeneity)

Identification: Leveraging Overlapping Groups of Consumers

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Identification of CCP's

- At first glance all hope looks lost!
- Remember, we don't observe $\sigma_{jt}^{(g)}(U)$,
- What we do observe is group-product market share $S_{jt}^{(g)}$
- For *J* products, there are *JxG* unknowns CCPs ($\sigma_{jt}^{(g)}(u)$) (J=50, G=3→ 150unknowns) for one period *t*

$$S_{jt}^{(1)} = \int \sigma_{jt}^{(1)}(u)\, dF_t^{(1)}(u)$$

$$\dots$$

$$S_{jt}^{(G)} = \int \sigma_{jt}^{(G)}(u)\, dF_t^{(G)}(u)$$

- **So how to identify the CCPs, $\boldsymbol{\sigma_{jt}^{(g)}(U)}$?**

Identification of *CCP's*

- Trick is to write CCP's in terms of the unobserved heterogeneity
  - **All groups and individuals face the same market state variables**
- We can write the G unknown functions $\sigma_{jt}^{(1)}(U), \ldots, \sigma_{jt}^{(G)}(U)$ as one unknown CCP function.
- Specifically, I will show that you can write group g's CCP as a function of group 1's

$$\boldsymbol{\sigma_{jt}^{(2)}(U) = \sigma_{jt}^{(1)}\left(U + \tau^{(2)}/\omega\right)}$$

$$S_{jt}^{(1)} = \int \sigma_{jt}^{(1)}\left(u + \tau^{(1)}/\omega\right) dF_t^{(1)}(u)$$

$$\ldots$$

$$S_{jt}^{(G)} = \int \sigma_{jt}^{(1)}(u + \tau^{G}/\omega)\, dF_t^{(G)}(u)$$

- *JxG* equations but only *J+G* unknowns (*J* unknown CCPs and *G-1* unknown $\tau^{(g)}$ and one ω)

Identification of *CCP’s:* Overlapping groups

- Consider consumer *h*arry from the group 1 and consumer *l*isa from the group 2
- There is a point U where these two consumers have the same price sensitivity

$$\alpha_h^{(1)} = \alpha^{(1)} + \omega U_h$$

$$\alpha_l^{(2)} = \alpha^{(1)} + \tau^2 + \omega U_l$$

$$\alpha_h^{(1)} = \alpha_l^{(2)} \quad \text{when } U_h = U_l + \tau^{(2)}/\,\omega$$

- This implies

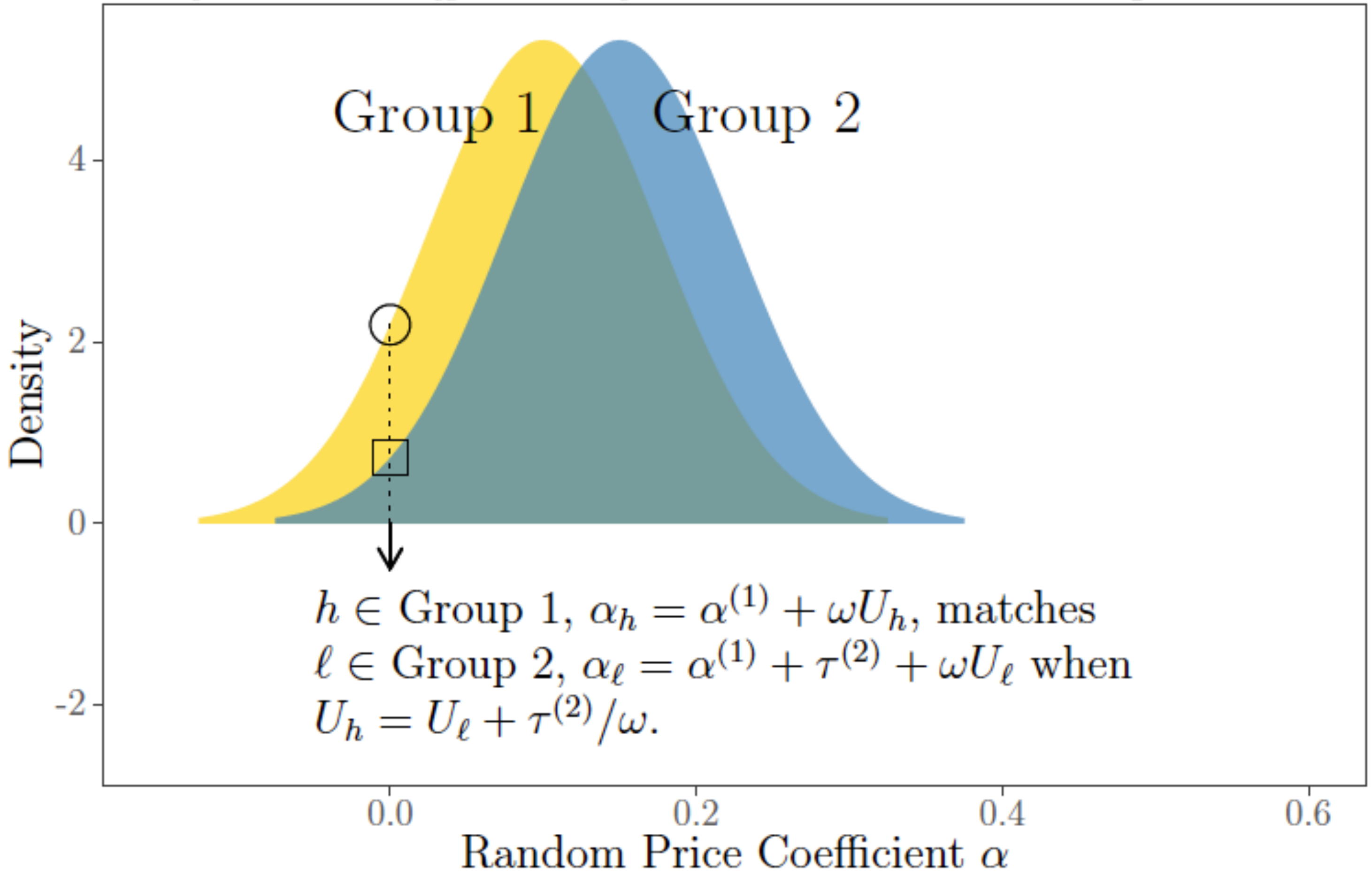
$$\sigma_{jt}^{(2)}(U_l) = \sigma_{jt}^{(1)}(U_h) \text{ when } U_h = U_l + \tau^{(2)}/\,\omega.$$

$$\sigma_{jt}^{(2)}(U) = \sigma_{jt}^{(1)}\left(U + \tau^{(2)}/\omega\right)$$

Illustration of overlapping groups

- Consider consumer *i* who is of type (g, U).
  - A consumer from group g (e.g. income bracket), with unobserved price sensitivity U

I: PDF of Price Coefficients from Two Similar Groups



Estimation: Leveraging Overlapping Groups of Consumers

Step 1: Estimation of *CCP's* in practice

- Employ series multinomial logit model for CCPs

$$L_j(c_1, \dots, c_J) \equiv \frac{\exp(c_j)}{1 + \sum_{k=1}^{J} \exp(c_k)}$$

$$c_K(U; \rho_{jt}) \equiv \rho_{jt1} + \rho_{jt2} U + \rho_{jt3} U^2$$

- Employ NLS to estimate $\rho's$, $\tau^{(g)}$ and ω: note ($\tau^{(1)} = 0$)
- Match observed group sales data to simulated group sales data employing a Gaussian Hermite quadrature approach
- $\Gamma_t^{(g)}$ captures the relative proportion of consumers of type U in period t

$$S_{jt}^{(G)} = \mathrm{E}\left[\sigma_{jt}^{(1)}(U + \tau^{(G)}/\omega; \rho_t)\Gamma_t^{(G)}(U)\right], \qquad U \sim N(0,1)$$

Recovering $Y_{jt}^{dynamic}$

- The log odds ratio for the **series multinomial logit specification** for group 1 given U is

$$\ln\left[\frac{\sigma_{jt}^{(1)}(U)}{\sigma_{1t}^{(1)}(U)}\right] = \left(\rho_{jt1} - \rho_{1t1}\right) + \left[\left(\frac{\rho_{jt2}}{\omega} - \frac{\rho_{1t2}}{\omega}\right)\right]\left(\omega U + \tau^{(1)}\right) + \left[\left(\frac{\rho_{jt3}}{\omega^2} - \frac{\rho_{1t3}}{\omega^2}\right)\right]\left(\omega U + \tau^{(1)}\right)^2$$

- For the impact of U on the series multinomial logit ***AND*** the structural model log odds ratios to be equivalent
  - We impose constraints $[-\omega\left(P_{jt} - P_{1t}\right) = \rho_{jt2} - \rho_{1t2}$ & $\rho_{jt3} - \rho_{1t3} = 0]$

- These give:

$$\ln\left[\frac{\sigma_{jt}^{(1)}(U)}{\sigma_{1t}^{(1)}(U)}\right] = \left(\rho_{jt1} - \rho_{1t1}\right) - \omega U\left(P_{jt} - P_{1t}\right) \text{ where } \tau^{(1)} = 0$$

Step 2: Estimation of Structural Parameters

- Integrating wrt to U for group 1, we have

$$\ln\left[\frac{\sigma_{jt}^{(1)}(U)}{\sigma_{1t}^{(1)}(U)}\right] = \left(\rho_{jt1} - \rho_{1t1}\right) - \omega U\left(P_{jt} - P_{1t}\right)$$

$$\boldsymbol{Y_{jt}^{dynamic} \equiv \int ln\left[\frac{\sigma_{jt}^{(1)}(U)}{\sigma_{1t}^{(1)}(U)}\right] dF_t^{(1)}(U) + \omega\left(P_{jt} - P_{1t}\right)\int U\, dF_t^{(1)}(U) = \rho_{jt1} - \rho_{1t1}}$$

- With $Y_{jt}^{dynamic}$ known

- Implement 2SLS to recover homogenous parameters

$$\boldsymbol{Y_{jt}^{dynamic}} = \boldsymbol{\rho_{jt1} - \rho_{1t1}} = \frac{\delta_j - \delta_1}{1-\beta} + \left(X_{jt} - X_{1t}\right)' \frac{\gamma}{1-\beta} - \alpha^{(1)}\left(P_{jt} - P_{1t}\right) + \frac{\xi_{jt} - \xi_{1t}}{1-\beta}$$

Estimation Summary

Step 1: Run NLS to recover ρ_{jt1}'s, ω, τ and

Step 2a: Form $\rho_{jt1} - \rho_{1t1}$

Step 2b: Run 2SLS to estimate structural parameters to account for price endogeneity

- Paper has more information about
  - Impact of dynamic selection
  - Muti-dimensional unobserved heterogeneity
  - Estimating the discount factor
  - Simulations

Empirical Application: EV Demand in WA

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Table 7: Estimation of EV Demand

Variables	Estimate	SE
Price	2.5576**	(0.7747)
Price × I[Medium Income]	0.6555**	(0.0130)
Price × I[Low Income]	0.6551**	(0.0198)
MPGe	3.0477	(2.1431)
MPGe × I[Medium Income]	–0.0084	(0.0172)
MPGe × I[Low Income]	–0.2383**	(0.0413)
ln[Electric Range] × BEV	0.7881*	(0.4616)
BEV	–2.7099**	(0.9975)
SUV	1.2123**	(0.4795)
SUV × BEV	3.4435**	(1.2727)
Horsepower	2.0532**	(0.7274)
Gas Price	13.7900**	(4.9848)
Gas Price × BEV	0.7102**	(0.3278)
EV Stations × BEV	0.0042**	(0.0012)
ω_{mpge} —MPGe	0.2926**	(0.0341)
ω_p —Price	0.4971**	(0.0510)
Discount Factor (β)	0.8625**	(0.2888)

Note: Make fixed effects are not reported to save space.

Price is scaled by 1/10,000. MPGe and HP are scaled by 1/100.

Estimates for observed charac. report values $\gamma/(1-\beta)$ or $\gamma/(1-\beta q)$.

NLS stage has a reported $R^2 = 0.99$.

** 95 percent significance; * 90 percent significance.

Counterfactuals

- Policy simulation to evaluate impact of Tax Credits on Battery Size vs Efficiency (Electric Range).
  1. Evaluate change in policy for observed data periods (permanent)

  - Permanent policy changes require an assumption on the state space: we use IVS for computational ease.

Counterfactual

- New Policy: linear function of Electric Range.
  - Tax credit= Electric Range*X
- Find X that equates total cost of new policy identical to old policy
  - X=$30.54 per mile of Electric Range

Tax Policy Example: Vehicles

BMW X5 PHEV: 9.2 kWh, 14-mile electric range
Old Policy: $4,668
New Policy (Perm): $427.56

Tesla Model S: 95 kWh, 250-mile electric range
Old Policy: $7,500
New Policy (Perm): $7,635

Table 9: Long-Term Policy Simulation Results: Electric Range Tax Credit

	Existing Policy (kWh)	Proposed Policy (Electric Range)	% change
Sales (units)	30,638	30,999	1.18%
BEV Sales (units)	25,287	27,399	8.35%
PHEV Sales (units)	5,352	3,600	-32.73%
Total CO2 (tons)	51,872	46150	-11.03%
Total Cost ($)	180,813,613	180,813,613	2.29e-04%

Note: Policy Rebate=30.54 per mile of electric range

Counterfactual 2

- Policy simulation to evaluate impact of investment in Level 3 DC Charging Infrastructure Network vs individual tax credits
  - New infrastructure policy changes growth rate of Level 3 DC Charging Stations in each market.
    - Data: 1.0311
    - CF: 1.0509
  - Assume each new Level 3 charging station costs $75,000 to install
  - Policy change removes ALL consumer tax credits
  - Policy change is permanent

Table 11: Long-Term Policy Simulation: Level 3 Charging Infrastructure Network

	Existing Policy	New Infrastructure Policy	% change
Sales (units)	30,638	38,323	25.08%
BEV Sales (units)	25,287	34,845	37.80%
PHEV Sales (units)	5,352	3,478	-35.02%
Total CO2 (tons)	51,872	11,004	-78.78%
Total Cost ($)	180,813,613	180,750,000	0.03%

Note: New infrastructure policy growth rate changes from 1.0311% to 1.0509%

All prior federal tax credits are eliminated

Thank You

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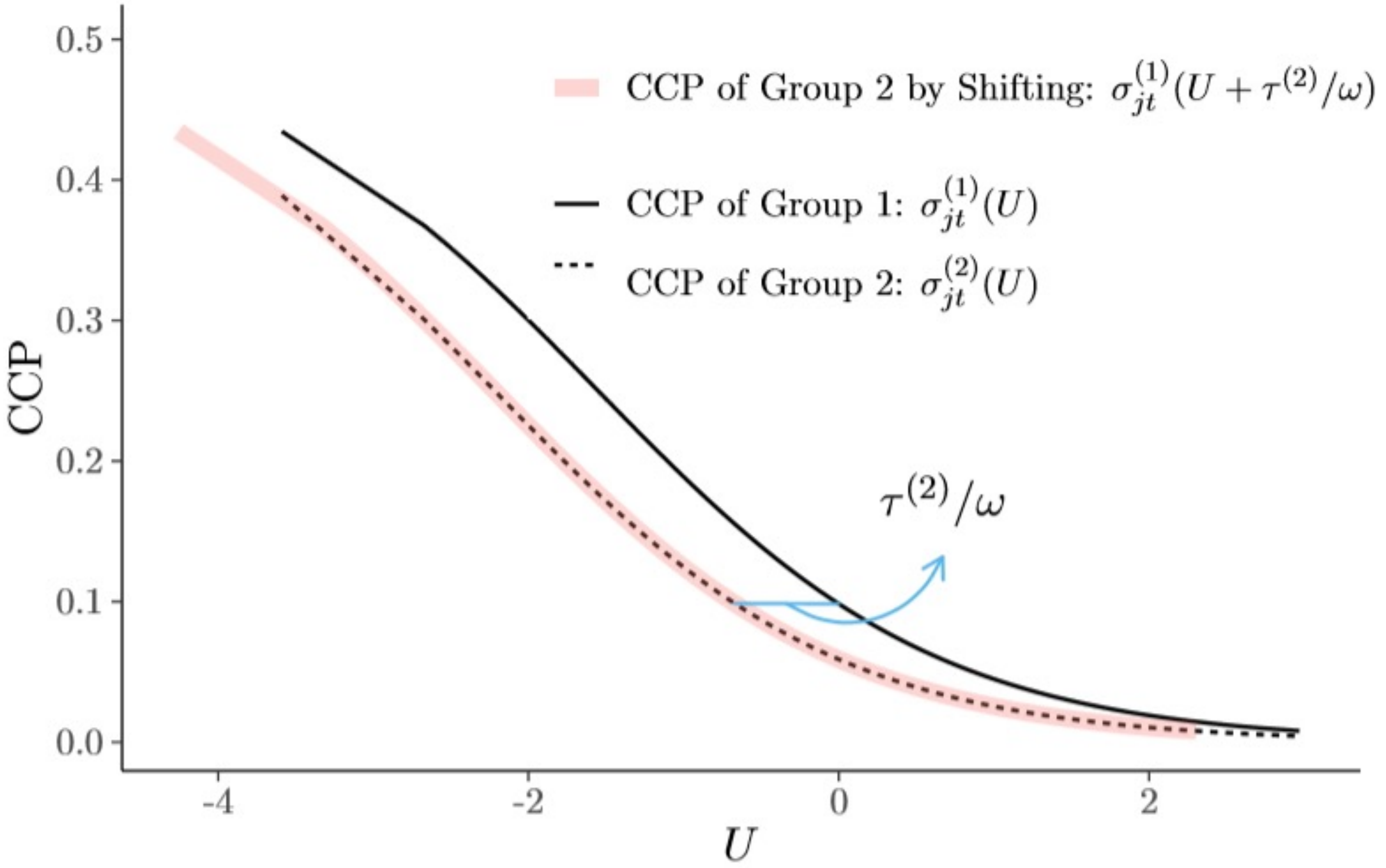
CCP of Group 2 by Shifting: $\sigma_{jt}^{(1)}(U + \tau^{(2)}/\omega)$
CCP of Group 1: $\sigma_{jt}^{(1)}(U)$
CCP of Group 2: $\sigma_{jt}^{(2)}(U)$
$\tau^{(2)}/\omega$
CCP
0.0
0.1
0.2
0.3
0.4
0.5
-4
-2
0
2
U

Table 2: Simulation Results: Comparison Across Within Heterogeneity

DGP: $M = 2$, $T = 12$ and $J = 8$

	$\omega = 0.025$	$\omega = 0.05$	$\omega = 0.075$
$\delta = -0.10$	-0.1043 (0.0083)	-0.1039 (0.0083)	-0.1028 (0.0083)
$\gamma = 0.03$	0.0317 (0.0037)	0.0316 (0.0037)	0.0314 (0.0037)
$\alpha^1 = 0.10$	0.1003 (0.0055)	0.1003 (0.0055)	0.1004 (0.0055)
$\tau^2 = 0.05$	0.0503 (1.44e-5)	0.0503 (1.27e-5)	0.0502 (1.63e-5)
$\tau^3 = 0.10$	0.1002 (2.75e-5)	0.1002 (2.18e-5)	0.1002 (2.72e-5)
$\tau^4 = 0.15$	0.1502 (4.09e-5)	0.1502 (2.96e-5)	0.1502 (3.50e-5)
$\tau^5 = 0.20$	0.2004 (5.34e-5)	0.2003 (3.59e-5)	0.2004 (4.09e-5)
$\tau^6 = 0.25$	0.2510 (6.66e-5)	0.2509 (4.22e-5)	0.2508 (4.62e-5)
ω	0.0272 (2.40e-4)	0.0512 (9.12e-5)	0.0760 (7.46e-5)
$\beta = 0.90$	0.8968 (7.39e-4)	0.8971 (7.31e-4)	0.8978 (7.20e-4)

Note: Mean and standard deviation (in parenthesis) for 50 simulations.

Table 3: Simulation Results: Comparison Across Number of Groups

DGP: $M = 2$, $J = 8$ and $\omega = 0.075$

	$G = 2, T = 12$	$G = 6, T = 12$	$G = 2, T = 36$	$G = 6, T = 36$
$\delta = -0.10$	-0.1042 (0.0082)	-0.1028 (0.0083)	-0.1046 (0.0032)	-0.0977 (0.0033)
$\gamma = 0.03$	0.0316 (0.0037)	0.0314 (0.0037)	0.0308 (0.0020)	0.0300 (0.0020)
$\alpha^1 = 0.10$	0.1006 (0.0055)	0.1004 (0.0055)	0.1011 (0.0027)	0.1003 (0.0027)
$\tau^2 = 0.05$	–	0.0502 (1.63e-5)	–	0.0499 (1.27e-5)
$\tau^3 = 0.10$	–	0.1002 (2.72e-5)	–	0.0997 (2.14e-5)
$\tau^4 = 0.15$	–	0.1502 (3.50e-5)	–	0.1496 (2.70e-5)
$\tau^5 = 0.20$	–	0.2004 (4.09e-5)	–	0.1997 (3.06e-5)
$\tau^6 = 0.25$	0.2551 (0.0015)	0.2508 (4.62e-5)	0.2489 (1.31e-4)	0.2501 (3.40e-5)
$\omega = .075$	0.0847 (0.0025)	0.0760 (7.46e-5)	0.0736 (2.00e-4)	0.0747 (5.10e-5)
$\beta = 0.90$	0.8970 (8.54e-4)	0.8978 (7.20e-4)	0.8983 (5.43e-4)	0.9009 (5.20e-4)

Note: Mean and standard deviation (in parenthesis) for 50 simulations.

Table 4: Simulation Results: Bias If Ignore Attrition

DGP: $M = 2$, $T = 12$, $G = 6$ and $J = 8$

	$\omega = 0.025$	$\omega = 0.05$	$\omega = 0.075$
$\delta = -0.10$	-0.1295 (0.0088)	-0.1844 (0.0096)	-0.2693 (0.0111)
$\gamma = 0.03$	0.0336 (0.0039)	0.0381 (0.0044)	0.0453 (0.0052)
$\beta = 0.90$	0.8907 (7.10e-4)	0.8758 (7.15e-4)	0.8525 (7.70e-4)

Note: Mean and standard deviation (in parenthesis) for 50 simulations.

Table 10: Long-Term Policy Simulation Results: Electric Range Tax Credit

	Income $\leq$ 75th Percentile	Income between 90th and 75th Percentile	Income $\geq$ 90th Percentile
BEV Sales (units)	4,274	5,372	15,640
BEV Sales CF (units)	4,630	5,675	17,093
PHEV Sales (units)	1,493	1,292	2,566
PHEV Sales CF (units)	835	951	1,812

Note: Policy Rebate=30.54 per mile of electric range. "CF" stands for counterfactual policy.