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Abstract

This paper modifies the Hausman and Taylor (1981) panel data estimator to allow for serial correlation in the remainder disturbances. It demonstrates the gains in efficiency of this estimator versus the standard panel data estimators that ignore serial correlation using Monte Carlo experiments.

JEL codes: C32
Keywords: Panel Data, Fixed Effects, Random Effects, Instrumental Variables, Serial Correlation.

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The Hausman-Taylor Panel Data Model with Serial Correlation

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Abstract

This paper modifies the Hausman and Taylor (1981) panel data estimator to allow for serial correlation in the remainder disturbances. It demonstrates the gains in efficiency of this estimator versus the standard panel data estimators that ignore serial correlation using Monte Carlo experiments.

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1 Introduction

The random effects (RE) panel data model assumes that all the explanatory variables are uncorrelated with the random individual effects, while the fixed effects (FE) panel data model assumes that all the explanatory variables are correlated with the random individual effects. Instead of this "all" or "nothing" assumption, the Hausman and Taylor (1981) panel data estimator allows *some* of the explanatory variables to be correlated with the individual effects. One of the main disadvatages of the fixed effects estimator is that it wipes out the effects of time-invariant variables. In contrast the Hausman and Taylor (HT) estimator recaptures the estimates of these time-invariant variables which are important in empirical applications, see Cornwell and Rupert (1988), Egger and Pfaffermayr (2004) and Serelenga and Shin (2007) to mention three applications of this estimator. This paper extends the Hausman and Taylor (HT) estimator to allow for serial correlation in the remainder disturbances of the AR(1) type. The standard fixed effects (FE) and random effects (RE) panel data models with serial correlation in the remainder disturbances have been considered by Bhargava, Franzini and Narendranathan (1982) and Baltagi and Li (1991) to mention a few. While the fixed effects AR(1) estimator (FE-AR(1)) considered by Bhargava, Franzini and Narendranathan (1982) is consistent for the HT model, it does not provide an estimator of the time-invariant variables coefficients which are usually of interest in most economic applications. The Baltagi and Li (1991) random effects AR(1) (RE-AR(1)) estimator provides estimates of the time-invariant variables coefficients, but these will be consistent only if the individual effects are uncorrelated with all the regressors. The modified HT estimator allowing for AR(1) disturbances (denoted by HT-AR(1)) is more efficient than the HT estimator that ignores this serial correlation. Unlike the FE-AR(1) estimator, it captures the effects of time-invariant variables, and unlike the Baltagi and Li (1991) RE-AR(1) estimator it allows for possible correlation between the regressors and the individual effects. The paper performs Monte Carlo experiments that demonstrate the gains in efficiency of this HT-AR(1) estimator over the standard HT estimator in the presence of serial correlation.

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2 The Model and Assumptions

Consider the following Hausman and Taylor (1981) panel data model:

$$y_{it} = X_{it}'\beta + Z_i'\gamma + u_{it}, \quad i = 1, \dots, N, \quad t = 1, \dots, T \tag{1}$$

where $u_{it} = \mu_i + \nu_{it}$, and β and γ are unknown vectors. The X_{it}'s are time varying regressors, while the Z_i's are time-invariant. This Hausman-Taylor (HT) model is allowed to have first order serial correlation in $\{\nu_{it}\}$ of the AR(1) type:

$$\nu_{it} = \rho\nu_{it-1} + \varepsilon_{it}, \qquad |\rho| < 1 \tag{2}$$

where ε_{it} is a white noise process with variance σ_ε^2. The μ_i's are independent of the ν_{it}'s for all i and t. In vector form, Equation (1) can be written as

$$y_i = W_i\delta + u_i, \quad i = 1, \dots, N \tag{3}$$

with

$$u_i = \mu_i \boldsymbol{\iota}_T + \nu_i,$$

where $y_i = (y_{i1}, \cdots, y_{iT})'$, $W_i = (X_i, \boldsymbol{\iota}_T Z_i')$, $X_i = (X_{i1}, \cdots, X_{iT})'$, $\delta' = (\beta', \gamma')$, $u_i = (u_{i1}, \cdots, u_{iT})'$ and $\boldsymbol{\iota}_T$ is a vector of ones of dimension T. Equation (3) can be also written as

$$y = W\delta + u, \tag{4}$$

with

$$u = (I_N \otimes \boldsymbol{\iota}_T)\,\mu + v,$$

where $y = (y_1', \cdots, y_N')'$, $W = (X, Z)$ with $X = (X_1', \cdots, X_N')'$, $Z = (Z_1', \cdots, Z_N')' \otimes \boldsymbol{\iota}_T$, $u = (u_1', \cdots, u_N')'$, $\mu = (\mu_1, \cdots, \mu_N)'$and $v = (v_1, \cdots, v_N)'$,

3 The GLS Estimator

Assuming that the individual effects μ_i are random with $\mu_i \sim iid(0, \sigma_\mu^2)$ and $E(\mu_i | X_{it}', Z_i') = 0$ for all i and t, the resulting random effects (RE) GLS type estimator correcting for AR(1) remainder disturbances will be the best linear unbiased estimator (BLUE), see Baltagi and Li (1991). In fact, this estimator applies the Prais-Winsten (PW) transformation in the first step to transform the remainder AR(1) disturbances into serially uncorrelated classical errors. More specifically, one premultiplies equation (4) by

$$C = \begin{bmatrix} \sqrt{1-\rho^2} & 0 & 0 & \cdots & 0 & 0 \\ -\rho & 1 & 0 & \cdots & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & -\rho & 1 & 0 \\ 0 & 0 & 0 & 0 & -\rho & 1 \end{bmatrix}$$

to get

$$y^* = W^*\delta + u^*, \tag{5}$$

where $y^* = (I_N \otimes C)\,y$, $W^* = (I_N \otimes C)\,W$ and $u^* = (I_N \otimes C)\,u$. Using the fact that $C\boldsymbol{\iota}_T = (1-\rho)\,\boldsymbol{\iota}_T^\alpha$, where $\boldsymbol{\iota}_T^{\alpha'} = (\alpha, \boldsymbol{\iota}_{T-1}')$ and $\alpha = \sqrt{(1+\rho)\,/\,(1-\rho)}$. The transformed regression disturbances are given by

$$u^* = (I_N \otimes C)\,u = (I_N \otimes C\boldsymbol{\iota}_T)\,\mu + (I_N \otimes C)\,v = (1-\rho)\,(I_N \otimes \boldsymbol{\iota}_T^\alpha)\,\mu + v^*, \tag{6}$$

where $v^* = (I_N \otimes C)\, v$. As shown in Baltagi and Li (1991), the variance-covariance matrix of the transformed disturbances is given by

$$\Omega^* = E\left(u^* u^{*\prime}\right) = \sigma_\mu^2 \left(1-\rho\right)^2 \left(I_N \otimes \boldsymbol{\iota}_T^\alpha \boldsymbol{\iota}_T^{\alpha\prime}\right) + \sigma_\varepsilon^2 \left(I_N \otimes I_T\right), \tag{7}$$

and

$$\sigma_\varepsilon \Omega^{*-1/2} = \left(I_N \otimes I_T\right) - \theta_\alpha \left(I_N \otimes \bar{J}_T^\alpha\right),$$

where $E_T^\alpha = I_T - \bar{J}_T^\alpha$, $\bar{J}_T^\alpha = \boldsymbol{\iota}_T^\alpha \boldsymbol{\iota}_T^{\alpha\prime}/d^2$, $d^2 = \alpha^2 + T - 1$, $\theta_\alpha = 1 - \frac{\sigma_\varepsilon}{\sigma_\alpha}$ and $\sigma_\alpha^2 = \sigma_\varepsilon^2 + d^2 \left(1-\rho\right)^2 \sigma_\mu^2$. Premultiplying the PW transformed observations by $\sigma_\varepsilon \Omega^{*-1/2}$, one gets

$$\sigma_\varepsilon \Omega^{*-1/2} y^* = \sigma_\varepsilon \Omega^{*-1/2} W^* \delta + \sigma_\varepsilon \Omega^{*-1/2} u^*. \tag{8}$$

The least squares estimator of the resulting equation gives us

$$\hat{\delta}_{GLS} = \left(W^{*\prime} \Omega^{*-1} W^*\right)^{-1} W^{*\prime} \Omega^{*-1} y^* \tag{9}$$

The best quadratic unbiased BQU estimators of the variance components are given by:

$$\hat{\sigma}_\varepsilon^2 = u^{*\prime} \left(I_N \otimes E_T^\alpha\right) u^* / N\left(T-1\right) \tag{10}$$

and

$$\hat{\sigma}_\alpha^2 = u^{*\prime} \left(I_N \otimes \bar{J}_T^\alpha\right) u^* / N. \tag{11}$$

As suggested by Baltagi and Li (1991), one can estimate ρ by

$$\widehat{\rho} = \sum_{i=1}^{N} \sum_{t=2}^{T} \widehat{\nu}_{it} \widehat{\nu}_{it-1} / \sum_{i=1}^{N} \sum_{t=2}^{T} \widehat{\nu}_{i,t-1}^2, \tag{12}$$

where $\widehat{\nu}_{it}$ is the within residual. Then $\hat{\sigma}_\varepsilon^2$ and $\hat{\sigma}_\alpha^2$ can be estimated from equation (10) and (11) by substituting the residuals $\hat{u}^*$ from the PW transformed equation using $\widehat{\rho}$.

4 The Within-GLS Estimator

A critical assumption for the GLS estimator is that $E\left(\mu_i | X_{it}', Z_i'\right) = 0$. Otherwise $\hat{\beta}_{GLS}$ would be biased and inconsistent. In fact, the classic paper by Mundlak (1978) assumes that the μ_i's are explicitly formulated as a function of the means of all the regressors over time, in this case $\left(\overline{X}_{i}.\right)$. The result is that under this Mundlak model, GLS suffers from omitted variable bias, i.e., the omission of $\overline{X}_{i}.$, while the within transformation wipes out this source of endogeneity and remains consistent. However for the AR(1) remainder disturbances, the within estimator will not be best linear unbiased estimator (BLUE). This can be easily rectified using a within-GLS estimator that uses the Prais-Winsten transformation to correct for serial correlation in the remainder error in the first step, then applying a quasi-within transformation to wipe out the transformed μ_i's in the second step. Premultiplying equation (5) by $\left(I_N \otimes E_T^\alpha\right)$, one gets

$$\left(I_N \otimes E_T^\alpha\right) y^* = \left(I_N \otimes E_T^\alpha\right) X^* \beta + \left(I_N \otimes E_T^\alpha\right) v^*, \tag{13}$$

using $E_T^\alpha \boldsymbol{\iota}_T^\alpha = 0$. Applying the least squares estimator to the resulting equation gives us the FE-PW GLS estimator

$$\begin{aligned} \hat{\beta}_{FE-PW} &= \left[X^{*\prime} \left(I_N \otimes E_T^\alpha\right) X^*\right]^{-1} X^{*\prime} \left(I_N \otimes E_T^\alpha\right) y^* && (14) \\ &= \left[X' \left(I_N \otimes C' E_T^\alpha C\right) X\right]^{-1} X' \left(I_N \otimes C' E_T^\alpha C\right) y. && (15) \end{aligned}$$

One can easily verify that this estimator is equivalent to the one suggested in Bhargava, Franzini and Narendranathan (1982). When there is no serial correlation, i.e., $\rho = 0$, the FE-GLS estimator in equation (14) reduces to the usual FE estimator $\hat{\beta}_{FE} = \left[x'\left(I_N \otimes E_T\right)x\right]^{-1} x'\left(I_N \otimes E_T\right)y$, where $E_T = I_T - \bar{J}_T$ and $\bar{J}_T$ is a $T \times T$ matrix with all elements equal to $1/T$. In fact, when $\rho = 0$, $C = I_T$, $\alpha = 1$, $\boldsymbol{\iota}_T^{\alpha} = \boldsymbol{\iota}_T$ and $E_T^{\alpha} = E_T$.

Despite several warnings not to omit the first observation when correcting for serial correlation, see Parks and Mitchell (1980), researchers still use the FE estimator using the Cochrane-Orcutt (CO) transformation to correct for serial correlation in the remainder error. The Monte Carlo experiments in Section 6 demonstrate the loss in efficiency in using this FE-Cochrane-Orcutt rather than FE-PW.

5 The Hausman-Taylor Estimator

Hausman and Taylor (1981) split the time varying X's and the time invariant Z's into two sets of variables: $X = (X_1, X_2)$ and $Z = (Z_1, Z_2)$ where X_1 and Z_1 are assumed exogenous in that they are not correlated with μ_i and ε_{it}, while X_2 and Z_2 are endogenous because they are correlated with μ_i, but not ε_{it}. The Within transformation would sweep the μ_i's and remove the bias, but in the process it would also remove the Z_i's and hence the Within estimator will not give an estimate of γ which in most empirical economic applications is important for policy purposes. In this section, we modify the Hausman and Taylor (1981) estimator to allow for AR(1) remainder errors. This can be done as follows:

Step 1: From the assumptions of our model, one can estimate β consistently using the FE-PW GLS estimator in equation (14) rather than the usual FE estimator used by Hausman and Taylor (1981) in the absence of serial correlation. Averaging the residuals from this regression over time as in HT but now weighting the initial period differently from the rest as in Baltagi and Li (1991), one gets

$$\hat{d} \equiv \bar{y}^* - \bar{X}^* \hat{\beta}_{FE-GLS}.$$

where $\bar{y}^* = \left(I_N \otimes \bar{J}_T^{\alpha}\right) y^*$ and $\bar{X}^* = \left(I_N \otimes \bar{J}_T^{\alpha}\right) X^*$.

Step 2: Run 2SLS of $\hat{d}$ on Z^* with the set of instruments $A^* = (X_1^*, Z_2^*)$. This yields

$$\hat{\gamma}_{2SLS} = \left(Z^{*\prime} P_{A^*} Z^*\right)^{-1} Z^{*\prime} P_{A^*} \hat{d},$$

where the projection matrix $P_{A^*} = A^*\left(A^{*\prime} A^*\right)^{-1} A^{*\prime}$.

Step 3: Estimate $\tilde{\sigma}_{\varepsilon}^2$ and $\tilde{\sigma}_{\alpha}^2$ from equation (10) and (11) by substituting $\tilde{u}^* = y^* - X^* \hat{\beta}_{FE-PW} - Z^* \hat{\gamma}_{2SLS}$.

Step 4: Once the variance components estimates are obtained, the model in Equation (8) is transformed using $\hat{\Omega}^{*-1/2}$ as follows:

$$\hat{\Omega}^{*-1/2} y^* = \hat{\Omega}^{*-1/2} W^* \delta + \hat{\Omega}^{*-1/2} u^*. \tag{16}$$

The Hausman-Taylor estimator is a 2SLS estimator of Equation (16) using $A_{HT} = \left(\tilde{X}^*, \bar{X}_1^*, Z_1^*\right)$ as instruments, where $\tilde{X}^* = \left(I_N \otimes E_T^{\alpha}\right) X^*$ and $\bar{X}_1^* = \left(I_N \otimes \bar{J}_T^{\alpha}\right) X_1^*$. More specifically,

$$\hat{\delta}_{HT-AR(1)} = \left(W^{*\prime} \hat{\Omega}^{*-1/2} P_{A^*} \hat{\Omega}^{*-1/2} W^*\right)^{-1} W^{*\prime} \hat{\Omega}^{*-1/2} P_{A^*} \hat{\Omega}^{*-1/2} y^*. \tag{17}$$

6 Monte Carlo Simulation

Following Im et al. (1999), we consider the following HT panel data model:

$$y_{it} = \beta_{11} X_{11,it} + \beta_{12} X_{12,it} + \beta_2 X_{2,it} + \gamma_1 Z_{1,i} + \gamma_2 Z_{2,i} + u_{it}, \quad i = 1, \ldots, N, \quad t = 1, \ldots, T \tag{18}$$

where $u_{it} = \mu_i + \nu_{it}$ and $\nu_{it} = \rho\nu_{it-1} + \varepsilon_{it}$. We let $\beta_{11} = \beta_{12} = \beta_2 = \gamma_1 = \gamma_2 = 1$. $\mu_i \overset{iid}{\sim} N(0, 1.5)$ and $\nu_{it} \overset{iid}{\sim} N(0, 1.5)$. ρ varies over the range $(0, 0.2, 0.4, 0.6, 0.8, 0.9)$. The variables $X_{11,it}$ and $X_{12,it}$ are generated by:

$$\begin{aligned} X_{11,it} &= 0.7 X_{11,i,t-1} + \delta_i + \zeta_{it}, \\ X_{12,it} &= 0.7 X_{12,i,t-1} + \theta_i + \omega_{it}, \end{aligned}$$

where δ_i, ζ_{it}, θ_i and ω_{it} are uniform on $[-2, 2]$. The variable $Z_{1,i}$ is a constant, i.e., $Z_{1,i} = 1$. We focus on the following two designs considered by Baltagi, Bresson and Pirotte (2003):

1. Case 1—A Hausman–Taylor world, where $Z_{2,i}$ and $X_{2,it}$ are correlated with μ_i by construction:

$$\begin{aligned} Z_{2,i} &= \mu_i + \delta_i + \theta_i + \xi_i, \\ X_{2,it} &= 0.7 X_{2,i,t-1} + \mu_i + \tau_{it}, \end{aligned}$$

   where ξ_i and τ_{it} are uniform on $[-2, 2]$. It is clear that the $Z_{2,i}$ variable is also correlated with $X_{11,it}$ (by the term δ_i) with $X_{12,it}$ (by the term θ_i) and with $X_{2,it}$ (by the term μ_i).

2. Case 2—A Random Effects world, where $Z_{2,i}$ and $X_{2,it}$ are not correlated with μ_i by construction:

$$\begin{aligned} Z_{2,i} &= \delta_i + \theta_i + \xi_i, \\ X_{2,it} &= 0.7 X_{2,i,t-1} + \lambda_i + \tau_{it}, \end{aligned}$$

where ξ_i and τ_{it} are the same defined as in case 1. It is clear that the $Z_{2,i}$ variable is still correlated with $X_{11,it}$ (by the term δ_i) with $X_{12,it}$ (by the term θ_i).

The sample sizes (N, T) are $(100, 5)$ and $(500, 10)$. For each experiment, we perform 1,000 replications. For each replication we estimate the model using FE, RE and HT with and without serial correlation in the disturbances. Table 1 and 2 report the root mean square error (RMSE) of β_2 and γ_2, the coefficients of the endogenous time-varying and time-invariant variables, respectively. This is done for various values of ρ over the range $(0, 0.2, 0.4, 0.6, 0.8, 0.9)$. Following Baltagi, Bresson and Pirotte (2003), we focus on the coefficients of the endogenous regressors $X_{2,it}$ and $Z_{2,i}$, i.e. β_2 and γ_2, respectively.

In case 1, the Hausman–Taylor world, as shown in Table 1, the RE estimator suffers from endogeneity bias and hence has a much larger RMSE than the FE and HT estimators. This is true for both sample sizes $(N, T) = (100, 5)$ and $(500, 10)$. The FE estimator performs well as it wipes out the endogeneity caused by correlation of the regressors with the individual effects. However, it does not yield an estimator of γ_2. Note that the FE estimator with Cochrane-Orcutt transformation performs worse than the FE estimator ignoring the autocorrelation in the error term for both sample sizes $(N, T) = (100, 5)$ and $(500, 10)$. The FE-PW estimator yields a lower RMSE than FE-CO and emphasizes the gains from not dropping the N observations of the initial time period. A practice still in use in standard econometrics software today. The HT estimator yields an estimator of γ_2, and this has lower RMSE than the RE estimator. Comparing FE, HT with their AR(1) counterparts, we note that the RMSE improves as long as $\rho > 0.2$.

In case 2, the Random Effects world, as shown in Table 2, the RE estimator controlling the autocorrelation in the error term is the efficient estimator by construction. FE and HT have larger RMSE than RE. The FE estimator with Cochrane-Orcutt transformation has larger RMSE than the FE estimator with Prais-Winsten transformation. Comparing RE, FE, HT with their AR(1) counterparts, we note that the RMSE improves as long as $\rho > 0.4$.

7 Conclusion

This paper shows how to modify the HT estimator to allow for AR(1) disturbances. Monte Carlo experiments show that this estimator works well in terms of RMSE.

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Table 1: RMSE of Panel Data Estimators in Case 1

		RE	RE-AR(1)	FE	FE-CO	FE-PW	HT	HT-AR(1)
$N = 100$, $T = 5$								
β_2	0	0.2456	0.2536	0.0614	0.0838	0.0610	0.0614	0.0652
	0.2	0.2236	0.2357	0.0613	0.0846	0.0584	0.0614	0.0621
	0.4	0.1957	0.2121	0.0615	0.0851	0.0582	0.0615	0.0619
	0.6	0.1610	0.1792	0.0615	0.0832	0.0573	0.0615	0.0609
	0.8	0.1250	0.1405	0.0624	0.0793	0.0567	0.0624	0.0602
	0.9	0.1113	0.1226	0.0646	0.0770	0.0574	0.0646	0.0609
γ_2	0	0.1970	0.1933				0.1663	0.1694
	0.2	0.2085	0.2032				0.1683	0.1688
	0.4	0.2221	0.2158				0.1723	0.1717
	0.6	0.2380	0.2315				0.1790	0.1765
	0.8	0.2548	0.2493				0.1913	0.1867
	0.9	0.2629	0.2583				0.2014	0.1957
$N = 500$, $T = 10$								
β_2	0	0.2142	0.2133	0.0161	0.0185	0.0159	0.0161	0.0165
	0.2	0.1962	0.2043	0.0168	0.0203	0.0168	0.0168	0.0173
	0.4	0.1728	0.1863	0.0180	0.0217	0.0177	0.0181	0.0183
	0.6	0.1389	0.1529	0.0198	0.0224	0.0182	0.0198	0.0188
	0.8	0.0922	0.1003	0.0224	0.0221	0.0185	0.0224	0.0191
	0.9	0.0688	0.0704	0.0248	0.0216	0.0189	0.0248	0.0195
γ_2	0	0.1788	0.1796				0.0607	0.0611
	0.2	0.1908	0.1865				0.0625	0.0627
	0.4	0.2050	0.1988				0.0655	0.0649
	0.6	0.2229	0.2180				0.0706	0.0681
	0.8	0.2439	0.2424				0.0804	0.0754
	0.9	0.2536	0.2545				0.0897	0.0843

Notes: 1,000 replications.

Table 2: RMSE of Panel Data Estimators in Case 2

		RE	RE-AR(1)	FE	FE-CO	FE-PW	HT	HT-AR(1)
$N = 100,\ T = 5$								
β_2	0	0.0462	0.0464	0.0617	0.0836	0.0593	0.0616	0.0632
	0.2	0.0469	0.0471	0.0615	0.0840	0.0586	0.0614	0.0623
	0.4	0.0483	0.0483	0.0616	0.0841	0.0584	0.0615	0.0621
	0.6	0.0505	0.0500	0.0617	0.0822	0.0577	0.0617	0.0613
	0.8	0.0548	0.0531	0.0631	0.0786	0.0574	0.0631	0.0610
	0.9	0.0588	0.0557	0.0658	0.0765	0.0584	0.0658	0.0620
γ_2	0	0.1071	0.1060				0.1679	0.1703
	0.2	0.1101	0.1091				0.1707	0.1710
	0.4	0.1150	0.1134				0.1754	0.1745
	0.6	0.1228	0.1201				0.1828	0.1798
	0.8	0.1355	0.1316				0.1951	0.1903
	0.9	0.1447	0.1402				0.2049	0.1991
$N = 500,\ T = 10$								
β_2	0	0.0137	0.0137	0.0163	0.0191	0.0159	0.0163	0.0164
	0.2	0.0142	0.0145	0.0170	0.0209	0.0170	0.0170	0.0175
	0.4	0.0152	0.0153	0.0182	0.0224	0.0180	0.0182	0.0185
	0.6	0.0169	0.0161	0.0201	0.0230	0.0186	0.0201	0.0191
	0.8	0.0200	0.0174	0.0228	0.0226	0.0188	0.0228	0.0194
	0.9	0.0228	0.0183	0.0250	0.0219	0.0190	0.0250	0.0196
γ_2	0	0.0437	0.0436				0.0611	0.0613
	0.2	0.0447	0.0447				0.0626	0.0631
	0.4	0.0467	0.0464				0.0654	0.0653
	0.6	0.0505	0.0493				0.0703	0.0685
	0.8	0.0592	0.0563				0.0803	0.0759
	0.9	0.0679	0.0643				0.0900	0.0848

Notes: 1,000 replications.