Estimation, inference and Monte Carlo analysis in dynamic panel data models with a small number of individuals

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October 22, 2004

Abstract

This study describes a new Stata routine that computes a bias-corrected LSDV estimator and its bootstrap variance-covariance matrix. A Monte Carlo analysis is carried out to compare the finite-sample performance of the corrected LSDV estimator with the inconsistent LSDV estimator and consistent estimators, such as the Arellano-Bond GMM estimator, Anderson-Hsiao IV estimator, and Blundell-Bond system estimator.

1. Introduction

Situations in which past decisions have an impact on current behaviour are ubiquitous in economics. To mention just one of the many examples that may come to mind, in the presence of employment adjustment costs the short-run labour demand of the firm will depend on past employment levels. Another crucial issue in empirical economics, strictly related to the modelling of dynamic relationships, is the presence of unobserved heterogeneity in individual behaviour and characteristics. Panel data sets, where the behaviour of N cross-sectional units is observed over T time periods, provide a solution to accommodating the joint presence of dynamics and unobserved individual heteogeneity in the fhonomena of interest.

Nickell (1981) has demonstrated that the Least Square Dummy Variable estimator (LSDV) for autoregressive panel data models is not consistent for finite T. Since then, a number of consistent estimators, based upon internal instrumental variables, have been proposed in the econometric literature. Anderson and Hsiao (1982) (AH) suggest two simple IV estimators that, upon transforming the model in first differences to eliminate the unbserved individual heterogeneity, use the second lags of the dependent variable, either differenced or in levels, as an instrument. Arellano and Bond (1991) (AB) propose a GMM estimator for the first differenced model which, relying on a greater number of internal instruments, is more efficient than AH. Blundell and Bond (1998) (BB) remark that with highly persistent data first-defferenced IV or GMM estimators may suffer of a severe small sample bias due to weak instruments. As a solution, they suggest a system GMM estimator with first-differenced instruments for the equation in levels and instrument in levels for the first-differenced equation.

One weakness of all foregoing estimators is that their properties hold for N large, so they can be severely biased and imprecise in panel data with a small number of cross-sectional units, such as most macro panels. An alternative approach to IV-GMM estimation, which is based on the bias-correction of LSDV, has recently gained popularity in the econometric literature. Nickell (1981), upon proving his inconsistency result, derives an expression for the inconsistency for $N \to +\infty$, which is bounded of order T^{-1}. Kiviet (1995) uses higher order asymptotic expansion techniques to approximate the small sample bias of the LSDV estimator to include terms of at most order $N^{-1}T^{-1}$. Those approximations are evaluated at the unobserved true parameter values, so they are of no direct use for estimation. To make them operational for bias correction and estimation, Kiviet (1995) suggests to replace, in the approximation formulae, the true parameters with the estimates from some consistent estimators. Monte Carlo evidence in Kiviet (1995) shows that the bias-corrected LSDV estimator (LSDVC) often outperform the IV-GMM estimators in terms of bias and root mean squared error (RMSE). Another piece of Monte Carlo evidence by Judson and Owen (1999) strongly supports the LSDVC when N is small or only moderately large. In Kiviet (1999) the bias expression is more accurate to include terms of at most order $N^{-1}T^{-2}$. Bun and Kiviet (2003), upon simplifying Kiviet's (1999) approximation, carry out Monte Carlo experiments showing that the first order term of the approximation evaluated at the true parameter values is already capable to account for more than

90% of the actual bias. Bruno (2004) extends the bias approximations in Bun and Kiviet (2003) to accommodate unbalanced panels with a strictly exogenous selection rule. Monte Carlo evidence therein parallels Bun and Kiviet's (2003).

This paper presents a *Stata* routine `xtlsdvc`, which 1) implements LSDVC building upon the theoretical approximation formulas in Bruno (2004) and 2) estimates a bootstrap variance covariance matrix for the corrected estimator. Monte Carlo experiments are also carried out to evaluate the performance of LSDVC and other dynamic panel data estimators in terms of bias and RMSE for N small (10 and 20 units). Results show that the three versions of LSDVC computed by `xtlsdvc` outperforms LSDV, AB, AH and BB in terms of both criteria, so confirming results in Judson and Owen (1999).

The structure of the paper is as follows. The next section briefly review the theoretical results for corrected LSDV estimators. Section 3 describes the `xtlsdvc` routine. Section 4 describe the implementation of the bootstrap variance-covariance matrix. Section 5 concludes presenting the Monte Carlo results.

2. Bias corrected LSDV estimator

We consider the standard dynamic panel data model

$$y_{it} = \gamma y_{i,t-1} + x_{it}'\beta + \eta_i + \epsilon_{it};\ |\gamma| < 1;\ i = 1, ..., N \text{ and } t = 1, ..., T, \qquad (2.1)$$

where y_{it} is the dependent variable; x_{it} is the $((k-1)\times 1)$ vector of strictly exogenous explanatory variables; η_i is an unobserved individual effect; and ϵ_{it} is an unobserved white noise disturbance. Collecting observations over time and across individuals gives

$$y = D\eta + W\delta + \epsilon,$$

where y and $W = \left[y_{-1} \vdots X\right]$ are the $(NT \times 1)$ and $(NT \times k)$ matrices of stacked observations; $D = I_N \otimes \iota_T$ is the $(NT \times N)$ matrix of individual dummies, (ι_T is the $(T \times 1)$ vector of all unity elements); η is the $(N \times 1)$ vector of individual effects; ϵ is the $(NT \times 1)$ vector of disturbances; and $\delta = \left[\gamma \vdots \beta'\right]'$ is the $(k \times 1)$ vector of coefficients.

It has been long recognized that the LSDV estimator for model (**??**) is not consistent for finite T. Nickell (1981) derives an expression for the inconsistency for $N \to +\infty$, which is $O\left(T^{-1}\right)$. Kiviet (1995) obtains a bias approximation that contains terms of higher order than T^{-1}. In Kiviet (1999) a more accurate bias approximation is derived. Bun and Kiviet (2003) reformulate the approximation in Kiviet (1999) with simpler formulas for each term. Bruno (2004) extends Bun and Kiviet (2003) formulas to a more general version of model (**??**), which allows missing observations in the interval $[0, T]$ for some individuals. Below, we briefly present the approximation formulae for unbalanced data and show their use to obtain the LSDVC.

Define a selection indicator r_{it} such that $r_{it} = 1$ if (y_{it}, x_{it}) is observed and $r_{it} = 0$ otherwise. From this define the dynamic selection rule $s\left(r_{it}, r_{i,t-1}\right)$ selecting only the observations that are usable for the dynamic model, namely those for which both current values and one-time lagged values are observable:

$$s_{it} = \begin{cases} 1 & \text{if } \left(r_{i,t}, r_{i,t-1}\right) = (1,1) \\ 0 & \text{otherwise} \end{cases} \qquad i = 1, ..., N \text{ and } t = 1, ..., T.$$

Thus, for any i the number of usable observations is given by $T_i = \sum_{t=1}^{T} s_{it}$. The total number of usable observations is given by $n = \sum_{i=1}^{N} T_i$; and $\overline{T} = n/N$ denotes the average group size. For each i define the $(T \times 1)$-vector $s_i = [s_{i1}..., s_{iT}]'$ and the $T \times T$ diagonal matrix S_i having the vector s_i on its diagonal. Define also the $(NT \times NT)$ block-diagonal matrix $S = diag\left(S_i\right)$. The (possibly) unbalanced dynamic model can then be written as

$$Sy = SD\eta + SW\delta + S\epsilon. \tag{2.2}$$

The LSDV estimator is given by $\delta_{LSDV} = \left(W'A_sW\right)^{-1} W'A_sy$, where $A_s = S\left(I - D\left(D'SD\right)^{-1} D'\right) S$ is the symmetric and idempotent $(NT \times NT)$ matrix wiping out individual means and selecting usable observations. Bias approximation formulae for unbalanced panel are the following

$$c_1\left(\overline{T}^{-1}\right) = \sigma_\epsilon^2 tr\left(\Pi\right) q_1;$$

$$c_2\left(N^{-1}\overline{T}^{-1}\right) = -\sigma_\epsilon^2 \left[Q\overline{W}'\Pi A_s\overline{W} + tr\left(Q\overline{W}'\Pi A_s\overline{W}\right) I_{k+1} + 2\sigma_\epsilon^2 q_{11} tr\left(\Pi'\Pi\Pi\right) I_{k+1}\right] q_1;$$

$$\begin{aligned} c_3\left(N^{-1}\overline{T}^{-2}\right) &= \sigma_\epsilon^4 tr\left(\Pi\right)\left\{2q_{11}Q\overline{W}'\Pi\Pi'\overline{W}q_1 + \right. \\ &\left.\left[\left(q_1'\overline{W}'\Pi\Pi'\overline{W}q_1\right) + q_{11}tr\left(Q\overline{W}'\Pi\Pi'\overline{W}\right) + 2tr\left(\Pi'\Pi\Pi'\Pi\right)q_{11}^2\right] q_1\right\}; \end{aligned}$$

where $Q = [E(W'A_sW)]^{-1} = \left[\overline{W}'A_s\overline{W} + \sigma_\epsilon^2 tr(\Pi'\Pi) e_1 e_1'\right]^{-1}$; $\overline{W} = E(W)$; $e_1 = (1, 0, ..., 0)'$ is a $(k \times 1)$ vector; $q_1 = Qe_1$; $q_{11} = e_1' q_1$; L_T is the $(T \times T)$ matrix with unit first lower subdiagonal and all other elements equal to zero; $L = I_N \otimes L_T$; $\Gamma_T = (I_T - \gamma L_T)^{-1}$; $\Gamma = I_N \otimes \Gamma_T$; and $\Pi = A_s L \Gamma$. With an increasing level of accuracy, the following three possible bias approximations emerge

$$B_1 = c_1\left(\overline{T}^{-1}\right);\ B_2 = B_1 + c_2\left(N^{-1}\overline{T}^{-1}\right);\ B_3 = B_2 + c_3\left(N^{-1}\overline{T}^{-2}\right). \tag{2.3}$$

In principle, the above may be for use to obtain bias corrected LSDV estimators by subtracting the bias approximation from the LSDV estimate. In practice, however, the approximations in (2.3) depend upon the unobserved parameters σ_ϵ^2 and γ. Consistent bias corrected estimators can still be obtained by plugging consistent estimators for σ_ϵ^2 and γ into the bias approximations formulae and then depuring the LSDV estimator from the resulting bias approximations estimates as follows:

$$LSDVC_i = LSDV - \widehat{B}_i,\ i = 1, 2,\ \text{and } 3.$$

AH, AB, or BB are all consistent estimators for γ, and can be for use to initialize the bias approximations. Consistent estimators for σ_ϵ^2 are obtained plugging the residuals in levels from the initial estimator of choice e_i, $i = AH, AB, BB$ into the formula

$$\widehat{\sigma}_i^2 = \frac{e'A_s e}{(N - k - T)}.$$

3. The xtlsdvc routine

The Stata routine `xtlsdvc` written by the author calculates LSDVC using the bias approximations derived by Kiviet (1999), Bun-Kiviet (2003) and Bruno (2004) for the standard autoregressive panel data model (2.1). The basic syntax of `xtlsdvc` is the following

```
xtlsdvc depvar [varlist], initial(estimator) [bias(#) vcov(#)]
```

So the routine can estimate the simple autoregressive model with no covariates. The option `initial(`*`estimator`*`)` is required and specifies which consistent *`estimator`* among AH (`ah`) AB (`ab`) and BB (`bb`) is to initialize the bias correction.

bias(#) determines the accuracy of the approximation: up to $O(1/T)$ (#=1); up to $O(1/NT)$ (#=2); up to $O(N^{-1}T^{-2})$ (#=3). The default is #=1.

vcov(#) determines the number of bootstrap repetitions. The default is no bootstrap computation

To work out the approximations xtlsdvc invokes the subroutine xtlsdvc_1, which does a lot of things. In the first place, xtlsdvc_1 obtains the uncorrected LSDV estimates via xtreg, fe.

Second, xtlsdvc_1 obtains initial estimates through one of the following instructions, according to which *estimator* is specified in initial(*estimator*)

```
if ‘‘‘initial’’’==‘‘ah’’ ivreg D.‘1’ D.(‘x’) (LD.‘1’=L2.‘1’), noconstant
if ‘‘‘initial’’’==‘‘ab’’ xtabond ‘1’ ‘x’, noconstant
if ‘‘‘initial’’’==‘‘bb’’ xtabond2 ‘1’ L.‘1’ ‘x’, gmm(L.‘1’) iv(‘x’)
noconstant
```

Notice that BB is implemented through the unofficial Stata routine xtabond2 by David Doorman.

Finally, xtlsdvc_1 computes the bias approximation formulae via Stata matrix commands, and use these to correct the LSDV estimates.

4. Bootstrap variance matrix

Bun and Kiviet (2001) derive the asymptotic variance of the LSDVC for N large. The estimated asymptotic standard errors, however, may provide poor approximations in small samples, so that t-statistics and confindence intervals thereby obtained are often not reliable. Bootstrap methods, instead, generally provide approximations to the sampling distribution of a statistic that are at least as accurate as approximations based upon first-order asymptotic theory (see Horowitz 2001). This is well recognized by Bun and Kiviet (2001), who also suggest a bootstrap approach to estimating the variance-covariance matrix of LSDVC. Given this, xtlsdvc estimates a bootstrap variance matrix to yield standard errors, t statistics and confidence interval.

One difficulty is brought about by the dependency in the data implied by the autoregressive data generation process, which does not permit to adopt the official Stata bootstrap instructions, such as bootstrap and bsample. I therefore adopt a parametric bootstrap that explicitly takes account of both the maintained normal distribution for the disturbances and the dependency in the DGP.

The subroutine `xtlsdvc_b` called in `xtlsdvc` by the option `vcov`, is designed to yield a bootstrap sample and bootstrap LSDVC estimates. It basically follows the steps below.

1. Upon obtaining LSDVC estimates for γ and β, $GAMMAC$ and $BETAC$, it works out residuals e to estimate the variance $\widehat{\sigma}^2 = e'A_s e/(N-k-T)$ and computes the N-vector of fixed effect estimates $THETAC = \overline{y} - GAMMAC \cdot \overline{y}_{-1} - BETAC \cdot \overline{x}$.

2. Obtains bootstrap errors ϵ^* from $N\left(0, \widehat{\sigma}^2\right)$.

3. Given x, S and y_0, obtains a bootstrap sample from $s_{it}y^*_{it} = s_{it}(GAMMAC \cdot y^*_{i,t-1} + BETAC \cdot x_{it} + THETAC_i + \epsilon^*_{it})$, $i = 1, ..., N$ and $t = 1, ..., T$

4. Applies CLSDV to (y^*, S, x) to yield $GAMMAC^*$ and $BETAC^*$.

While computational aspects of steps 1 and 2 are straightforward and step 4 only requires a call to the subroutine `xtlsdvc_1` to calculate the corrected estimates from the bootstrap sample, step 3 is instructive and deserves some explanation. One possible way to implement step 3 would be to "manually" generate y^* by recursion as a function of ϵ^*, y_0 and x. But this is both computationally cumbersome and unnecessary in Stata. In fact one can exploit the ability of `replace` to work sequentially[1] to obtain y^* in an effortless way:

```
by ivar:  gen obs=_n
replace y= GAMMAC*L.y + BETAC*x +THETAC +EPSILON if obs>1
```

If the the `vcov` option is on then a `simulate` call in `xtlsdvc` yields a data set of bootstrap LSDVC estimates for each coefficients, of dimension equal to the number of repetitions `vcov`, from which it is then relatively easy to get the bootstrap variance matrix via `matrix accum`.

5. Monte Carlo experiments

We extend Monte Carlo results in Judson and Owen (1999) under four respects. First, we evaluate LSDVC in the presence of various unbalanced designs; second

[1] I learnt this from the messages by N. J. Cox and D. Kantor to Statalist on May 25, 2004 in the thread originated by a question of Dimitriy V. Masterov.

the performance of LSDVC is examined for each level of accuracy in the bias approximation; third initial observations for the simulated data are generated following the procedure by McLeod and Hipel (1978), also adopted in Kiviet (1995) and Bruno (2004), which avoids the waste of random numbers and small sample non-stationary problems; finally, we extend the comparison to the Blundell and Bond system estimator.

Data for y_{it} are generated by model (**??**) and for x_{it} by

$$x_{it} = \rho x_{i,t-1} + \xi_{it},\ \xi_{it} \sim N\left(0, \sigma_{\xi}^{2}\right),\ i = 1, ..., N \text{ and } t = 1, ..., T$$

Initial observations y_{i0} and x_{i0} are generated following the McLeod and Hipel procedure, and are kept fixed across replications. The long-run coefficient $\beta/\left(1-\gamma\right)$ is kept fixed to unity, so $\beta = 1-\gamma$; σ_{ϵ}^{2} is normalized to unity; γ and ρ alternate between 0.2 and 0.8. The individual effects η_i are generated by assuming $\eta_i \sim N\left(0, \sigma_{\eta}^{2}\right)$ and $\sigma_{\eta} = \sigma_{\epsilon}\left(1-\gamma\right)$.

Two different sample sizes are considered, $\left(N, \overline{T}\right) = (20, 20)$ and $\left(N, \overline{T}\right) = (10, 40)$. Then, following Baltagi and Chang (1994), we control for the extent of unbalancedness as measured by the Ahrens and Pincus index: $\omega = N/\left[\overline{T}\sum_{i=1}^{N}\left(1/T_i\right)\right]$ $(0 < \omega \leq 1,\ \omega = 1$ when the panel is balanced). For each sample size we analyze a case of mild unbalancedness ($\omega = 0.96$) and a case of severe unbalancedness ($\omega = 0.36$). Individuals are partitioned into two sets of equal dimension: one set contains the first $N/2$ individuals, each with the last h observations discarded, so $T_i = T - h$; the other contains the remaining $N/2$ individuals, each with $T_i = T$. We set T and h so that $\overline{T}$ and ω take on the desired values (the four panel designs are summarized in Table 1).

Table 1
Unbalanced designs

N	$\overline{T}$	T	T_i	ω
20	20	24	16 ($i \leq 10$), 24 ($i > 10$)	0.96
		36	4 ($i \leq 10$), 36 ($i > 10$)	0.36
10	40	48	32 ($i \leq 5$), 48 ($i > 5$)	0.96
		72	8 ($i \leq 5$), 72 ($i > 5$)	0.36

Results are presented in Tables 2 to 8. Columns 1 to 4 show the parametrizations for each panel design. Columns 5 to 8 show the actual biases and RMSE, as estimated by 1000 Monte Carlo replications. There are the following results:

1) LSDVC estimators and AH have smaller bias than AB, BB and LSDV, with $LSDVC_3$ performing slightly better than $LSDVC_1$ and $LSDVC_2$;

2) The LSDVC estimators have always the smallest RMSE (with almost no difference among their values); BB outperforms AB and AH in terms of RMSE when $\gamma = 0.8$, which confirms the good properties of this estimator compared to the other IV-GMM estimators in the presence of persistent data.

3) Similarly to what found for the LSDV estimator (Bruno 2004), the AB bias for γ is always negative, and for given sample size it increases in absolute value from a situation of severe unbalancedness to one of mild unbalancedness.

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Table 2 - Bias and RMSE for LSDVC1

T_bar	gamma	rho	omega	biasg	biasb	rmseg	rmseb
20	.2	.2	.36	.0009245	-.0004889	.0316791	.0338265
			.96	-.0010353	.0002179	.0317222	.0317046
		.8	.36	-.0001824	.001967	.0415252	.0509138
			.96	-.0028064	.0013429	.0416356	.0478705
	.8	.2	.36	-.0044393	.0005215	.0420813	.0466577
			.96	-.0109681	.0023227	.0493088	.0437075
		.8	.36	-.0090435	.0102203	.0442876	.0976472
			.96	-.0160311	.007573	.0522807	.0946199
40	.2	.2	.36	-.0007711	.000533	.0291177	.03064
			.96	.0004107	.0009087	.0301973	.0314352
		.8	.36	-.0016842	.0017955	.0371284	.0457735
			.96	-.002104	.0024408	.0390377	.0475498
	.8	.2	.36	-.0045677	.0011056	.035633	.0418122
			.96	-.0046756	.0019419	.0402499	.0431623
		.8	.36	-.0078901	.0051748	.0369022	.0828885
			.96	-.0081098	.0068609	.0417089	.0903033

Table 3 - Bias and RMSE for LSDVC2

T_bar	gamma	rho	omega	biasg	biasb	rmseg	rmseb
20	.2	.2	.36	.0013828	-.0005394	.031752	.0338287
			.96	-.0005959	.0001571	.0317667	.0317073
		.8	.36	.0016328	.0006377	.0417097	.0509261
			.96	-.0010311	.0000655	.0417097	.0479059
	.8	.2	.36	-.0018164	.0002438	.0417066	.046602
			.96	-.0093658	.0020657	.048605	.0436447
		.8	.36	-.0051701	.0086439	.0433376	.0970544
			.96	-.0133335	.0065981	.0509757	.0942635
40	.2	.2	.36	-.0002465	.0004508	.029162	.0306411
			.96	.0008694	.0008377	.0302575	.0314349
		.8	.36	.0002452	.0003092	.0372328	.0458098
			.96	-.0003106	.0011665	.0391328	.0475448
	.8	.2	.36	-.0012931	.0009272	.0353549	.0417702
			.96	-.0019162	.0017056	.0398336	.0431113
		.8	.36	-.0031026	.0035811	.0360539	.0824068
			.96	-.0041066	.0052805	.040722	.0896985

Table 4 - Bias and RMSE for LSDVC3

T_bar	gamma	rho	omega	biasg	biasb	rmseg	rmseb
20	.2	.2	.36	.0014641	-.0005441	.031759	.0338289
			.96	-.0005014	.0001509	.0317704	.0317075
		.8	.36	.0018484	.0004942	.0417344	.0509306
			.96	-.000765	-.0001018	.0417271	.0479154
	.8	.2	.36	.0000738	.0003515	.0421739	.0466294
			.96	-.0069319	.0022293	.0488864	.0436908
		.8	.36	-.002921	.0083706	.0436828	.0969786
			.96	-.010371	.0065259	.0510864	.0942876
40	.2	.2	.36	-.0002043	.000447	.0291636	.0306412
			.96	.0009136	.0008354	.0302609	.0314349
		.8	.36	.0003583	.0002292	.0372419	.0458137
			.96	-.0001895	.0010897	.0391422	.0475468
	.8	.2	.36	-.0001048	.0010342	.0356005	.041791
			.96	-.0004599	.0018114	.0402802	.0431432
		.8	.36	-.0016648	.0035682	.0362392	.0824121
			.96	-.0023425	.0051547	.0411135	.08966

Table 5 - Bias and RMSE for LSDV

T_bar	gamma	rho	omega	biasg	biasb	rmseg	rmseb
20	.2	.2	.36	-.0186003	.0026124	.03475969	.03171351
			.96	-.0206904	.0024458	.036033	.03094203
		.8	.36	-.0341074	.0237528	.05177297	.05319765
			.96	-.0384191	.0259202	.05474859	.05394533
	.8	.2	.36	-.071874	.0009678	.08149128	.04341144
			.96	-.102302	.0025734	.10974099	.04250643
		.8	.36	-.0764733	.0198458	.08611078	.09603974
			.96	-.1079767	.0227776	.11529486	.10091283
40	.2	.2	.36	-.0106499	.0018243	.03075492	.03115142
			.96	-.0111183	.0016097	.03117665	.03035194
		.8	.36	-.0191085	.0141342	.0423936	.04769103
			.96	-.020125	.0138981	.04292468	.04824044
	.8	.2	.36	-.0403881	.0005159	.05310024	.04233602
			.96	-.0509953	.0011064	.06187778	.04148672
		.8	.36	-.0431944	.0112386	.05571677	.08523298
			.96	-.0541936	.0153366	.06495815	.09248403

Table 6 - Bias and RMSE for AB

T_bar	gamma	rho	omega	biasg	biasb	rmseg_ab	rmseb_ab
20	.2	.2	.36	-.0128776	.0015874	.0347909	.0350232
			.96	-.0239933	.0017314	.0420994	.0355005
		.8	.36	-.0246808	.0187586	.0492928	.0564952
			.96	-.0479408	.0277483	.0679876	.0679272
	.8	.2	.36	-.0631038	.000915	.0747191	.048357
			.96	-.1251995	-.0044139	.1361182	.0489714
		.8	.36	-.0675136	.0222996	.0791658	.1102517
			.96	-.1325255	.0105755	.1437831	.1333462
40	.2	.2	.36	-.0095857	.0020386	.0315973	.0313583
			.96	-.0103288	.002389	.031875	.0318943
		.8	.36	-.0166076	.0136266	.041525	.0496638
			.96	-.0212308	.0160233	.0444612	.0511996
	.8	.2	.36	-.0361703	.0016914	.0508281	.0430401
			.96	-.0541241	.0021377	.066266	.0437742
		.8	.36	-.0391365	.016738	.0535898	.0931464
			.96	-.058333	.0206379	.0704791	.1005256

Table 7 - Bias and RMSE for AH

T_bar	gamma	rho	omega	biasg	biasb	rmseg	rmseb
20	.2	.2	.36	.0007931	-.0006818	.0530118	.0432421
			.96	.001949	.0002788	.0545912	.0414707
		.8	.36	.0027442	-.0018707	.0795219	.0867377
			.96	.0036936	-.0024141	.0845096	.0821282
	.8	.2	.36	.0015273	-.001124	.1162832	.0600471
			.96	.005175	-.0002034	.1264431	.0583466
		.8	.36	-.000178	-.0037288	.119818	.1936035
			.96	.0036215	-.0039259	.1307414	.1849488
40	.2	.2	.36	.0009434	.0004701	.0506028	.0402221
			.96	.0024968	.0014705	.048068	.0399225
		.8	.36	.0018987	-.0012918	.0758458	.0816262
			.96	.0031666	.0016689	.0725531	.0809884
	.8	.2	.36	.0025558	.0005222	.1047245	.0574333
			.96	.0040237	.0010672	.1042672	.056041
		.8	.36	.0013405	-.0016681	.10872	.183177
			.96	.0019004	.0034271	.1075766	.1829914

Table 8 - Bias and RMSE for BB

T_bar	gamma	rho	omega	biasg	biasb	rmseg	rmseb
20	.2	.2	.36	.2003259	-.0608659	.2026836	.070825
			.96	.2311884	.0181487	.2329426	.049151
		.8	.36	.2892433	-.2482261	.2916414	.2522156
			.96	.2887421	-.1399847	.2922255	.1605972
	.8	.2	.36	.0468783	-.0087899	.0551085	.0489663
			.96	.0545528	.0190505	.0600887	.0606384
		.8	.36	.0472787	-.0330972	.0557519	.0838365
			.96	.0527988	.0322133	.0593314	.1057405
40	.2	.2	.36	.2139006	-.0107267	.2157289	.0346844
			.96	.1308392	-.069821	.1345409	.0766476
		.8	.36	.2860101	-.1769951	.2880623	.1827782
			.96	.2037343	-.2530963	.2074915	.2564813
	.8	.2	.36	.0484516	.00534	.05493087	.04341313
			.96	.0299227	-.0166865	.0426183	.0458308
		.8	.36	.047214	.0065783	.05429365	.07332394
			.96	.0287126	-.076941	.0420022	.1061275