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AJAE appendix for:

BENEFIT TRANSFER FROM MULTIPLE CONTINGENT EXPERIMENTS: A FLEXIBLE TWO-STEP MODEL COMBINING INDIVIDUAL CHOICE DATA WITH COMMUNITY CHARACTERISTICS

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July 10, 2009

The material contained herein is supplementary to the article named in the title and published in the American Journal of Agricultural Economics (AJAE).

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Gibbs Sampler Details

For simplicity we will omit the "*s*" subscript for the sample size *N* and the number of menus per respondent, *T*.

<u>Priors:</u>

$$p(\boldsymbol{\beta},\boldsymbol{\Sigma}) = p(\boldsymbol{\beta})\,p(\boldsymbol{\Sigma}) \quad \text{where}$$

$$p(\boldsymbol{\beta}) = (2\pi)^{-k_f/2}\left|\mathbf{V_0}\right|^{-1/2}\exp\left(-\tfrac{1}{2}(\boldsymbol{\beta}-\boldsymbol{\mu_0})'\,\mathbf{V_0^{-1}}\,(\boldsymbol{\beta}-\boldsymbol{\mu_0})\right)$$

(1) $$p(\boldsymbol{\Sigma}) = \prod_{j=1}^{k_r} p(\Sigma_{jj}) \quad \text{with}$$

$$p(\Sigma_{jj}) = \frac{\tau_0^{\,v_0}}{\Gamma(v_0)}(\Sigma_{jj})^{-(v_0+1)}\exp\left(-\frac{\tau_0}{\Sigma_{jj}}\right), \quad \text{where}$$

$$E(\Sigma_{jj}) = \frac{\tau_0}{v_0-1}, \quad V(\Sigma_{jj}) = \frac{\tau_0^2}{(v_0-1)^2(v_0-2)}$$

We will use two layers of data augmentation: one for the $\boldsymbol{\alpha}_\mathbf{i}$ terms and one for $\mathbf{U}$, the vector of latent utility differences. The fully augmented joint posterior takes the generic form of

(2) $$p(\boldsymbol{\beta},\boldsymbol{\Sigma},\boldsymbol{\alpha}_\mathbf{i}\,(i=1\cdots N),\mathbf{U}\,|\,\mathbf{y},\mathbf{X}) \propto$$
$$p(\boldsymbol{\beta})\,p(\boldsymbol{\Sigma})\,p(\boldsymbol{\alpha}_\mathbf{i}\,|\,\boldsymbol{\beta},\boldsymbol{\Sigma})\,p(\mathbf{U}\,|\,\boldsymbol{\beta},\boldsymbol{\Sigma},\mathbf{X})\,p(\mathbf{y}\,|\,\mathbf{U})$$

As suggested in Layton and Levine (2003) we do NOT condition draws of **U** on $\boldsymbol{\alpha}_\mathbf{i}$. We will also draw $\boldsymbol{\beta}$ without conditioning on $\boldsymbol{\alpha}_\mathbf{i}$. However, we will need to draw the $\boldsymbol{\alpha}_\mathbf{i}$ terms to feed into the draws of $\boldsymbol{\Sigma}$.

Let's take a closer look at $p(\mathbf{U}\,|\,\boldsymbol{\beta},\boldsymbol{\Sigma},\mathbf{X})$. For the full sample we can write

$$p\left(\mathbf{U}\,|\,\boldsymbol{\beta},\boldsymbol{\Sigma},\mathbf{X}\right)=\prod_{i=1}^{N}\left(2\pi\right)^{-JT/2}\left|\mathbf{D_i}\mathbf{V_i}\mathbf{D}_i'\right|^{-1/2}\exp\left(-\tfrac{1}{2}\left(\mathbf{U_i}-\mathbf{D_i}\boldsymbol{\mu}_\mathbf{i}\right)'\left(\mathbf{D_i}\mathbf{V_i}\mathbf{D}_i'\right)^{-1}\left(\mathbf{U_i}-\mathbf{D_i}\boldsymbol{\mu}_\mathbf{i}\right)\right)=$$

(3) $$\left(2\pi\right)^{-NJT/2}\left|\mathbf{D_i}\mathbf{V_i}\mathbf{D}_i'\right|^{-N/2}\exp\left(-\tfrac{1}{2}\sum_{i=1}^{N}\left(\mathbf{U_i}-\mathbf{D_i}\boldsymbol{\mu}_\mathbf{i}\right)'\left(\mathbf{D_i}\mathbf{V_i}\mathbf{D}_i'\right)^{-1}\left(\mathbf{U_i}-\mathbf{D_i}\boldsymbol{\mu}_\mathbf{i}\right)\right)$$ with

$$\boldsymbol{\mu}_\mathbf{i}=\mathbf{X_i}\boldsymbol{\beta},\qquad \mathbf{V_i}=\mathbf{X_{ri}}\boldsymbol{\Sigma}\mathbf{X}_\mathbf{ri}'+\mathbf{I_{JxT}}$$

The last term of the augmented posterior kernel in (2) can be written as

$$p\left(\mathbf{y}\,|\,\mathbf{U}\right)=\prod_{i=1}^{N}\left(\prod_{t=1}^{T}\left(\sum_{k=1}^{J}I\left(y_{it}=k\right)I\left(\max\left\{\left\{U_{ijt}\right\}_{j=1}^{J}\right\}=U_{ikt}\right)\right)\right)$$

The explicit form of the augmented posterior kernel can now be written as:

$$p\left(\boldsymbol{\beta},\boldsymbol{\Sigma},\boldsymbol{\alpha}_\mathbf{i}\left(i=1\cdots N\right),\mathbf{U}\,|\,\mathbf{y},\mathbf{X}\right)\propto$$

$$\exp\left(-\tfrac{1}{2}\left(\boldsymbol{\beta}-\boldsymbol{\mu}_\mathbf{0}\right)'\mathbf{V_0^{-1}}\left(\boldsymbol{\beta}-\boldsymbol{\mu}_\mathbf{0}\right)\right)*\prod_{j=1}^{k_r}\left(\Sigma_{jj}\right)^{-\left(v_0+1\right)}\exp\left(-\frac{\tau_0}{\Sigma_{jj}}\right)$$

(4) $$\left|\boldsymbol{\Sigma}\right|^{-N/2}\exp\left(\sum_{i-1}^{N}-\tfrac{1}{2}\boldsymbol{\alpha}_\mathbf{i}'\boldsymbol{\Sigma}^{-1}\boldsymbol{\alpha}_\mathbf{i}\right)*$$

$$\left(2\pi\right)^{-NJT/2}\left|\mathbf{D_i}\mathbf{V_i}\mathbf{D}_i'\right|^{-N/2}\exp\left(-\tfrac{1}{2}\sum_{i=1}^{N}\left(\mathbf{U_i}-\mathbf{D_i}\boldsymbol{\mu}_\mathbf{i}\right)'\left(\mathbf{D_i}\mathbf{V_i}\mathbf{D}_i'\right)^{-1}\left(\mathbf{U_i}-\mathbf{D_i}\boldsymbol{\mu}_\mathbf{i}\right)\right)$$

$$\prod_{i=1}^{N}\left(\prod_{t=1}^{T}\left(\sum_{k=1}^{J}I\left(y_{it}=k\right)I\left(\max\left\{\left\{U_{ijt}\right\}_{j=1}^{J}\right\}=U_{ikt}\right)\right)\right)$$

This leads to the following conditional posterior for $\boldsymbol{\beta}$:

$$p\left(\boldsymbol{\beta}\,|\,\boldsymbol{\Sigma},\mathbf{U},\mathbf{X}\right)\propto$$

(5) $$\exp\left(-\tfrac{1}{2}\left(\left(\boldsymbol{\beta}-\boldsymbol{\mu}_\mathbf{0}\right)'\mathbf{V_0^{-1}}\left(\boldsymbol{\beta}-\boldsymbol{\mu}_\mathbf{0}\right)+\sum_{i=1}^{N}\left(\mathbf{U_i}-\mathbf{D_i}\boldsymbol{\mu}_\mathbf{i}\right)'\left(\mathbf{D_i}\mathbf{V_i}\mathbf{D}_i'\right)^{-1}\left(\mathbf{U_i}-\mathbf{D_i}\boldsymbol{\mu}_\mathbf{i}\right)\right)\right)$$

This is equivalent to the conditional posterior for the generalized regression model. We can immediately derive the conditional posterior moments as:

$$\boldsymbol{\beta} \mid \boldsymbol{\Sigma}, \mathbf{U}, \mathbf{X} \sim n\left(\boldsymbol{\mu}_{\mathbf{1}}, \mathbf{V}_{\mathbf{1}}\right) \quad \text{with}$$

(6) $$\mathbf{V}_{\mathbf{1}} = \left(\mathbf{V}_{\mathbf{0}}^{-\mathbf{1}} + \sum_{i=1}^{N} \mathbf{X}_{\mathbf{i}}' \left(\mathbf{D}_{\mathbf{i}} \mathbf{V}_{\mathbf{i}} \mathbf{D}_i'\right)^{-1} \mathbf{X}_{\mathbf{i}} \right)^{-1} = \left(\mathbf{V}_{\mathbf{0}}^{-\mathbf{1}} + \sum_{i=1}^{N} \mathbf{X}_{\mathbf{i}}' \left(\mathbf{D}_{\mathbf{i}} \left(\mathbf{X}_{\mathbf{ri}} \boldsymbol{\Sigma} \mathbf{X}_{\mathbf{ri}}' + \mathbf{I}_{\mathbf{JxT}}\right) \mathbf{D}_i'\right)^{-1} \mathbf{X}_{\mathbf{i}} \right)^{-1}$$

$$\boldsymbol{\mu}_{\mathbf{1}} = \mathbf{V}_{\mathbf{1}} \left(\mathbf{V}_{\mathbf{0}}^{-\mathbf{1}} \boldsymbol{\mu}_{\mathbf{0}} + \sum_{i=1}^{N} \mathbf{X}_{\mathbf{i}}' \left(\mathbf{D}_{\mathbf{i}} \mathbf{V}_{\mathbf{i}} \mathbf{D}_i'\right)^{-1} \mathbf{U}_{\mathbf{i}} \right) = \left(\mathbf{V}_{\mathbf{0}}^{-\mathbf{1}} \boldsymbol{\mu}_{\mathbf{0}} + \sum_{i=1}^{N} \mathbf{X}_{\mathbf{i}}' \left(\mathbf{D}_{\mathbf{i}} \left(\mathbf{X}_{\mathbf{ri}} \boldsymbol{\Sigma} \mathbf{X}_{\mathbf{ri}}' + \mathbf{I}_{\mathbf{JxT}}\right) \mathbf{D}_i'\right)^{-1} \mathbf{U}_{\mathbf{i}} \right)$$

Next, it is convenient to draw the individual random vectors $\boldsymbol{\alpha}_{\mathbf{i}}$. We aim to draw $\boldsymbol{\alpha}_{\mathbf{i}}$ from $p\left(\boldsymbol{\alpha}_{\mathbf{i}} \mid \boldsymbol{\beta}, \boldsymbol{\Sigma}, \mathbf{U}_{\mathbf{i}}, \mathbf{X}_{\mathbf{i}}\right)$. Note that only data corresponding to individual "*i*" are relevant. Letting $\tilde{\mathbf{U}}_{\mathbf{i}} = \mathbf{U}_{\mathbf{i}} - \mathbf{D}_{\mathbf{i}} \mathbf{X}_{\mathbf{i}} \boldsymbol{\beta} = \mathbf{D}_{\mathbf{i}} \mathbf{X}_{\mathbf{ri}} \boldsymbol{\alpha}_{\mathbf{i}} + \mathbf{D}_{\mathbf{i}} \boldsymbol{\varepsilon}_{\mathbf{i}}$ yields:

(7) $$p\left(\boldsymbol{\alpha}_{\mathbf{i}} \mid \boldsymbol{\beta}, \boldsymbol{\Sigma}, \mathbf{U}_{\mathbf{i}}, \mathbf{X}_{\mathbf{i}}\right) \propto \exp\left(-\tfrac{1}{2} \left(\left(\tilde{\mathbf{U}}_{\mathbf{i}} - \mathbf{X}_{\mathbf{ri}} \boldsymbol{\alpha}_{\mathbf{i}}\right)' \left(\mathbf{D}_{\mathbf{i}} \mathbf{D}_{\mathbf{i}}'\right)^{-1} \left(\tilde{\mathbf{U}}_{\mathbf{i}} - \mathbf{X}_{\mathbf{ri}} \boldsymbol{\alpha}_{\mathbf{i}}\right) + \boldsymbol{\alpha}_{\mathbf{i}}' \boldsymbol{\Sigma}^{-\mathbf{1}} \boldsymbol{\alpha}_{\mathbf{i}} \right) \right)$$

The conditional kernel then emerges as

$$\boldsymbol{\alpha}_{\mathbf{i}} \mid \boldsymbol{\beta}, \boldsymbol{\Sigma}, \mathbf{U}_{\mathbf{i}}, \mathbf{X}_{\mathbf{i}} \sim n\left(\boldsymbol{\mu}_{\mathbf{1}}, \mathbf{V}_{\mathbf{1}}\right) \qquad \text{with}$$

(8) $$\mathbf{V}_{\mathbf{1}} = \left(\boldsymbol{\Sigma}^{-\mathbf{1}} + \mathbf{X}_{\mathbf{ir}}' \left(\mathbf{D}_{\mathbf{i}} \mathbf{D}_{\mathbf{i}}'\right)^{-1} \mathbf{X}_{\mathbf{ir}} \right)^{-1}$$

$$\boldsymbol{\mu}_{\mathbf{1}} = \mathbf{V}_{\mathbf{1}} \left(\mathbf{X}_{\mathbf{ir}}' \left(\mathbf{D}_{\mathbf{i}} \mathbf{D}_{\mathbf{i}}'\right)^{-1} \tilde{\mathbf{U}}_{\mathbf{i}} \right) = \mathbf{V}_{\mathbf{1}} \left(\mathbf{X}_{\mathbf{ir}}' \left(\mathbf{D}_{\mathbf{i}} \mathbf{D}_{\mathbf{i}}'\right)^{-1} \left(\mathbf{U}_{\mathbf{i}} - \mathbf{X}_{\mathbf{i}} \boldsymbol{\beta}\right) \right)$$

We have to repeat this *N* times, for each of the *N* $\boldsymbol{\alpha}_{\mathbf{i}}$'s.

The next step in our GS is the draw of the diagonal terms of the hierarchical variance $\boldsymbol{\Sigma}$. We obtain

(9) $$p\left(\Sigma_{jj} \mid \boldsymbol{\alpha}_{\mathbf{ij}}\right) = ig\left(v_1, \tau_1\right) \quad \text{where}$$

$$v_1 = \frac{2v_0 + N}{2} \qquad \text{and} \qquad \tau_1 = \frac{2\tau_0 + \boldsymbol{\alpha}_{\mathbf{ij}}' \boldsymbol{\alpha}_{\mathbf{ij}}}{2}$$

For a given individual and choice occasion the conditional posterior for latent utility takes the form of

$$
\begin{aligned}
& p\left(\mathbf{U_i} \mid \boldsymbol{\beta}, \boldsymbol{\Sigma}, \mathbf{y_i}, \mathbf{X_{it}}\right) \propto \\
(10) \quad & \exp\left(-\tfrac{1}{2}\left(\mathbf{U_i} - \mathbf{D_i}\boldsymbol{\mu}_\mathbf{i}\right)'\left(\mathbf{D_i}\mathbf{V_i}\mathbf{D}_i'\right)^{-1}\left(\mathbf{U_i} - \mathbf{D_i}\boldsymbol{\mu}_\mathbf{i}\right)\right) * \\
& \prod_{t=1}^{T}\left(\sum_{k=1}^{J} I\left(y_{it} = k\right) I\left(\max\left\{\left\{U_{ijt}\right\}_{j=1}^{J}\right\} = U_{ikt}\right)\right)
\end{aligned}
$$

Draws from this density can be obtained via a "Gibbs-within-Gibbs" algorithm as described in Layton and Levine (2003) and (2005). We use 50 iterations for this sub-routine.

Posterior Predictive Draws

Draws from the PPDs of compensating surplus can be obtained as follows:

For each of the R draws of $\boldsymbol{\beta}$ and $\boldsymbol{\Sigma}$ from the original Gibbs Sampler perform the following:

1) Draw a vector $\boldsymbol{\alpha}$ of random deviation terms from $f\left(\boldsymbol{\alpha} \mid \boldsymbol{\Sigma}\right)$ and compute

$C_{sp} \mid \boldsymbol{\alpha}, \boldsymbol{\beta} = -\delta^{-1}\left(\mathbf{x}_{\mathbf{p}}'\boldsymbol{\beta}_{-P} + \mathbf{x}_{\mathbf{pr}}'\boldsymbol{\alpha}\right)$.

2) Repeat the first step r_2 times for smoothness of the PPD (statistically, this is optional).

In our case, we first thin the original GS by retaining every 10th draw to weaken autocorrelation in the sequence. We then draw 25 $\boldsymbol{\alpha}$-vectors per original parameter set, yielding a total of 25,000 draws from.

First-step estimation results, Set 1

See Table 1.

First-step estimation results, Set 2

See Table 2.

Community Characteristics and Distances

See Table 3.

Auxiliary regression model

This model produces the "regression weights" shown in the next table of this document, and ultimately the relative overlap results under the "regression" column in Table 1 of the main paper.

We declare one of the 8 communities as a "target site". We compute the OLR statistic (described in the main paper) for each of the remaining sites, based on their step 1 distributions for the policy-relevant welfare measure. Let y_{jk} be the OLR for a pair of sites *j*,*k*. We then compute $\tilde{y}_{jk} = 1 - y_{jk}$ as our dependent variable. This metric is bounded by 0 and 1 (since y_{jk} is bounded by 0 and 1). It takes a value of zero under perfect overlap (i.e. when $y_{jk} = 1$).

On the right hand side we use the distance between *j* and *k*, in 10-mile units (let's call it D_{jk}), plus a few aggregate community characteristics. For example, let x_j and x_k be the population density (residents / acre) in communities *j* and *k*. We then construct the following regressor:

$\tilde{x}_{jk} = 1 - \left(\min\left(x_j, x_k\right) / \max\left(x_j, x_k\right)\right)$. Thus, under perfect compatibility of the two sites with respect to this specific characteristic we have $\tilde{x}_{jk} = 0$. This transformation allows for a meaningful regression model without a constant term - the closer distance and $\tilde{x}_{ij}$ are to zero, the closer $\tilde{y}_{jk}$ should be to zero as well. In words: The more "similar" the two sites are based on our chosen community characteristics, the better they should overlap in step 1 welfare densities.

Formally, the doubly-truncated regression model is given as

$$\tilde{y}_{jk} = \tilde{x}_{p,jk} + \tilde{x}_{u,jk} + D_{jk} + \varepsilon_{jk}, I\left(0 < \tilde{y}_{jk} < 1\right) \qquad \varepsilon_{jk} \sim n\left(0, \sigma^2\right)$$

where $\tilde{x}_{p,jk}$ is the aforementioned population density variable and $\tilde{x}_{u,jk}$ is the transformed ratio of the share of urban homes to suburban and rural homes (this was elicited in the

survey but could probably be derived through secondary sources as well). We chose this specification after experimenting with numerous other (similar) models. With a sample size of 21 (all possible pairs from 7 sites) we can only include a few regressors.

We estimate this model, via MLE, sequentially for all *S* target site cases. So for example, in the first run, GT is the target site, and the remaining 7 town feed into the regression model. In the second run, MF is the target and GT returns to the regression sites, etc. For most of these runs, the overall fit is quite good but individual parameter significance is lacking in most cases. This is not unexpected, given the small sample size and the very general nature of our regressors.

The next step is key as it links the regression model to the target site. Assume GT is the target. Let GT be the "*j*" site. Compute $\tilde{x}_{p,jk}, \tilde{x}_{u,jk}, D_{jk}$ for GT with respect to all other sites. For each case, use the regression results to predict $\tilde{y}_{jk}$, and convert back to $y_{jk} = 1 - \tilde{y}_{jk}$. Thus we obtain 7 predictions of OLR of the regression sites with GT. Call these predictions $\hat{y}_{jk}, k \neq j$. The mixture weights are then computed as $\psi_k = \hat{y}_{jk} / \sum_{k=1}^{S-1} \hat{y}_{jk}, k \neq j$. The intuition is that we would like to allocate more weight to sites that are expected to have better welfare overlap with the target, based solely on secondary attributes.

After drawing from the resulting mixture density, we compare the resulting distribution of compensating surplus to GT's actual distribution from step 1, based again on the OLR ratio. This is captured in the "regression" column of Table 1 in the main text.

Second-stage Weights for Benefit-Transfer Distributions

See Table 4.

How to draw form the mixture distribution

With empirical weight vector $\boldsymbol{\psi} = \begin{bmatrix} \psi_1 & \psi_2 & \cdots & \psi_{S-1} \end{bmatrix}$ in hand, we can easily draw from

$p\left(C_{pp}\right) = \sum_{s=1}^{S-1} \psi_s p\left(C_{sp} \mid \mathbf{y_s}, \mathbf{X_s}\right)$ as follows:

1. Generate a vector $\boldsymbol{\psi}_{sum}$ containing the cumulative sum of $\boldsymbol{\psi}$. Thus, the first element of this vector will be ψ_1 and the last element will be 1.
2. Draw a random uniform term, say *u*, from the [0,1] interval.
3. If $u < \psi_{sum(1)}$, take a draw from C_{1p}. If $\psi_{sum(1)} < u < \psi_{sum(2)}$, draw from C_{2p}, and so on.

We repeat this process 25,000 times to obtain the same number of draws as we have for the individual welfare distributions.

It is important to note that this is NOT equivalent to averaging draws from the *S*-1 underlying densities. We are not aiming to obtain a weighted average or expectation, but an entire weighted distribution.

References:

Layton, D.F., and R.A. Levine. 2003. "How Much Does the Far Future Matter? A Hierarchical Bayesian Analysis of the Public's Willingness to Mitigate Ecological Impacts of Climate Change." *Journal of the American Statistical Association* 98:533-544.

Layton, D.F., and R.A. Levine. 2005. "Bayesian Approaches to Modeling Stated Preference Data." In R. Scarpa and A. Alberini, eds. *Applications of Simulation Methods in Environmental and Resource Economics*. Dordrecht, The Netherlands: Springer, pp. 187-205.

Table 1: First-step estimation results, Set 1

	Georgetown			Mansfield			Preston			Smyrna		
	mean	std	nse	mean	std	nse	mean	std	nse	mean	std	nse
fixed												
cost($10s)	-0.09	0.01	0.00	-0.06	0.01	0.00	-0.07	0.01	0.00	-0.07	0.01	0.00
random means												
acres (10s)	-1.41	0.56	0.04	-0.39	0.30	0.01	-0.86	0.43	0.02	-0.70	0.35	0.01
nursery*acres	-0.74	0.55	0.01	-0.51	0.40	0.01	-0.47	0.61	0.05	-0.46	0.59	0.04
food*acres	-0.32	0.56	0.02	0.22	0.40	0.01	-0.64	0.63	0.06	-0.07	0.66	0.04
dairy*acres	-0.52	0.59	0.03	0.01	0.38	0.01	-0.10	0.49	0.02	0.27	0.46	0.02
forest*acres	-0.60	0.75	0.06	0.16	0.49	0.02	0.07	0.46	0.01	-0.15	0.47	0.02
walking*acres	1.48	0.65	0.05	1.35	0.37	0.02	0.91	0.52	0.02	1.43	0.47	0.02
hunting*acres	1.29	0.57	0.02	0.16	0.38	0.01	0.29	0.49	0.03	0.47	0.40	0.01
random stds												
acres (10s)	2.73	0.61	0.06	2.34	0.37	0.04	2.76	0.50	0.05	1.85	0.46	0.04
nursery*acres	0.94	0.44	0.05	1.05	0.56	0.08	1.87	1.13	0.23	1.94	1.00	0.13
food*acres	1.22	0.77	0.12	1.55	0.82	0.18	2.02	1.09	0.18	3.34	1.65	0.27
dairy*acres	1.27	0.69	0.09	1.54	0.68	0.10	1.42	0.80	0.14	1.23	0.65	0.08
forest*acres	1.91	1.10	0.22	2.89	1.28	0.23	1.01	0.47	0.06	1.57	0.90	0.11
walking*acres	2.54	1.46	0.22	1.00	0.50	0.09	2.49	1.14	0.17	1.50	0.84	0.11
hunting*acres	1.47	0.96	0.14	1.23	0.64	0.10	1.95	0.90	0.11	1.08	0.52	0.06

*nse = numerical standard error
**stds = standard deviations

Table 2: First-step estimation results, Set 2

	Brooklyn			Pomfret			Thompson			Woodstock		
	mean	std	nse	mean	std	nse	mean	std	nse	mean	std	nse
fixed												
cost($10s)	-0.07	0.01	0.00	-0.06	0.01	0.00	-0.06	0.01	0.00	-0.04	0.01	0.00
random means												
acres (10s)	-0.74	1.62	0.02	-0.10	1.60	0.02	-1.12	1.60	0.02	-0.20	1.59	0.02
trees*acres	-0.13	1.62	0.02	-0.26	1.60	0.02	-0.46	1.60	0.02	-0.19	1.59	0.02
food*acres	-0.26	1.63	0.02	0.09	1.59	0.02	-0.21	1.59	0.02	-0.02	1.60	0.02
dairy*acres	-0.31	1.63	0.02	-0.04	1.59	0.02	-0.53	1.61	0.02	0.00	1.60	0.02
walking*acres	1.78	0.40	0.02	0.98	0.28	0.01	1.92	0.41	0.02	1.18	0.31	0.01
random stds												
acres (10s)	2.08	0.46	0.03	1.82	0.33	0.02	2.84	1.36	0.08	1.69	0.37	0.02
trees*acres	1.28	0.56	0.05	1.01	0.43	0.05	0.94	0.80	0.06	0.81	0.31	0.03
food*acres	1.33	0.56	0.06	0.92	0.37	0.04	0.82	0.72	0.06	0.85	0.35	0.04
dairy*acres	1.24	0.69	0.08	0.78	0.27	0.03	1.60	1.78	0.26	1.07	0.49	0.05
walking*acres	1.26	0.57	0.07	1.28	0.45	0.04	3.27	2.41	0.20	1.26	0.46	0.04

*nse = numerical standard error
**stds = standard deviations

Table 3: Community Characteristics and Distances

Community Characteristics

	pop. / acre	homes / acre	fraction urban HHs	fraction rental HHs	average HH size	average yrs. of residence
Georgetown	0.194	0.066	0.099	0.109	2.560	18.660
Mansfield	0.709	0.188	0.085	0.091	2.510	20.110
Preston	0.231	0.094	0.025	0.065	2.690	20.170
Smyrna	0.224	0.080	0.179	0.046	2.750	15.750
Brooklyn	0.387	0.146	0.362	0.106	2.820	19.950
Pomfret	0.147	0.058	0.139	0.073	2.790	19.800
Thompson	0.284	0.119	0.409	0.042	2.691	22.150
Woodstock	0.183	0.077	0.155	0.066	2.730	19.630

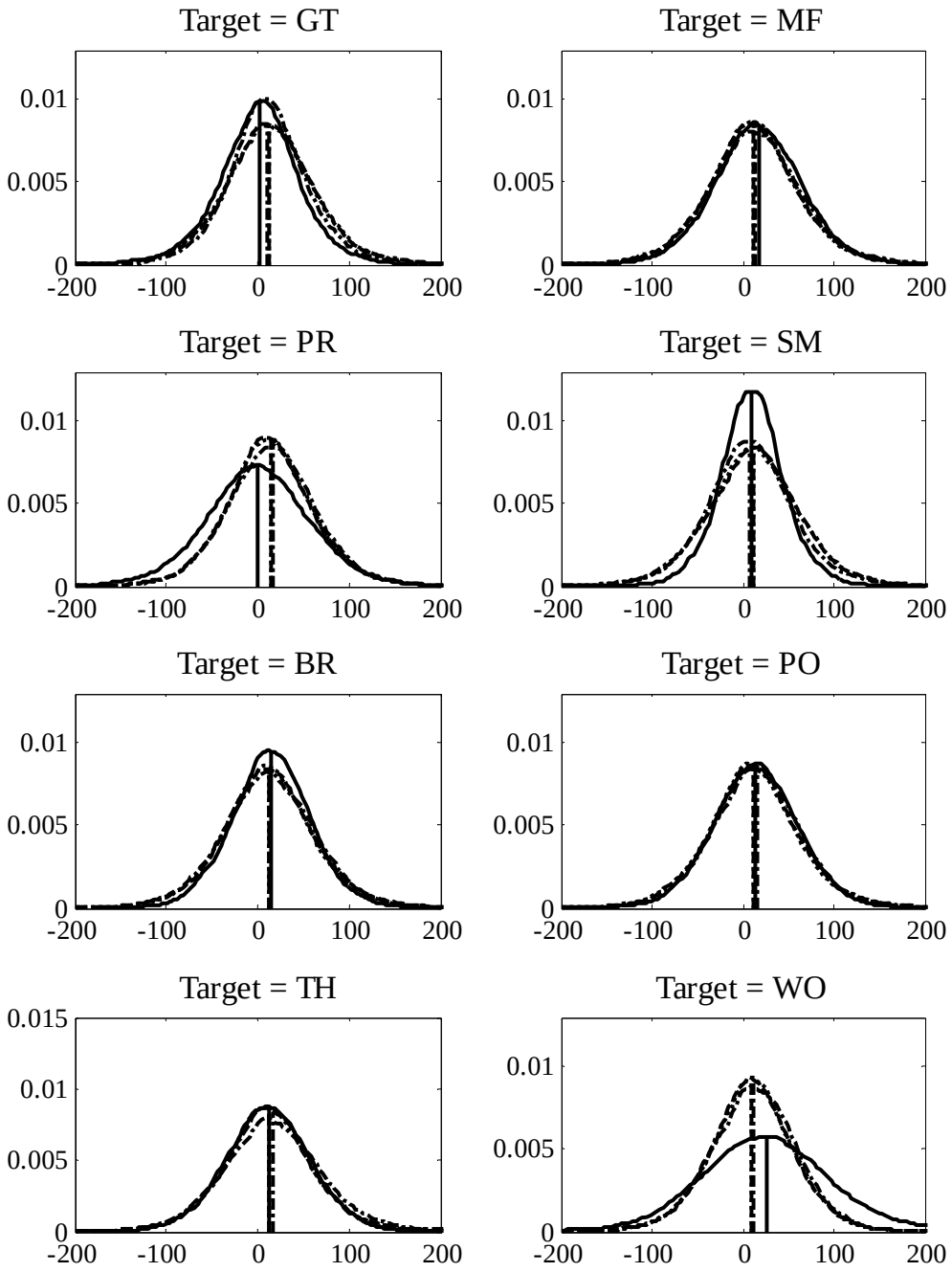
Distances in Miles

	Georgetown	Mansfield	Preston	Smyrna	Brooklyn	Pomfret	Thompson
Mansfield	270	-	-	-	-	-	-
Preston	265	27	-	-	-	-	-
Smyrna	44	244	241	-	-	-	-
Brooklyn	281	22	21	258	-	-	-
Pomfret	286	20	28	262	6	-	-
Thompson	292	30	36	269	17	12	-
Woodstock	288	25	39	264	17	13	10

Table 4: Second-stage Weights for Benefit-Transfer Distributions

	Target = GT			Target = MF	
	regression	distance		regression	distance
MF	0.151	0.084	GT	0.136	0.017
PR	0.136	0.085	PR	0.145	0.173
SM	0.158	0.516	SM	0.133	0.019
BR	0.143	0.080	BR	0.144	0.213
PO	0.140	0.079	PO	0.150	0.234
TH	0.138	0.077	TH	0.143	0.156
WO	0.135	0.078	WO	0.148	0.187
	Target = PO			Target = WO	
	regression	distance		regression	distance
GT	0.131	0.008	GT	0.129	0.011
MF	0.146	0.119	MF	0.152	0.130
PR	0.141	0.085	PR	0.133	0.083
SM	0.132	0.009	SM	0.137	0.012
BR	0.151	0.397	BR	0.148	0.191
TH	0.147	0.198	PO	0.154	0.249
WO	0.151	0.183	TH	0.147	0.324

Figure 1: Posterior distribution of compensating surplus, original vs. benefit transfer models



Legend:	solid line:	original model
	dashed:	BT via empirical weights
	dashed-dotted:	BT via distance weights
	dotted:	BT via uniform weights