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Estimating Panel VARs from Macroeconomic Data: Some Monte Carlo Evidence and an Application to OECD Public Spending Shocks

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Abstract

This paper compares the performance of six widely applied techniques to estimate panel VARs from macroeconomic (large T) data. We show that the bias of the popular least squares dummy variable estimator remains substantial even when the time dimension of the dataset is relatively large. Adopting a bias correction to the simple fixed-effects estimator is strongly recommended to obtain consistent estimates of the implied impulse response functions. Multivariate extensions of the GMM-type estimators usually applied for estimating single-equation dynamic panel data models perform reasonably well in terms of bias, but poorly in terms of root mean square error, in particular if the variance of the fixed effects is large relative to the variance of the innovations. To illustrate the methodological arguments we present an application in which we use annual OECD country data to estimate the effects of changes in government consumption on aggregate output, private consumption, investment, and real wages.

Keywords: Panel Vector Autoregressions, Simulation, Fiscal Policy Effects
JEL classification: C13, C33, E62, E00

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1 Introduction

Macroeconomists make extensive use of vector autoregressive models (VARs) to estimate the evolution and the interdependencies between multiple time series. Estimating VARs from panel data has generated interest, mainly because panel VARs allow one to control for unobserved heterogeneity and provide more precise estimates of the VAR coefficients and thus the implied impulse response functions.

Many macro studies have estimated panel VARs using existing techniques for single-equation dynamic panel data models, see Section 2 for a list of applications. In such models, it is well-known that the simple least squares dummy variable (LSDV) estimator is not consistent for a finite time dimension T even when the cross-sectional dimension N gets large, see e.g. Nickell (1981). Previous studies estimating macro panel VARs have typically followed one of two strategies to address this issue. The first strategy is to use instrumental variables or generalized method of moments techniques. A second strategy is to adhere to the simple LSDV estimator, referring to the fact that its bias approaches zero if the time dimension of the panel dataset approaches infinity.

Both strategies have their relative merits. The GMM techniques have been designed for the case of a large cross-sectional dimension relative to the time dimension. Since the number of cross-sectional units (e.g. countries) is often small in macro applications, GMM estimators may appear less suited for estimating macro panel VARs. Concerning the simple LSDV estimator, the critical question is whether the number of time periods encountered in macro studies is sufficiently large to make its bias unimportant from an economic point of view. In fact, the economic importance of the bias of the simple LSDV estimator has been a matter of debate in many studies estimating macro panel VARs (see Section 2 for a list of applications).

Recent advances in the study of single-equation dynamic panel data models have opened up a third strategy to estimate panel VARs. Kiviet (1995), Hahn and Kuersteiner (2002), Bun and Kiviet (2003, 2006), Bun and Carree (2005, 2006), and Bruno (2005) have suggested bias-corrections to the simple LSDV estimator. In single-equation simulation studies, such bias-corrected estimators have often turned out to be more efficient than GMM-type estimators.[4]

In this paper we examine the properties of various techniques to estimate panel vector autoregressive models. Throughout the paper, we have macroeconomic applications in mind, which means that we consider highly though not perfectly persistent time series and datasets having relatively small N and relatively large T. The estimation techniques we consider are representatives of the aforementioned three widely applied strategies to estimate macro panel VARs—simple fixed-effects procedures, bias-corrected fixed effects

[4] Panel VARs can also be estimated using Bayesian techniques (see e.g. Canova and Ciccarelli 2004 and Canova, Ciccarelli, and Ortega 2007) or likelihood-based procedures (see e.g. Binder, Hsiao, and Pesaran 2005, Yu, de Jong, and Lee 2008, and Mutl 2009).

procedures, and IV or GMM-type techniques.

Specifically, we compare six estimation techniques. The first set consists of least–squares-type estimators: (1) pooled OLS, (2) the simple least squares dummy variable (i.e. fixed effects) estimator (LSDV), and (3) a bias-corrected least squares dummy variable estimator. We consider with Hahn and Kuersteiner's (2002) estimator a bias corrected version of the fixed-effects estimator that does not require a preliminary consistent estimator, e.g. a GMM estimator. Hahn and Kuersteiner (2002) argue that their estimator may therefore be understood as an implementable version of Kiviet's (1995) estimator.

A second set of estimators consists of 'first-generation' IV and GMM techniques. In particular, we consider (4) the Anderson and Hsiao (1982) IV estimator and (5) the 'standard' Arellano and Bond (1991) GMM estimator. We use generalizations of the single-equation estimators to work on a system of equations, see Binder, Hsiao, and Pesaran (2005). Finally, as estimation technique (6), we consider 'second-generation' GMM techniques that exploit additional moment conditions. We consider the three versions of 'extended' GMM estimators that have been generalized to the multi-equation setting by Binder, Hsiao, and Pesaran (2005).

Our focus on macroeconomic panel VARs relates our paper to two branches in the literature. First, our paper complements previous simulation studies that have investigated estimation techniques for single-equation dynamic panel data models in a macroeconomic context, see Judson and Owen (1999), Ramalho (2005), and Bruno (2005). We consider multi-equation panel VARs instead of single-equation models. Second, our paper complements previous Monte Carlo evidence for the estimation of panel VARs presented in Binder, Hsiao, and Pesaran (2005). They focus on short panels typically used in microeconometrics ($T = 3$ or 10 and N being large) and do not consider the class of fixed effects estimators due to their focus on small-T data.

We compare the various estimation techniques in terms of their biases and root mean square errors (RMSEs). Since the applied macroeconomist using panel VARs is typically not interested in the VAR coefficients *per se* but uses impulse response functions to investigate the dynamic behavior of the system of equations, we also investigate how strongly potential biases in VAR coefficient estimates affect the implied IRFs. We proceed in two steps. First, in the framework of our Monte Carlo study, we compare the estimated IRFs to their true counterparts. Second, we present an empirical application and compare the IRFs obtained using different estimation techniques.

In the application, we use annual observations on 19 OECD countries spanning the years between 1960 and 2008 to quantify the macroeconomic effects of fiscal policy shocks. Quantifying the effects of government spending is of obvious policy relevance and previous papers have uncovered several theoretically interesting and surprising responses, such as the positive effect of government spending shocks on private consumption (e.g. Blanchard and Perotti 2002, Galí, López-Salido, and Vallés 2007) or real wages (e.g. Monacelli and

Perotti 2008); much of this literature is surveyed in Perotti (2007). Studies that use datasets closest to the one used in our application are Beetsma, Giuliodori, and Klaassen (2006, 2008), who study international spillover effects from fiscal spending in a panel with yearly EU country data using the LSDV estimator.

Our results can be summarized as follows. First, our Monte Carlo experiments show that the bias of the widely applied least squares dummy variable estimator remains substantial even when T is relatively large. Adopting a bias correction to the simple fixed-effects estimator is strongly recommended to obtain consistent estimates of the implied impulse response functions. Multivariate extensions of the GMM-type estimators usually applied for estimating single-equation dynamic panel data models perform reasonably well in terms of bias, but poorly in terms of root mean square error, in particular if the variance of the fixed effects is large relative to the variance of the innovations. This leads us to conclude that bias-corrected versions of the fixed-effects estimator are the estimators of choice for estimating macro panel VARs. Overall, our findings corroborate and extend previous studies that have investigated single-equation dynamic panel models, see e.g. Judson and Owen (1999).

Since impulse responses (which are the objects of interest in most applied panel VAR studies) are complicated nonlinear functions of all estimated parameters, the effects of biases in individual coefficients on the resulting impulse responses are in general hard to predict. To provide an example for how strongly the shape of impulse response functions may depend on the specific estimation technique used, we estimate a fiscal panel VAR and compare the IRFs obtained using different estimation techniques. In our application, we find that the impulse responses following government spending shocks obtained using the widely applied simple fixed effects (LSDV) estimator are still reasonably close to the bias-corrected ones, though they tend to understate the persistence of shock effects notably. This relation is in line with the Monte Carlo evidence, which documented a substantial negative bias of the simple LSDV coefficient estimates.

The remainder is organized as follows. Section 2 motivates our Monte Carlo analysis by presenting a collection of previous papers that have estimated macro panel VARs using (similar) estimation techniques as the ones considered in this paper. Section 3 introduces the setup of the Monte Carlo study. Section 4 briefly describes the six estimation techniques considered. The results of the simulations are presented in Section 5. The application where we estimate a fiscal panel VAR for OECD countries can be found in Section 6. The last section concludes.

2 Applied macro panel VAR studies

In this section, we briefly gather empirical publications that have estimated panel VARs from datasets having properties similar to those considered in the subsequent Monte Carlo study and that have applied similar estimation techniques as the ones considered in this

Table 1: A collection of studies estimating macro panel VARs

Study	N	T	Estimator	Area of research
Alesina et al. (2002)	18	37	LSDV	Fiscal policy and investment
Ardagna, Caselli, and Lane (2007)	16	42	LSDV	Government debt
Asdrubali and Kim (2004)	22 (50)	31 (28)	OLS	Risk sharing
Asdrubali and Kim (2008)	12	26	OLS	EU budget
Beetsma, Giuliodori, and Klaassen (2006)	11	38	LSDV	Fiscal policy
Beetsma, Giuliodori, and Klaassen (2008)	14	35	LSDV	Public spending shocks
Becker and Hoffmann (2006)	28(50)	47 (28)	GMM	Risk sharing
Binet (2003)	27	10	LSDVC	Fiscal competition
Blanco (2009)	18	44	GMM	Finance and Growth
Buch, Carstensen, and Schertler (2010)	17	108*	LSDV	International banking
Doménech, Taguas, and Varela (2000)	18	≈33	LSDV	Ricardian equivalence
Erdil and Yetkiner (2009)	75	11	LSDV	Health care expenditures
Gavin and Theodorou (2005)	15	88*	LSDV	Common macro dynamics
Goodhart and Hofmann (2008)	17	136 (88)*	LSDV	House prices and credit
Justesen (2008)	40-70	6	LSDVC	Growth and economic freedom
Kim and Lee (2008)	7	23	LSDV	Demography and savings
Lee (2007)	16	16	LSDV	Housing investment
Love and Zicchino (2006)	36	11	GMM	Financial development
Ravn, Schmitt-Grohé, and Uribe (2007)	4	124*	LSDV	Government spending shocks
Rousseau and Wachtel (2000)	47	16	GMM	Financial intermediation
Tagkalakis (2008)	19	32	LSDV	Fiscal policy and consumption
Tani (2003)	166	10	LSDV	Regional evolutions

Notes: N : number of cross-sectional units; T : number of time periods (years); studies using quarterly data are marked with an asterisk (*). The studies are broadly classified as: LSDV: least squares dummy variable estimator; LSDVC: bias-corrected version of the least squares dummy variable estimator; GMM: generalized method of moments techniques (either 'first-generation' GMM or 'extended' GMM) paper.

Table 1 presents a collection of such studies. Of course, we do not claim that the list of papers is comprehensive, but it nevertheless serves as a motivation for the subsequent Monte Carlo analysis.[5] The papers are ordered alphabetically and we report the dimensions of the datasets employed, the estimation techniques applied, and some keywords describing the area of research. For simplicity, we do not give details on the specific estimation technique but classify the papers only broadly along the dimensions 'fixed effects (LSDV)', 'bias-corrected fixed effects (LSDVC)', or 'GMM' techniques, respectively.

The table shows that the simple LSDV estimator is widely applied to estimate panel VARs from macro data. In Section 5, we investigate the small-sample performance of this estimator using a Monte Carlo study and compare it to various alternatives, such as a bias-corrected LSDV estimator or GMM-type techniques.

3 Monte Carlo setup

Our simulation setup for the panel VAR closely follows Binder, Hsiao, and Pesaran (2005) and Mutl (2009). Yet, we consider long instead of short panels, which relates our setup to the single-equation analysis presented in Judson and Owen (1999). Consider a first-order panel VAR for K variables given by

$$\mathbf{y}_{it} = \mathbf{\Phi}\mathbf{y}_{i,t-1} + (\mathbf{I}_k - \mathbf{\Phi})\, \boldsymbol{\mu}_i + \boldsymbol{\varepsilon}_{it}, \tag{1}$$

where the subscript $i \in \{1, ..., N\}$ refers to the cross-sectional dimension and $t \in \{1, ..., T\}$ to the time dimension of the panel of observations $\mathbf{y}_{it}$. The model contains K equations so that the observations $\mathbf{y}_{it}$, the individual-specific effects $\boldsymbol{\mu}_i$, and the disturbances $\boldsymbol{\varepsilon}_{it}$ are $K \times 1$ vectors. The coefficients on the lagged endogenous variables are summarized in a $K \times K$ matrix $\mathbf{\Phi}$.

The disturbances $\boldsymbol{\varepsilon}_{it}$ are normally distributed with $E(\boldsymbol{\varepsilon}_{it}) = 0$ and a positive definite variance-covariance matrix $\mathbf{\Omega}_\varepsilon$. The disturbances are assumed to be independent across $i = 1, ..., N$ and $t = 1, ..., T$. We consider only fixed-effects specifications of the individual-specific effects $\boldsymbol{\mu}_i$. They are generated as

$$\begin{aligned} \boldsymbol{\mu}_i &= \sqrt{\tau}\left(\frac{q_i - 1}{\sqrt{2}}\right)\eta_i, \\ q_i &\sim \chi^2(1), \text{ and } \eta_i \sim N(\mathbf{0}, \mathbf{\Omega}_\varepsilon), \end{aligned}$$

with q_i and η_i being distributed independently of each other and of $\boldsymbol{\varepsilon}_{it}$ for all i and t. The parameter τ measures the degree of cross-section to time-series variation. While the performance of the LSDV estimator does not depend on τ, the performance of GMM-type

[5] Note that the list does not include contributions that have applied Bayesian panel VAR techniques, see e.g. Canova, Ciccarelli, and Ortega (2007), because a closer investigation of such techniques is beyond the scope of this paper.

estimators has been shown to deteriorate with increasing the ratio of the variance of the individual effects to the variance of the innovations, see e.g. Kitazawa (2001) and Binder, Hsiao, and Pesaran (2005). We follow Binder, Hsiao, and Pesaran (2005) and consider the cases of $\tau = 1$ and $\tau = 5$.

In our baseline simulations, we use one of Binder, Hsiao, and Pesaran's (2005) types of designs for the matrix of slope coefficients, $\mathbf{\Phi}$, for a two-variable ($K = 2$) first-order ($p = 1$) stationary panel VAR. Since we focus on macroeconomic applications where time series are typically highly persistent, we restrict most of our attention to the case where the maximum eigenvalue of $\mathbf{\Phi}$ is 0.95. Results for an alternative Monte Carlo design, where time series are somewhat less persistent and $\mathbf{\Phi}$ has maximum eigenvalue of 0.8 will be discussed briefly. For the case of high persistence, $\mathbf{\Phi}$ and $\mathbf{\Omega}_\varepsilon$ are specified as[6]

$$\mathbf{\Phi} = \begin{pmatrix} 0.7 & 0.25 \\ 0.25 & 0.7 \end{pmatrix}, \mathbf{\Omega}_\varepsilon = \begin{pmatrix} 0.08 & -0.05 \\ -0.05 & 0.08 \end{pmatrix}.$$

The simulations are replicated 1,000 times and the resulting estimates are saved. To initialize the $\mathbf{y}_{it}$ process, we follow Judson and Owen (1999) by choosing $\mathbf{y}_{i0} = 0$ and then discarding the first 50 observations of the simulated data for each cross-sectional unit.

In the simulations, we vary the size of our simulated panel. For our baseline exercises, we choose $N = 20$ for the cross-sectional dimension and for the time dimension T, we consider values of $10, 20, 30, ..., 80$. These choices are made having annual and quarterly time series used in macroeconomic research in mind, see Table 1.

4 Estimators

(1) Pooled OLS The multivariate OLS estimator for VARs can be found in Lütkepohl (2006, p. 60). In the presence of fixed effects, pooled OLS provides upwards biased estimates of autoregressive coefficients even when T is large, see e.g. Hsiao (1986).

(2) Simple least squares dummy variable estimator (LSDV) The LSDV, fixed effect, or within group estimator is discussed in e.g. Bun and Kiviet (2006, p. 415). The within transformation of the LSDV estimator eliminates the fixed effects but introduces a correlation between lagged dependent variables and the time-averaged idiosyncratic error term. The associated bias decreases in T, see e.g. Nickell (1981) or Hahn and Kuersteiner (2002).

(3) Bias-corrected least squares dummy variable estimator developed by Hahn and Kuersteiner (2002) (LSDVC) We use the bias-corrected fixed-effects estimator developed by Hahn and Kuersteiner (2002). Hahn and Kuersteiner (2002) understand their estimator as an implementable version of Kiviet's (1995) estimator, because

[6] We follow Binder, Hsiao, and Pesaran (2005) in using different error variance matrices $\mathbf{\Omega}_\varepsilon$ for different designs so as to obtain similar population R^2 values for all equations of the PVAR model and across designs.

their procedure does not require a preliminary consistent estimator for initialization as is required for Kiviet's approach. The estimator we implement is given by equations (3) and (4) in Hahn and Kuersteiner (2002). Note that this estimator is not designed for samples with small T.

(4) Anderson and Hsiao (1982) estimator (AH) The Anderson and Hsiao (1982) estimator takes first differences of the dynamic system to eliminate the fixed effects. This introduces a correlation between lagged dependent variables and differenced errors. Anderson and Hsiao (1982) have shown that the level of the endogenous variable lagged two periods can serve as an instrument.

(5) Standard GMM estimator à la Arellano and Bond (1991) (SGMM) Building on the work of Anderson and Hsiao (1982), Holtz-Eakin et al. (1988) and Arellano and Bond (1991) have developed GMM estimators that use all linear moment restrictions specified by the model, as more lagged instruments become available for the differenced equation. Binder, Hsiao, and Pesaran (2005) have derived the multi-equation extension of the Arellano and Bond (1991) estimator, which we use to estimate the panel VAR (we refer to their paper for computational details). Note that the number of moment restrictions increases at the order T^2, which has implications for the finite-sample performance since very remote lags are unlikely to be informative instruments. For this reason, we do not use all available moment restrictions but use a maximum of four lagged levels as instruments.

(6) Extended GMM estimators à la Ahn and Schmidt (1995), Arellano and Bover (1995), and Blundell and Bond (1998) (EGMM) Subsequent extensions of the Arellano and Bond (1991) estimator use an augmented set of moment conditions. These extended GMM estimators consider moment conditions implied by homoskedasticity (Ahn and Schmidt 1995) and initialization restrictions (Arellano and Bover 1995, and Blundell and Bond 1998). While the standard Arellano and Bond (1991) estimator works on the differenced equation only, the Blundell and Bond (1998) estimator additionally uses moment conditions in which lagged differences are used as instruments for the level equation. Blundell and Bond (1998) and Blundell, Bond, and Windmeijer (2000) have shown that this estimator exploiting the levels equation performs better than the Arellano and Bond (1991) estimator when time series are highly persistent. To estimate the panel VAR, we use the multivariate versions of the extended GMM estimators as presented in Binder, Hsiao, and Pesaran (2005). We use their extended GMM estimator that uses only the moment conditions implied by orthogonality and initialization restrictions (EGMM1) and the GMM estimator that uses only the moment conditions implied by orthogonality and homoskedasticity (EGMM2). The estimator that uses all three sets of moment conditions will be referred to as EGMM3. The corresponding designs for the instrument matrices can be found on page 812 in Binder, Hsiao, and Pesaran (2005). For each version of the estimator, we allow for a maximum lag length of four when constructing the matrix of instruments.

5 Monte Carlo Results

In the first part of this section, we compare the various estimation techniques in terms of their biases and root mean square errors (RMSEs). Thereafter, we illustrate for some selected cases how strongly potential estimation biases affect the shape of the implied impulse response functions (IRFs).

5.1 Comparison in terms of biases and RMSEs

Tables 2 and 3 (at the end of the paper) summarizes the simulation results from the various designs. To facilitate a convenient comparison of the various estimation results, we illustrate them also graphically. Figure 1 displays the average bias (first row) and root mean square error (second row) of the different estimators over 1,000 simulations, for our baseline setting with $N = 20$ and $\tau = 1$. To save on space, we display the results only for the coefficients Φ_{11} and Φ_{21}. The results for Φ_{12} and Φ_{22} are very similar since the coefficient matrix Φ is symmetric (detailed results are available upon request).

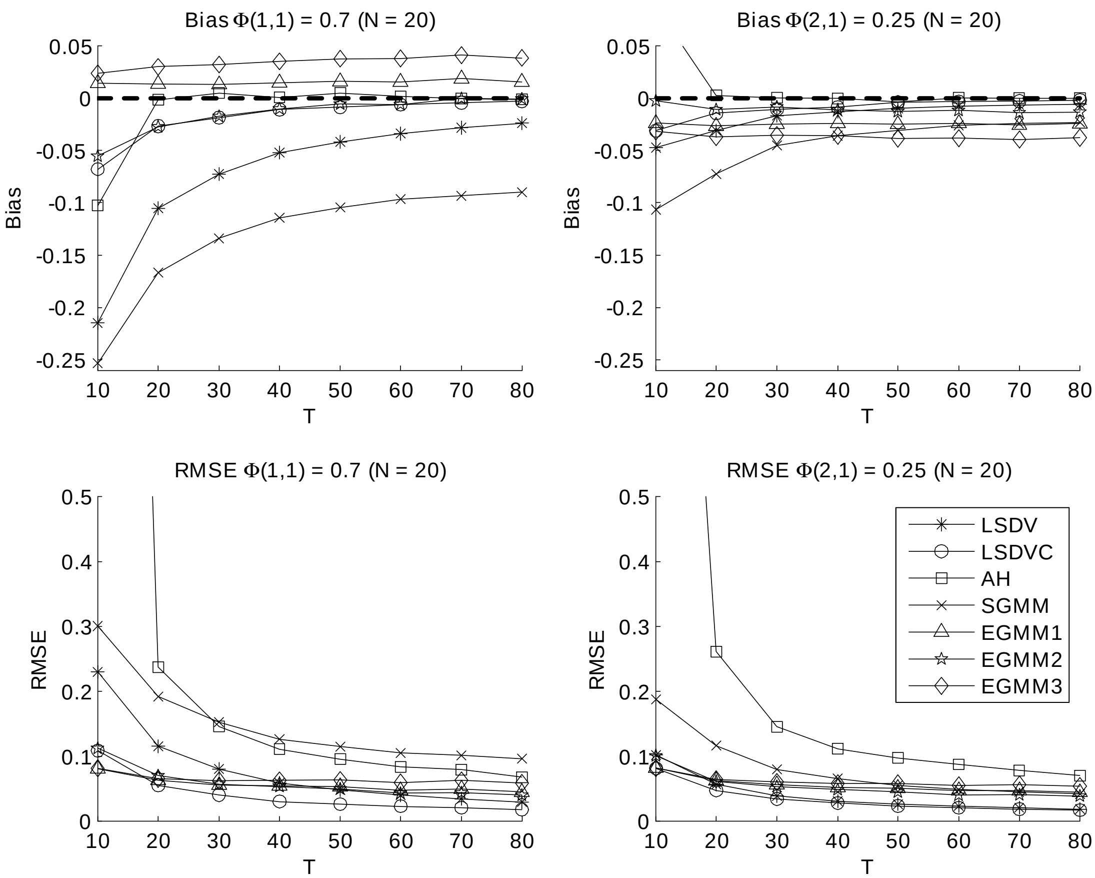
To make the figure less crowded, Figure 1 does not display the results for pooled OLS. In the presence of fixed effects, pooled OLS provides upward biased estimates of autoregressive coefficients. As can be seen from Tables 2 and 3, this bias does not vanish when T is increased. For larger values of τ, the bias of pooled OLS becomes even more pronounced.

Figure 1 shows that the simple LSDV estimator has a substantial negative bias for Φ_{11} even when T becomes relatively large. Its bias decreases as the time dimension gets larger, however it remains large even if $T = 80$. This result is important, since using the simple LSDV estimator to estimate panel VARs from datasets having T less than 40 or so is not uncommon. The negative bias of the LSDV estimator results in impulse response functions that fade out much too quickly (see Section 5.2 for an illustration).[7]

Figure 1 also shows that adopting a bias-correction leads to drastic improvements in the performance of the simple LSDV estimator. While the Hahn and Kuersteiner (2002) (LSDVC) estimator is not successful at removing the bias completely as long as T is about 50 or less, this estimator is clearly preferable over the simple LSDV estimator. While alternative bias-correction procedures exploiting an initial consistent estimator (see e.g. Bun and Kiviet 2003, 2006, or Bun and Carree 2005, 2006) may be even more accurate than the relatively simple bias-correction of Hahn and Kuersteiner (2002), the guideline for practitioners is nevertheless clear-cut: In any case, adopting a bias-corrected version of the LSDV estimator is strongly recommended instead of using its uncorrected version. This is even recommended when quarterly data are available and the time dimension gets

[7] Our results are in line with the single-equation evidence presented in Judson and Owen (1999). For instance, for their specification with an autoregressive coefficient of 0.8 and $T = 10, N = 20$, they report a bias of the LSDV estimator of -0.238.

Figure 1: Bias and RMSE of various estimators for N=20, $\tau = 1$



Notes: The figure displays the average bias (first row) and root mean square error (second row) for two of the four coefficients in the symmetric matrix Φ over 1,000 simulations. Table 2 (at the end of the paper) provides the numbers underlying the figure. The Monte Carlo design is
$N = 20, p = 1, \tau = 1, \Phi = \begin{pmatrix} 0.7 & 0.25 \\ 0.25 & 0.7 \end{pmatrix}, \Omega_\varepsilon = \begin{pmatrix} 0.08 & -0.05 \\ -0.05 & 0.08 \end{pmatrix}$. The data-generating process is the panel VAR given by equation (1).

LSDV: Simple least squares dummy variable estimator; LSDVC: Hahn and Kuersteiner's (2002) bias-corrected LSDV estimator; AH: multivariate Anderson and Hsiao (1982) estimator; SGMM: multivariate Arellano and Bond (1991) GMM estimator; EGMM1: multivariate extended GMM estimator using the instrument matrices P_{1i} and P_{2i} as given in Binder et al. (2005); EGMM2: multivariate extended GMM estimator using the instrument matrices P_{1i} and P_{3i} as given in Binder et al. (2005); EGMM3: multivariate extended GMM estimator using the instrument matrices P_{1i},P_{2i}, and P_{3i} as given in Binder et al. (2005) (see page 812 in their paper).

as large as 80. Note that this recommendation does not depend on the choice of the specific evaluation criterion, since it holds irrespective of whether one considers bias or RMSE.

The multivariate version of the Anderson and Hsiao (1982) estimator is found to be almost unbiased in this setting when T is larger than about 20. This reflects that this IV estimator is consistent irrespective of whether the number of time periods, the number of cross-sectional units, or both tend to infinity, see Arellano (1989). However, as can be seen from the second row in Figure 1, this estimator performs poorly in terms of RMSE. This apparent lack of precision makes the Anderson and Hsiao (1982) estimator unattractive for empirical applications.

Among the GMM-type estimators, the extended GMM estimators clearly outperform the estimator based on the standard Arellano and Bond (1991) moment conditions. This is not surprising since previous single-equation studies have documented that the Arellano and Bond (1991) estimator can perform poorly if the time series are highly persistent (e.g. Blundell and Bond 1998, Blundell, Bond, and Windmeijer, 2000) as is the case in our simulations. In fact, the multivariate Arellano and Bond (1991) estimator is found to perform worst among all estimators considered. Macroeconomists should therefore abandon this estimator when having prior knowledge that their data may have characteristics similar to the ones considered in this Monte Carlo design.

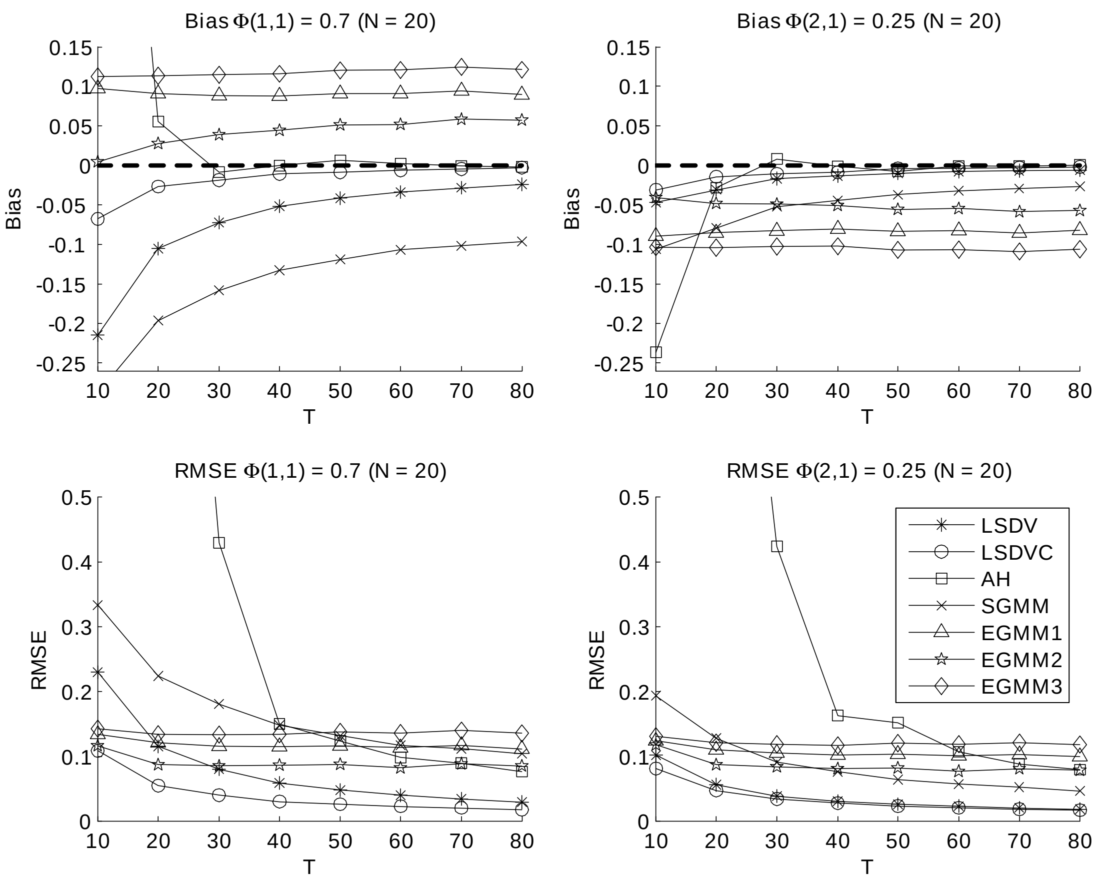
As has been documented for single-equation models, the additional instruments used by the extended GMM estimators result in a substantial reduction in the finite sample bias of GMM estimators. It is noteworthy that, in general, the extended GMM estimators perform relatively well in our setting, although these estimators are designed for datasets with a large number of cross-sectional units and few time period. In terms of bias, the performance of the EGMM2 estimator is approximately equal to the one of the Hahn and Kuersteiner (2002) bias-corrected LSDV estimator. However, the apparent drawback of the GMM estimators is that their standard errors and RMSEs are relatively large in comparison to fixed-effects estimators. This finding is in line with previous single-equation studies that have documented that the bias-corrected LSDV estimators seem to have better finite sample properties than various GMM estimators, see e.g. Judson and Owen (1999) or Ramalho (2005).

The other two extended GMM estimators (EGMM1 and EGMM3, respectively) are found to display a positive bias for Φ_{11} which does not vanish if T is increased. Thus, we conclude that, among the extended GMM estimators, the version EGMM2 tends to perform best for the Monte Carlo design under investigation.[8]

We now consider a Monte Carlo design in which we increase the ratio of the variance

[8] We also checked the performance of the conventional single-equation versions of the Arellano and Bond (1991) and Blundell and Bond (1998) GMM estimators, respectively, when these techniques are used to estimate the panel VAR equation-by-equation. The results are qualitatively the same and quantitatively very similar to the ones obtained using the multivariate extensions (detailed results are available upon request).

Figure 2: Bias and RMSE of various estimators for N=20, $\tau = 5$



Notes: The figure displays the average bias (first row) and root mean square error (second row) for two of the four coefficients in the symmetric matrix Φ over 1,000 simulations. Table 2 (at the end of the paper) provides the numbers underlying the figure. The Monte Carlo design is the same as in Figure 1, but for $\tau = 5$ instead of $\tau = 1$. For details, see the notes to Figure 1 and Sections 3 and 4.

LSDV: Simple least squares dummy variable estimator; LSDVC: Hahn and Kuersteiner's (2002) bias-corrected LSDV estimator; AH: multivariate Anderson and Hsiao (1982) estimator; SGMM: multivariate Arellano and Bond (1991) GMM estimator; EGMM1: multivariate extended GMM estimator using the instrument matrices P_{1i} and P_{2i} as given in Binder et al. (2005); EGMM2: multivariate extended GMM estimator using the instrument matrices P_{1i} and P_{3i} as given in Binder et al. (2005); EGMM3: multivariate extended GMM estimator using the instrument matrices P_{1i},P_{2i}, and P_{3i} as given in Binder et al. (2005) (see page 812 in their paper).

of the individual effects to the variance of the innovations ($\tau = 5$ instead of $\tau = 1$). Figure 2 and Table 2 (at the end of the paper) summarize the corresponding simulation results. In line with Kitazawa (2001) and Binder, Hsiao, and Pesaran (2005), we find that the performance of the GMM-type estimators deteriorates dramatically in such setting (note the different scaling of the y-axis in comparison to Figure 1). By contrast, the performance of the bias-corrected LSDV estimator is unaffected by the degree of cross-section to time-series variation. In macroeconomic applications, the degree of cross-section to time-series variation can often be expected to be large, for instance when a panel of OECD countries is investigated. This is a further argument in favor of using bias-correction procedures when estimating macro panel VARs.

We also provide the results for an alternative Monte Carlo design where we increase the number of cross-sectional units from 20 to 50 (for $\tau = 1$ and $\tau = 5$, respectively). While a cross-section of 50 units is typically not available in macro cross-country panel datasets, it is often available at lower levels of geographical aggregation, for instance if states or regions within a country are the units of investigation. To save on space, we do not present the results graphically but refer to Tables 2 and 3 for detailed results.

In general, the IV and GMM-type estimators tend to become more efficient as the cross-sectional dimension N is increased. The performance of the fixed-effects estimators, by contrast, does not depend on N. This makes even the standard SGMM estimator less biased than the simple LSDV estimator for $T \leq 40$. Among the extended GMM estimators, the improvement in the performance of the EGMM1 estimator is most pronounced. This estimator becomes even less biased than the bias-corrected fixed-effects estimator (but only for $\tau = 1$). Yet, as before, the bias-corrected estimator tends to perform better in terms of RMSE. Concerning EGMM2, we find that its bias is smaller than the one of the Hahn and Kuersteiner (2002) estimator if $T \leq 40$ and $\tau = 1$ (while the ordering remains reversed with respect to RMSE). The RMSE of the Anderson and Hsiao (1982) estimator remains the highest among the estimators considered. Overall, the trade-off between bias and RMSE of the various estimators tends to become less pronounced if more cross-sectional units are available. In other words, the EGMM1 estimator may become an option if the panel dataset has relatively large N. However, the bias-corrected LSDV estimator clearly dominates the GMM-type procedures for the case $\tau = 5$.

Finally, we run a Monte Carlo experiment for a design in which the maximum eigenvalue of the coefficient matrix $\mathbf{\Phi}$ is 0.8 instead of 0.95. The results of this Monte Carlo design are summarized in Table 3 (at the end of the paper). The RMSE of the Anderson and Hsiao (1982) estimator decreases substantially but still remains larger than the one of the bias-corrected LSDV estimator. For the case $\tau = 1$, EGMM1 and EGMM3 perform worse than under the previous design assuming a maximum eigenvalue of 0.95. As before, EGMM2 performs similarly in terms of bias as the Hahn and Kuersteiner (2002) estimator, but its bias for $\mathbf{\Phi}_{1,1}$ changes sign for $T \gtrapprox 40$ (getting positive). When $\tau = 5$, the performance of EGMM2 worsens substantially, as already documented for our baseline Monte Carlo design. Similarly, EGMM1 and EGMM3 perform badly when $\tau = 5$ (the bias is positive and does not decrease with T).

5.2 Implied impulse response functions

The applied macroeconomist using panel VARs is typically not interested in the VAR coefficients *per se* but uses impulse response functions to investigate the dynamic behavior of the system of equations. The IRFs reflect complex nonlinear interactions of the estimated VAR coefficients at different time horizons. For this reason, it may be difficult to assess the overall performance of an estimation technique by looking at biases and RMSEs of particular VAR coefficients alone.

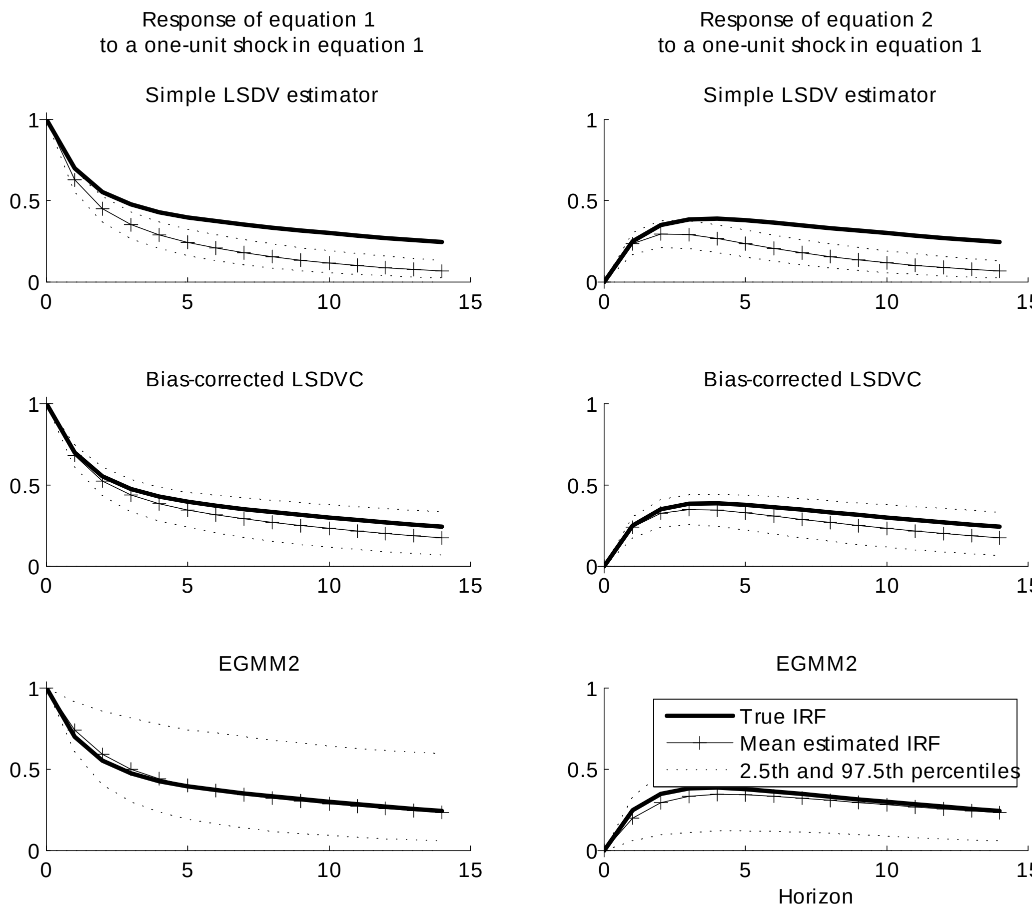
To illustrate the economic importance of potential estimation biases, Figure 3 displays the mean (reduced-form) IRFs over the 1,000 Monte Carlo repetitions at each time horizon, for the intermediate case $T = 30, N = 20$, and $\tau = 5$. The figure shows the responses of equations 1 and 2, respectively, to a one-unit shock in equation 1. The dashed lines are the 2.5th and 97.5th percentiles of the estimated responses at each time horizon, respectively. The true impulse responses are given by the bold lines. To save on space, we restrict our attention to three selected estimators: the simple LSDV estimator (first row), its bias-corrected version LSDVC (second row), and the EGMM2 system GMM estimator (third row).

The first row in Figure 3 illustrates that the negative bias of the simple LSDV estimator has a non-neglible effect on the implied IRFs even if the time dimension of the dataset is 30 years. While the researcher would infer the correct signs of the effects in this setting, the IRFs fade out too quickly. Our results show that the bias of the simple LSDV estimator should not be neglected even when T is relatively large. These findings can thus be seen as a natural extension of Judson and Owen's (1999) results for the single-equation case.

The second row in Figure 3 shows the mean IRFs obtained with the bias-corrected LSDVC estimator for the same setting. One can see that the IRFs are relatively close to the true ones.

Perhaps surprisingly, the mean IRFs obtained using the extended GMM estimator EGMM2 appear close to the true ones (see the third line in Figure 3), although we know from the Monte Carlo studies that this estimator is biased in the setting considered. Yet, a closer examination of Table 2 shows that, for this estimator, the direction of the bias differs between ϕ_{11} and ϕ_{21} (being positive for ϕ_{11} and negative for ϕ_{21}). Since the IRFs are nonlinear combinations of all VAR coefficients, a pattern like in Figure 3 can emerge. Of course, this observation should not be taken as evidence that the EGMM2 estimator is a good choice at all in this setting. The poor precision of the EGMM2 estimator translates into broad confidence bands.

Figure 3: True and estimated IRFs for T=30, N=20, and τ=5; three selected estimators



Notes: The figure displays the mean IRFs over the 1,000 Monte Carlo repetitions at each time horizon, for the intermediate case $T = 30, N = 20$ and $\tau = 5$ (the associated biases and RMSEs are displayed in Figure 2). The figure shows the responses of equations 1 and 2, respectively, to a one-unit shock in equation 1. The dashed lines are the 2.5th and 97.5th percentiles of the estimated responses at each time horizon, respectively. The true impulse responses are given by the bold lines.

6 Application: Panel VAR estimates of fiscal policy effects

In this section, we present an application to illustrate the methodological arguments made in the Monte Carlo study. We present panel VAR estimates for the effects of changes in government consumption on aggregate output, private consumption, investment, and real wages for a sample of OECD countries. Quantifying the effects of government spending is of obvious policy relevance and previous papers have uncovered several theoretically interesting and surprising responses, such as the positive effect of government spending shocks on private consumption (e.g. Blanchard and Perotti, 2002, Galí, López-Salido, and Vallés 2007) or real wages (e.g. Monacelli and Perotti, 2008); much of this literature is surveyed in Perotti (2007).

Most previous papers in this tradition have used quarterly data. Yet, there are relatively few countries for which quarterly fiscal data of undisputed quality are available. Accordingly, the largest part of the previous literature has used data for the US and only a small number of other countries like Canada, the UK, Australia, and Germany (e.g. Perotti, 2004) or Canada, Japan, the UK, and the aggregate Euro area (Pappa, 2009), or used panel VARs on quarterly data from these countries like Ravn, Schmitt-Grohe, and Uribe (2007).

In this paper, we use annual observations on 19 OECD countries spanning the years between 1960 and 2008 to quantify the macroeconomic effects of fiscal policy shocks. Studies that use datasets closest to the one used in this application are Beetsma, Giuliodori, and Klaassen (2006, 2008), who study international spillover effects from fiscal spending in a panel with yearly EU country data.

The application we present is ideally suited in the present context, for several reasons. First, using annual data allows us to provide evidence based on a broader country sample, which is of obvious interest. Second, annual data allows us to address the point made by Beetsma, Giuliodori, and Klaassen (2006, 2008) that, in current institutional settings, budget decisions are taken mostly once a year, such that an empirical approach using annual data provides a more natural interpretation of the estimated shocks than quarterly data do. Annual data frequencies might also mitigate the potential problem of anticipation of fiscal policy changes, as has been argued by Ramey (2009). Third, and most importantly in the present context, the Monte Carlo experiments presented in Section 5 have been conducted for datasets having similar dimensions as our annual dataset for OECD countries ($N = 19$ and $T = 49$). Therefore, it is interesting to compare results obtained using different estimation techniques in this application.

6.1 VAR specification

Our fiscal panel VAR consists of real (deflated with the deflator of gross domestic product) government consumption expenditure g_t, real gross domestic product y_t, real private final consumption expenditures c_t, real gross fixed investment i_t, and real compensation per employee as a measure of the real wage rate w_t. All variables except for w_t are converted to a per capita basis by dividing through the population number and all variables enter the panel VAR in natural logarithms. The data are taken from the European Commission's annual macroeconomic database (AMECO) and are described in more detail in the appendix.

While the Monte Carlo evidence presented in Section 5 has focused on panel VARs of first order, we want to be less restrictive in the present application and use a second order model (robustness checks show, however, that using either only one or three lags of the endogenous variables has no substantial effects on the results presented below). In the following, we briefly explain how the bias-correction of the Hahn and Kuersteiner (2002) estimator can be implemented for general VAR models. To make the Hahn and Kuersteiner (2002) estimator suitable for models with higher order VAR dynamics, one can use the fact that any VAR(p) process can be written in VAR(1) form by imposing blockwise zero and identity restrictions on the VAR slope coefficients, see e.g. Lütkepohl (2006, p. 15 and p. 194) and also Hahn and Kuersteiner (2002, p. 1640). To model higher order dynamics, we therefore use an extended version of the Hahn and Kuersteiner (2002) estimator that allows for linear constraints. To control for time effects, we use a projection matrix to average the observations over individuals and then use the transformed data in the estimations (which is equivalent to including the matrix of time dummies as regressors). As in Beetsma, Giuliodori, and Klaassen (2006, 2008), we control for linear country-specific time trends.

6.2 Identification of spending shocks

We identify fiscal spending shocks by ordering government spending first and orthogonalize impulse responses by a Cholesky decomposition. This recursive identification approach assumes that government spending is exogenous within the period and responds to other shocks than its own only with a lag. This way of identifying fiscal shocks is standard in the fiscal VAR literature (e.g. Perotti, 2007; identification is of course more involved if the estimation of tax shocks is aimed at, which is not the case here; see e.g. Blanchard and Perotti, 2002).

However, the recursive identification scheme is potentially problematic if data are at annual frequency. For quarterly or higher frequency data, lags in the planning and implementation of fiscal policy decisions can plausibly be assumed to rule out any endogenous reaction of government spending to the state of the business cycle within a quarter. At annual frequency, the government might, in principle, react to changing economic conditions within a period. Beetsma, Giuliodori, and Klaassen (2009) have studied the possible identification problem by comparing VARs on annual and quarterly data for countries where both frequencies are available. They find that the assumption of a zero response of government spending to output within a year is not rejected by their data. Therefore, they conclude that the recursive identification is a sensible procedure even with annual

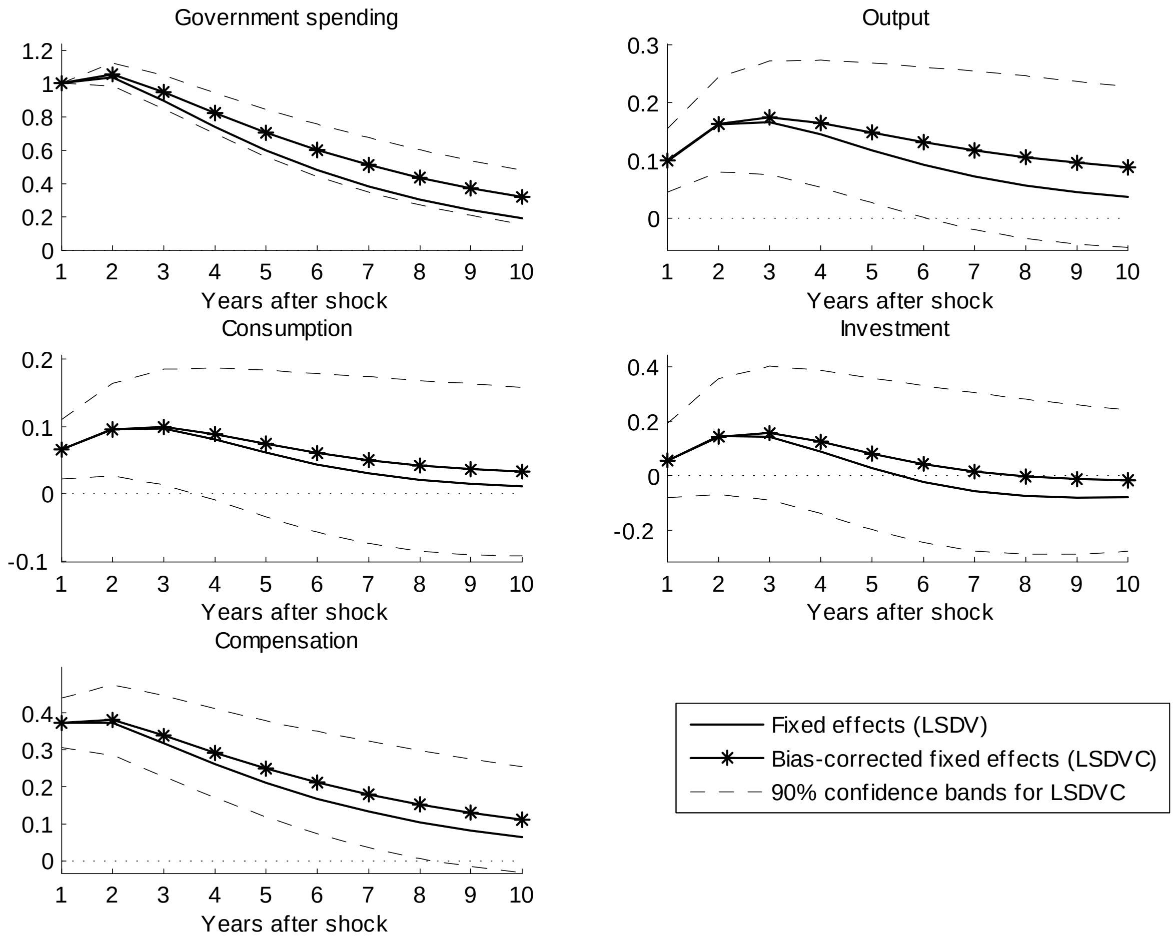


Figure 4: Impulse responses to a one percent shock to government spending in period 1

data. The interpretation is that the budget is set once a year and the variations within the year are comparatively small. Our empirical identification approach uses this argument.

6.3 Results

The main conclusion suggested by the Monte Carlo evidence presented in Section 5 was that (i) the simple fixed effects estimator commonly used in the applied macro panel VAR literature is potentially problematic even when T is relatively large and that (ii) the bias-corrected version of the fixed effects estimator due to Hahn and Kuersteiner (2002) is quite successful at removing the bias while being an efficient estimator at the same time. Accordingly, in our fiscal panel VAR application, we restrict our attention to these two estimation techniques and compare the implied impulse response functions obtained using both estimators.

Figure 4 shows the estimated impulse responses to a one percent shock to government spending in period 1. The solid lines are the IRFs that are implied by the simple (fixed effects) LSDV estimates and the IRFs from the bias-corrected fixed effects estimator LSDVC (Hahn and Kuersteiner 2002) are marked with asterisks. To make the figure less crowded, only the latter impulse responses are accompanied by 90% bootstrapped confidence bands (shown by the dashed lines in the figure; number of bootstrap repetitions is 1,000).

All responses are estimated to be positive. The bias-corrected estimates show markedly more persistence than the simple fixed effects estimates. This observation reflects the negative bias of the simple fixed effects estimator in samples of this size (see Section 5). In fact, there is a remarkable level of endogenous persistence in the estimates obtained using the Hahn and Kuersteiner (2002) bias correction. Output is still as high as on impact after 8 years, i.e. at a time when the exogenous persistence of fiscal spending itself has reduced the increase in government consumption to about half its impact value.

Other than with respect to persistence, the impulse responses from the fixed effects (LSDV) and bias-corrected (LSDVC) estimates turn out to be fairly similar (with the LSDV responses lying within the confidence bands of the LSDVC-based ones). Note that this result is not in conflict with the finding of substantial biases in the LSDV coefficient estimates that has been reported in the Monte Carlo study in Section 5. The reason is that impulse responses are complicated nonlinear functions of all estimated parameters, such that the effects of biases in individual coefficients on the resulting impulse responses are in general hard to predict.

To interpret the size of the responses, note that a one percent shock to government spending increases real gdp on impact by about 0.1 percent. In the literature, as well as in policy discussions, fiscal spending effects are often quoted in terms of the 'fiscal output multiplier', i.e. the response of real gdp to a government shock of the size of one percent of gdp. The fiscal output multiplier can be recovered by dividing the output response by the sample mean of the share of government consumption in gdp, which is 18.19% in our sample. Hence, the results presented in Figure 4 imply an impact multiplier on output of about 0.55%. Over the course of the following periods, however, the gdp response increases further with a marked hump-shape, such that the maximum fiscal output multiplier reaches a level of almost one after about two to three years.

To compare these numbers to previous literature, note that our estimates are close in size to those reported by Ravn, Schmitt-Grohe, and Uribe (2007) for their quarterly panel comprising four countries, and somewhat less than estimates for quarterly US data from Perotti (2007) or Monacelli and Perotti (2008). The latter studies find an output multiplier reaching 1 to 1.5 percent for a shock equalling one percent of gdp, depending on the exact sample and method used. Our estimated output multipliers are also somewhat smaller than the ones documented by Beetsma, Giuliodori, and Klaassen (2008) for their annual EU country panel.

In our sample, consumption is on average 57.62% of gdp, so that the estimated impact response translates into a consumption multiplier of about 0.11 . The peak response is about 0.17 for a shock sized one percent of gdp. This number is substantially smaller than what has been reported in some previous studies; for example, Perotti (2007) estimates the consumption response to be one percent for the US, and about half that value for the other countries for which he has quarterly data (Australia, Canada, UK). At the same time, our estimates are quite well in line with those of Ravn, Schmitt-Grohe, and Uribe (2007). In any case, we find the positive response of consumption to be statistically significant. Note that some studies, e.g. Perotti (2004), have found that the consumption response becomes smaller, or turns negative, for sample periods starting in the 1980s. When we restrict the sample to cover the years 1980 to 2008, we can confirm this finding for our broader country set, in that the private consumption response is initially notably smaller and generally insignificant.[9]

Our estimate of a strongly positive response of the real product wage is consistent with findings for the US presented by Monacelli and Perotti (2008). The effect documented here is larger than for Monacelli and Perotti's (2008) broadest measures of the real wage, although consistent with the one they report for the manufacturing sector. The most obvious difference of our results with respect to earlier literature is the positive investment response in Figure 4, while the typical finding in the literature (e.g. Perotti, 2007) shows a negative response. However, we do not find the investment response to be statistically significant at the chosen confidence level.

For the sake of completeness, we also experimented with the extended GMM estimators EGMM1, EGMM2, and EGMM2. These estimation techniques yield impulse response functions that are in general more persistent than under our preferred estimation technique LSDVC. This finding is in line with the Monte Carlo evidence presented in Section 5. As can be seen from Table 2, the positive bias of the extended GMM estimators is particularly pronounced when the degree of cross-sectional heterogeneity is large, which is a likely characteristic of our dataset for OECD countries (as noted before, the effects of biases in individual coefficients on the resulting impulse responses are in general hard to predict). Finally, the small number of cross-sectional units ($N = 19$) makes the extended GMM estimators less suited for our application.

7 Conclusion

This paper aimed at providing macroeconomic practitioners with guidelines for estimating panel VARs. We have extended the existing Monte Carlo evidence for estimating panel VARs from panels with short time and large cross-sectional dimension to panels that are characterized by a relatively large time but a small cross-sectional dimension as typically encountered in macroeconomic applications. We have compared widely used estimation

[9] These results are not reported for brevity, but are available upon request.

techniques that have hitherto been studied in the literature in a single equation context. Our results for multi-equation models complement the ones presented by Binder, Hsiao, and Pesaran (2005), who have restricted their attention to the case where $T \leq 10$ and N is large.

We have shown that the simple LSDV estimator that is widely applied in the macro panel VAR literature remains problematic even when is T large. Our analysis suggests that bias-corrected versions of the least squares dummy variable estimator are the estimators of choice for estimating macro panel VARs. This recommendation is also supported by the fact that bias-corrections are relatively easy to implement.[10] Our results for multivariate panel VARs are in line with previous evidence for dynamic single-equation panel data models, see e.g. Kiviet (1995), Judson and Owen (1999), Bun and Kiviet (2003), Ramalho (2005), or Bruno (2005).

Since macroeconomic practioners usually focus on the impulse response functions implied by the estimated VAR coefficients, we have illustrated how strongly IRFs are affected by the estimation biases of individual VAR coefficients. To investigate the practical importance of the methodological arguments made in the Monte Carlo analysis, we have presented an application in which we use a panel VAR to estimate the effects of government spending shocks in OECD countries. In this application, the resulting impulse responses from simple fixed effects estimates are still reasonably close to the bias-corrected ones, though they tend to understate the persistence of shock effects notably. Since impulse responses depend nonlinearly on all estimated VAR coefficients, the effects of biases in individual coefficients on the resulting IRFs can take various forms. For this reason, we recommend to use bias-correction procedures when estimating fixed-effects specifications of panel VARs from macroeconomic datasets. In any case, it is advisable to compare results obtained using different estimation techniques in empirical applications.

In this paper, we have restricted our attention to those estimation procedures that have actually been used by previous studies to estimate macro panel VARs (and for which barriers for efficient application by practitioners are low). Specifically, we have considered with Hahn and Kuersteiner's (2002) estimator only one possible approach to implement a bias-correction to conventional estimators. The theoretical literature on bias-correction procedures is evolving rapidly and alternative estimation procedures to estimate macro panel VARs may therefore be considered. However, the recent advances in the econometrics literature are typically developed for single-equation models and are usually tested for small-T data, see for instance Bun and Carree (2005) and Bun and Kiviet (2006). Hahn, Hausman, and Kuersteiner (2007) have used 'long difference techniques' to derive a new bias-corrected instrumental variables estimator. Extending these recent estimators

[10] This does, of course, not mean that such estimation techniques are necessarily superior for all parameter combinations and panel dimensions (also see Bun and Carree 2005 and Bun and Kiviet 2006 for a discussion on this issue in the single-equation context).

to the multivariate case and investigating their appropriateness for datasets having different dimensions than the usual microeconometric datasets is an important task for future research.[11]

[11] Estimation techniques not considered in this paper are likelihood-based procedures (see e.g. Binder, Hsiao, and Pesaran, 2005 or Yu, de Jong, and Lee 2008), and Bayesian approaches (see e.g. Canova, Ciccarelli, and Ortega 2007). For the case of nonstationary data, we refer to Breitung (2005) and Larsson and Lyhagen (2007), who consider cointegration in panel VARs. Finally, the issue of cross-sectional dependence in panel VARs (see e.g. Huang 2008) is clearly an important issue but an investigation is beyond the scope of this paper.

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A Appendix: Data for the fiscal panel VAR application

The countries included in the panel VAR are all OECD countries for which the required data are available over the length of the sample period from 1960 to 2008. These countries are Australia, Austria, Belgium, Canada, Denmark, Finland, France, Greece, Ireland, Italy, Japan, Luxembourg, the Netherlands, Norway, Portugal, Spain, Sweden, the United Kingdom, and the United States (Germany has been omitted to avoid problems with structural breaks due to German unification).

The source of all data is the website of the European Union's Directorate General for Economics and Finance Annual Macroeconomic Database (AMECO). The variables included in the fiscal VAR are defined as follows.

- y_t: Real gdp per capita: Gross domestic product at 2000 market prices, divided by total population.
- g_t: Real government spending per capita: Final consumption expenditure of general government at current prices, divided by the price deflator of gdp, and divided by total population.
- c_t: Real private consumption per capita: Private final consumption expenditure at 2000 prices, divided by total population.
- i_t: Real gross investment per capita: Gross fixed capital formation at 2000 prices, total economy, divided by total population.
- w_t: Real wage rate: Index of real compensation per employee, deflator GDP, total economy (2000=100).

All variables enter the panel VAR in natural logarithms.

Table 2: Summary of various simulation results for Φ having maximum eigenvalue of 0.95 (table continues on next page)

		$\phi_{11} = 0.7$								$\phi_{21} = 0.25$							
		Bias				RMSE				Bias				RMSE			
		$N = 20$		$N = 50$		$N = 20$		$N = 50$		$N = 20$		$N = 50$		$N = 20$		$N = 50$	
		$\tau = 1$	$\tau = 5$	$\tau = 1$	$\tau = 5$	$\tau = 1$	$\tau = 5$	$\tau = 1$	$\tau = 5$	$\tau = 1$	$\tau = 5$	$\tau = 1$	$\tau = 5$	$\tau = 1$	$\tau = 5$	$\tau = 1$	$\tau = 5$
T = 10	OLS	0.0708	0.1704	0.0824	0.1876	0.0942	0.1808	0.0934	0.1923	-0.0658	-0.1511	-0.0753	-0.1643	0.0883	0.1598	0.0850	0.1680
	LSDV	-0.2149	-0.2149	-0.2113	-0.2080	0.2302	0.2301	0.2174	0.2142	-0.0471	-0.0470	-0.0512	-0.0505	0.1019	0.1018	0.0747	0.0728
	LSDVC	-0.0679	-0.0678	-0.0634	-0.0592	0.1086	0.1085	0.0827	0.0797	-0.0311	-0.0311	-0.0320	-0.0316	0.0812	0.0811	0.0581	0.0586
	AH	-0.1028	0.8687	0.0127	0.0663	3.0212	17.5802	0.2817	1.6183	0.0880	-0.2366	0.0019	-0.0576	1.6537	11.7673	0.2819	1.9529
	SGMM	-0.2533	-0.2875	-0.1564	-0.2065	0.3004	0.3332	0.2028	0.2554	-0.1066	-0.1061	-0.1006	-0.1194	0.1874	0.1932	0.1639	0.1941
	EGMM1	0.0143	0.0972	0.0035	0.0630	0.0806	0.1341	0.0617	0.1026	-0.0239	-0.0896	-0.0152	-0.0565	0.0817	0.1238	0.0606	0.0912
	EGMM2	-0.0553	0.0046	-0.0367	-0.0001	0.1123	0.1163	0.0838	0.0912	-0.0026	-0.0408	-0.0101	-0.0271	0.1006	0.1176	0.0736	0.0907
	EGMM3	0.0238	0.1120	0.0107	0.0778	0.0815	0.1425	0.0591	0.1095	-0.0317	-0.1035	-0.0201	-0.0680	0.0818	0.1306	0.0591	0.0961
T = 20	OLS	0.0717	0.1692	0.0848	0.1884	0.0894	0.1780	0.0940	0.1928	-0.0682	-0.1508	-0.0770	-0.1643	0.0830	0.1576	0.0844	0.1675
	LSDV	-0.1053	-0.1053	-0.1053	-0.1049	0.1154	0.1153	0.1096	0.1092	-0.0311	-0.0310	-0.0274	-0.0267	0.0565	0.0564	0.0404	0.0403
	LSDVC	-0.0267	-0.0266	-0.0259	-0.0253	0.0551	0.0550	0.0404	0.0401	-0.0144	-0.0143	-0.0172	-0.0160	0.0474	0.0473	0.0327	0.0321
	AH	-0.0016	0.0554	-0.0006	0.0486	0.2375	1.5299	0.1185	1.3413	0.0025	-0.0280	-0.0006	-0.1362	0.2612	1.2320	0.1196	4.4545
	SGMM	-0.1666	-0.1967	-0.0863	-0.1228	0.1915	0.2242	0.1095	0.1507	-0.0721	-0.0795	-0.0429	-0.0622	0.1162	0.1277	0.0758	0.1006
	EGMM1	0.0135	0.0905	0.0036	0.0588	0.0632	0.1210	0.0447	0.0876	-0.0264	-0.0854	-0.0155	-0.0521	0.0624	0.1104	0.0461	0.0782
	EGMM2	-0.0274	0.0274	-0.0172	0.0137	0.0702	0.0871	0.0509	0.0617	-0.0110	-0.0485	-0.0094	-0.0268	0.0613	0.0871	0.0473	0.0609
	EGMM3	0.0300	0.1130	0.0154	0.0777	0.0655	0.1341	0.0458	0.0985	-0.0371	-0.1040	-0.0208	-0.0671	0.0644	0.1211	0.0461	0.0856
T = 30	OLS	0.0727	0.1693	0.0844	0.1898	0.0895	0.1781	0.0931	0.1939	-0.0669	-0.1495	-0.0766	-0.1655	0.0807	0.1561	0.0837	0.1685
	LSDV	-0.0725	-0.0725	-0.0688	-0.0677	0.0804	0.0804	0.0724	0.0710	-0.0167	-0.0166	-0.0179	-0.0188	0.0390	0.0390	0.0280	0.0285
	LSDVC	-0.0186	-0.0186	-0.0144	-0.0135	0.0401	0.0401	0.0272	0.0259	-0.0108	-0.0108	-0.0113	-0.0104	0.0342	0.0342	0.0234	0.0222
	AH	0.0048	-0.0085	-0.0023	0.0075	0.1455	0.4292	0.0928	0.1137	0.0004	0.0081	0.0023	-0.0035	0.1454	0.4238	0.0901	0.1193
	SGMM	-0.1339	-0.1581	-0.0646	-0.0828	0.1525	0.1805	0.0785	0.1023	-0.0450	-0.0525	-0.0247	-0.0422	0.0799	0.0908	0.0497	0.0711
	EGMM1	0.0129	0.0881	0.0026	0.0586	0.0556	0.1153	0.0381	0.0835	-0.0249	-0.0827	-0.0133	-0.0511	0.0563	0.1051	0.0390	0.0740
	EGMM2	-0.0173	0.0388	-0.0136	0.0201	0.0572	0.0853	0.0405	0.0557	-0.0085	-0.0491	-0.0059	-0.0271	0.0537	0.0836	0.0370	0.0552
	EGMM3	0.0322	0.1146	0.0170	0.0809	0.0623	0.1335	0.0402	0.0981	-0.0354	-0.1028	-0.0200	-0.0685	0.0602	0.1186	0.0400	0.0842
T = 40	OLS	0.0757	0.1702	0.0853	0.1894	0.0917	0.1789	0.0933	0.1936	-0.0697	-0.1506	-0.0766	-0.1654	0.0825	0.1571	0.0831	0.1684
	LSDV	-0.0519	-0.0519	-0.0514	-0.0512	0.0589	0.0589	0.0544	0.0539	-0.0130	-0.0130	-0.0127	-0.0128	0.0309	0.0308	0.0222	0.0218
	LSDVC	-0.0108	-0.0108	-0.0103	-0.0100	0.0304	0.0304	0.0210	0.0200	-0.0087	-0.0087	-0.0063	-0.0067	0.0282	0.0282	0.0177	0.0180
	AH	0.0006	-0.0001	0.0006	-0.0069	0.1110	0.1497	0.0686	0.0856	-0.0004	-0.0013	-0.0018	0.0056	0.1113	0.1627	0.0735	0.0869
	SGMM	-0.1145	-0.1327	-0.0526	-0.0688	0.1261	0.1479	0.0643	0.0826	-0.0357	-0.0447	-0.0209	-0.0293	0.0656	0.0765	0.0430	0.0514
	EGMM1	0.0144	0.0877	0.0048	0.0559	0.0547	0.1148	0.0334	0.0788	-0.0240	-0.0807	-0.0148	-0.0487	0.0522	0.1021	0.0351	0.0691
	EGMM2	-0.0104	0.0444	-0.0097	0.0224	0.0534	0.0863	0.0348	0.0529	-0.0113	-0.0511	-0.0069	-0.0287	0.0488	0.0811	0.0327	0.0516
	EGMM3	0.0352	0.1158	0.0182	0.0793	0.0630	0.1342	0.0380	0.0951	-0.0359	-0.1023	-0.0203	-0.0669	0.0580	0.1169	0.0372	0.0812

Table 2 (continued)

		$\phi_{11} = 0.7$								$\phi_{21} = 0.25$							
		Bias				RMSE				Bias				RMSE			
		$N = 20$		$N = 50$		$N = 20$		$N = 50$		$N = 20$		$N = 50$		$N = 20$		$N = 50$	
		$\tau = 1$	$\tau = 5$	$\tau = 1$	$\tau = 5$	$\tau = 1$	$\tau = 5$	$\tau = 1$	$\tau = 5$	$\tau = 1$	$\tau = 5$	$\tau = 1$	$\tau = 5$	$\tau = 1$	$\tau = 5$	$\tau = 1$	$\tau = 5$
T = 50	OLS	0.0761	0.1716	0.0834	0.1888	0.0922	0.1804	0.0915	0.1928	-0.0698	-0.1514	-0.0752	-0.1648	0.0826	0.1579	0.0817	0.1677
	LSDV	-0.0417	-0.0417	-0.0397	-0.0392	0.0483	0.0482	0.0424	0.0420	-0.0099	-0.0099	-0.0101	-0.0106	0.0263	0.0263	0.0177	0.0182
	LSDVC	-0.0086	-0.0086	-0.0065	-0.0061	0.0262	0.0262	0.0166	0.0166	-0.0039	-0.0039	-0.0051	-0.0053	0.0232	0.0232	0.0150	0.0149
	AH	0.0049	0.0065	0.0009	0.0016	0.0955	0.1236	0.0610	0.0709	-0.0037	-0.0075	-0.0005	0.0004	0.0974	0.1516	0.0604	0.0719
	SGMM	-0.1047	-0.1190	-0.0472	-0.0592	0.1149	0.1317	0.0564	0.0707	-0.0307	-0.0372	-0.0151	-0.0213	0.0551	0.0643	0.0338	0.0412
	EGMM1	0.0159	0.0908	0.0043	0.0546	0.0531	0.1161	0.0311	0.0770	-0.0250	-0.0835	-0.0124	-0.0476	0.0506	0.1035	0.0313	0.0674
	EGMM2	-0.0057	0.0513	-0.0082	0.0258	0.0497	0.0877	0.0315	0.0538	-0.0129	-0.0560	-0.0063	-0.0296	0.0451	0.0820	0.0291	0.0516
	EGMM3	0.0379	0.1203	0.0185	0.0805	0.0634	0.1373	0.0366	0.0956	-0.0385	-0.1068	-0.0191	-0.0672	0.0584	0.1205	0.0346	0.0809
T = 60	OLS	0.0765	0.1725	0.0835	0.1883	0.0904	0.1804	0.0917	0.1922	-0.0697	-0.1516	-0.0758	-0.1643	0.0813	0.1576	0.0823	0.1671
	LSDV	-0.0338	-0.0338	-0.0330	-0.0332	0.0402	0.0402	0.0356	0.0358	-0.0077	-0.0077	-0.0082	-0.0078	0.0234	0.0234	0.0158	0.0154
	LSDVC	-0.0061	-0.0061	-0.0054	-0.0054	0.0230	0.0230	0.0146	0.0148	-0.0034	-0.0033	-0.0031	-0.0041	0.0209	0.0209	0.0129	0.0133
	AH	0.0015	0.0022	0.0000	-0.0001	0.0835	0.0983	0.0537	0.0602	0.0003	-0.0006	-0.0010	-0.0003	0.0874	0.1069	0.0541	0.0626
	SGMM	-0.0966	-0.1066	-0.0443	-0.0521	0.1048	0.1168	0.0513	0.0610	-0.0259	-0.0322	-0.0137	-0.0189	0.0487	0.0574	0.0297	0.0358
	EGMM1	0.0154	0.0907	0.0039	0.0533	0.0477	0.1135	0.0303	0.0728	-0.0241	-0.0826	-0.0127	-0.0459	0.0470	0.1008	0.0307	0.0637
	EGMM2	-0.0061	0.0515	-0.0078	0.0253	0.0434	0.0823	0.0290	0.0495	-0.0117	-0.0549	-0.0059	-0.0273	0.0404	0.0769	0.0273	0.0465
	EGMM3	0.0379	0.1206	0.0184	0.0796	0.0594	0.1358	0.0357	0.0931	-0.0382	-0.1067	-0.0194	-0.0657	0.0551	0.1187	0.0340	0.0782
T = 70	OLS	0.0798	0.1756	0.0854	0.1894	0.0939	0.1835	0.0931	0.1936	-0.0719	-0.1541	-0.0769	-0.1658	0.0832	0.1599	0.0830	0.1688
	LSDV	-0.0283	-0.0283	-0.0283	-0.0283	0.0346	0.0346	0.0308	0.0306	-0.0066	-0.0065	-0.0062	-0.0065	0.0206	0.0206	0.0138	0.0138
	LSDVC	-0.0045	-0.0045	-0.0045	-0.0044	0.0206	0.0206	0.0131	0.0126	-0.0028	-0.0028	-0.0031	-0.0030	0.0186	0.0186	0.0125	0.0122
	AH	-0.0006	-0.0005	0.0005	-0.0044	0.0792	0.0895	0.0499	0.0548	0.0000	-0.0007	0.0001	0.0038	0.0781	0.0884	0.0501	0.0556
	SGMM	-0.0934	-0.1018	-0.0421	-0.0476	0.1014	0.1118	0.0488	0.0550	-0.0241	-0.0294	-0.0117	-0.0163	0.0453	0.0526	0.0272	0.0313
	EGMM1	0.0185	0.0944	0.0042	0.0551	0.0496	0.1168	0.0278	0.0760	-0.0256	-0.0853	-0.0127	-0.0483	0.0471	0.1029	0.0280	0.0669
	EGMM2	-0.0004	0.0584	-0.0060	0.0280	0.0440	0.0887	0.0271	0.0510	-0.0140	-0.0587	-0.0061	-0.0297	0.0408	0.0810	0.0250	0.0484
	EGMM3	0.0412	0.1245	0.0193	0.0816	0.0627	0.1398	0.0346	0.0961	-0.0395	-0.1089	-0.0196	-0.0680	0.0564	0.1210	0.0324	0.0813
T = 80	OLS	0.0757	0.1716	0.0867	0.1904	0.0892	0.1794	0.0951	0.1945	-0.0690	-0.1512	-0.0782	-0.1664	0.0800	0.1572	0.0849	0.1694
	LSDV	-0.0238	-0.0238	-0.0243	-0.0243	0.0296	0.0296	0.0266	0.0266	-0.0059	-0.0059	-0.0054	-0.0054	0.0184	0.0184	0.0122	0.0122
	LSDVC	-0.0029	-0.0029	-0.0034	-0.0034	0.0180	0.0180	0.0113	0.0113	-0.0020	-0.0020	-0.0023	-0.0023	0.0169	0.0169	0.0109	0.0109
	AH	-0.0013	-0.0018	-0.0006	-0.0009	0.0677	0.0763	0.0443	0.0494	0.0000	0.0007	0.0024	0.0026	0.0703	0.0795	0.0444	0.0497
	SGMM	-0.0900	-0.0965	-0.0394	-0.0441	0.0962	0.1041	0.0449	0.0501	-0.0232	-0.0265	-0.0107	-0.0136	0.0422	0.0467	0.0243	0.0270
	EGMM1	0.0152	0.0894	0.0056	0.0571	0.0450	0.1113	0.0274	0.0770	-0.0242	-0.0821	-0.0133	-0.0497	0.0444	0.0996	0.0276	0.0667
	EGMM2	-0.0009	0.0572	-0.0037	0.0314	0.0403	0.0852	0.0248	0.0524	-0.0133	-0.0573	-0.0079	-0.0324	0.0389	0.0787	0.0239	0.0488
	EGMM3	0.0386	0.1210	0.0210	0.0841	0.0586	0.1355	0.0357	0.0980	-0.0377	-0.1061	-0.0207	-0.0698	0.0540	0.1181	0.0328	0.0821

Table 3: Summary of various simulation results for Φ having maximum eigenvalue of 0.8 (table continues on next page)

		$\phi_{11} = 0.6$								$\phi_{21} = 0.2$							
		Bias				RMSE				Bias				RMSE			
		$N = 20$		$N = 50$		$N = 20$		$N = 50$		$N = 20$		$N = 50$		$N = 20$		$N = 50$	
		$\tau = 1$	$\tau = 5$	$\tau = 1$	$\tau = 5$	$\tau = 1$	$\tau = 5$	$\tau = 1$	$\tau = 5$	$\tau = 1$	$\tau = 5$	$\tau = 1$	$\tau = 5$	$\tau = 1$	$\tau = 5$	$\tau = 1$	$\tau = 5$
T = 10	OLS	0.1146	0.2464	0.1280	0.2722	0.1425	0.2567	0.1421	0.2773	-0.0666	-0.1358	-0.0731	-0.1449	0.0911	0.1428	0.0827	0.1477
	LSDV	-0.1901	-0.1906	-0.1865	-0.1893	0.2029	0.2029	0.1915	0.1944	-0.0300	-0.0332	-0.0339	-0.0329	0.0850	0.0828	0.0578	0.0582
	LSDVC	-0.0506	-0.0511	-0.0457	-0.0489	0.0921	0.0916	0.0659	0.0687	-0.0134	-0.0172	-0.0174	-0.0164	0.0749	0.0724	0.0470	0.0471
	AH	0.0040	0.0507	0.0024	-0.0030	0.1879	1.2581	0.1120	0.1461	0.0109	-0.0277	-0.0014	-0.0126	0.1993	1.1439	0.1142	0.1519
	SGMM	-0.1837	-0.2270	-0.0927	-0.1422	0.2171	0.2637	0.1216	0.1717	-0.0428	-0.0508	-0.0272	-0.0510	0.1192	0.1353	0.0815	0.1076
	EGMM1	0.0403	0.1514	0.0189	0.1130	0.1028	0.1839	0.0662	0.1425	-0.0280	-0.0812	-0.0148	-0.0514	0.0879	0.1136	0.0590	0.0846
	EGMM2	-0.0452	0.0358	-0.0312	0.0187	0.1073	0.1266	0.0732	0.0893	-0.0160	-0.0461	-0.0058	-0.0294	0.0962	0.1068	0.0669	0.0822
	EGMM3	0.0529	0.1704	0.0279	0.1301	0.1093	0.1978	0.0698	0.1551	-0.0356	-0.0923	-0.0181	-0.0611	0.0882	0.1183	0.0593	0.0884
T = 20	OLS	0.1143	0.2485	0.1335	0.2768	0.1369	0.2587	0.1454	0.2816	-0.0685	-0.1349	-0.0762	-0.1470	0.0835	0.1408	0.0831	0.1494
	LSDV	-0.0917	-0.0924	-0.0897	-0.0899	0.1021	0.1030	0.0939	0.0942	-0.0195	-0.0182	-0.0158	-0.0160	0.0500	0.0499	0.0320	0.0321
	LSDVC	-0.0169	-0.0177	-0.0143	-0.0145	0.0500	0.0507	0.0324	0.0330	-0.0100	-0.0086	-0.0068	-0.0070	0.0449	0.0450	0.0275	0.0274
	AH	-0.0019	-0.0034	-0.0028	0.0011	0.1042	0.1352	0.0693	0.0836	-0.0017	0.0032	0.0012	0.0053	0.1102	0.1319	0.0700	0.0839
	SGMM	-0.1227	-0.1537	-0.0541	-0.0809	0.1390	0.1739	0.0690	0.0989	-0.0286	-0.0366	-0.0124	-0.0191	0.0717	0.0874	0.0447	0.0555
	EGMM1	0.0342	0.1502	0.0170	0.1125	0.0836	0.1788	0.0479	0.1355	-0.0297	-0.0795	-0.0125	-0.0515	0.0650	0.1015	0.0408	0.0729
	EGMM2	-0.0164	0.0735	-0.0122	0.0422	0.0711	0.1208	0.0451	0.0757	-0.0186	-0.0523	-0.0054	-0.0288	0.0617	0.0861	0.0408	0.0571
	EGMM3	0.0573	0.1790	0.0329	0.1366	0.0947	0.1996	0.0571	0.1550	-0.0391	-0.0950	-0.0172	-0.0646	0.0681	0.1116	0.0421	0.0813
T = 30	OLS	0.1151	0.2487	0.1325	0.2768	0.1370	0.2585	0.1440	0.2813	-0.0662	-0.1341	-0.0745	-0.1473	0.0798	0.1392	0.0813	0.1494
	LSDV	-0.0617	-0.0602	-0.0583	-0.0578	0.0712	0.0695	0.0623	0.0620	-0.0097	-0.0097	-0.0093	-0.0099	0.0374	0.0375	0.0238	0.0242
	LSDVC	-0.0107	-0.0091	-0.0070	-0.0065	0.0383	0.0372	0.0236	0.0240	-0.0034	-0.0033	-0.0031	-0.0036	0.0349	0.0349	0.0213	0.0216
	AH	0.0030	-0.0024	0.0001	0.0041	0.0854	0.0964	0.0531	0.0611	-0.0011	-0.0024	0.0013	-0.0011	0.0894	0.0977	0.0549	0.0621
	SGMM	-0.1026	-0.1241	-0.0441	-0.0579	0.1151	0.1381	0.0558	0.0704	-0.0183	-0.0229	-0.0082	-0.0134	0.0549	0.0624	0.0341	0.0401
	EGMM1	0.0334	0.1489	0.0167	0.1069	0.0766	0.1755	0.0432	0.1269	-0.0285	-0.0785	-0.0124	-0.0493	0.0590	0.0969	0.0348	0.0675
	EGMM2	-0.0044	0.0826	-0.0065	0.0488	0.0631	0.1220	0.0369	0.0740	-0.0152	-0.0528	-0.0062	-0.0295	0.0535	0.0790	0.0353	0.0499
	EGMM3	0.0596	0.1813	0.0343	0.1364	0.0932	0.2010	0.0544	0.1519	-0.0366	-0.0946	-0.0175	-0.0632	0.0621	0.1085	0.0384	0.0769
T = 40	OLS	0.1175	0.2472	0.1310	0.2740	0.1390	0.2575	0.1426	0.2785	-0.0683	-0.1328	-0.0742	-0.1457	0.0806	0.1385	0.0802	0.1478
	LSDV	-0.0434	-0.0455	-0.0424	-0.0424	0.0522	0.0543	0.0465	0.0464	-0.0065	-0.0066	-0.0071	-0.0071	0.0302	0.0297	0.0201	0.0205
	LSDVC	-0.0045	-0.0067	-0.0035	-0.0035	0.0302	0.0312	0.0198	0.0196	-0.0018	-0.0018	-0.0022	-0.0022	0.0288	0.0282	0.0184	0.0188
	AH	0.0008	-0.0044	0.0006	-0.0012	0.0703	0.0785	0.0446	0.0472	0.0004	0.0023	-0.0000	0.0003	0.0705	0.0808	0.0466	0.0506
	SGMM	-0.0908	-0.1074	-0.0388	-0.0477	0.0996	0.1186	0.0476	0.0564	-0.0155	-0.0178	-0.0086	-0.0104	0.0442	0.0480	0.0286	0.0316
	EGMM1	0.0359	0.1465	0.0169	0.1016	0.0764	0.1729	0.0391	0.1202	-0.0278	-0.0752	-0.0140	-0.0470	0.0529	0.0945	0.0308	0.0627
	EGMM2	0.0042	0.0854	-0.0019	0.0500	0.0616	0.1223	0.0317	0.0710	-0.0174	-0.0506	-0.0077	-0.0284	0.0482	0.0753	0.0291	0.0456
	EGMM3	0.0639	0.1805	0.0357	0.1330	0.0950	0.2000	0.0531	0.1475	-0.0370	-0.0920	-0.0186	-0.0612	0.0587	0.1061	0.0342	0.0736

Table 3 (continued)

		$\phi_{11} = 0.6$								$\phi_{21} = 0.2$							
		Bias				RMSE				Bias				RMSE			
		$N = 20$		$N = 50$		$N = 20$		$N = 50$		$N = 20$		$N = 50$		$N = 20$		$N = 50$	
		$\tau = 1$	$\tau = 5$	$\tau = 1$	$\tau = 5$	$\tau = 1$	$\tau = 5$	$\tau = 1$	$\tau = 5$	$\tau = 1$	$\tau = 5$	$\tau = 1$	$\tau = 5$	$\tau = 1$	$\tau = 5$	$\tau = 1$	$\tau = 5$
T = 50	OLS	0.1198	0.2514	0.1355	0.2726	0.1411	0.2608	0.1465	0.2771	-0.0691	-0.1359	-0.0760	-0.1448	0.0810	0.1407	0.0820	0.1470
	LSDV	-0.0352	-0.0364	-0.0344	-0.0346	0.0437	0.0449	0.0380	0.0382	-0.0057	-0.0056	-0.0054	-0.0044	0.0262	0.0280	0.0173	0.0175
	LSDVC	-0.0040	-0.0053	-0.0032	-0.0033	0.0268	0.0273	0.0166	0.0168	-0.0018	-0.0017	-0.0015	-0.0005	0.0250	0.0268	0.0161	0.0165
	AH	0.0012	-0.0041	0.0005	0.0003	0.0641	0.0686	0.0406	0.0441	0.0000	-0.0003	-0.0006	-0.0003	0.0626	0.0713	0.0398	0.0443
	SGMM	-0.0877	-0.0985	-0.0380	-0.0435	0.0950	0.1066	0.0448	0.0515	-0.0146	-0.0160	-0.0075	-0.0079	0.0386	0.0433	0.0246	0.0267
	EGMM1	0.0375	0.1487	0.0172	0.0973	0.0769	0.1727	0.0380	0.1158	-0.0292	-0.0781	-0.0141	-0.0441	0.0516	0.0935	0.0296	0.0595
	EGMM2	0.0080	0.0906	-0.0007	0.0489	0.0606	0.1218	0.0296	0.0685	-0.0176	-0.0519	-0.0082	-0.0264	0.0446	0.0729	0.0266	0.0425
	EGMM3	0.0673	0.1844	0.0371	0.1303	0.0971	0.2019	0.0536	0.1448	-0.0389	-0.0950	-0.0193	-0.0588	0.0586	0.1064	0.0335	0.0712
T = 60	OLS	0.1195	0.2536	0.1330	0.2707	0.1386	0.2625	0.1442	0.2752	-0.0679	-0.1368	-0.0752	-0.1441	0.0792	0.1414	0.0812	0.1462
	LSDV	-0.0291	-0.0302	-0.0285	-0.0283	0.0376	0.0380	0.0322	0.0320	-0.0041	-0.0042	-0.0038	-0.0043	0.0250	0.0247	0.0154	0.0154
	LSDVC	-0.0030	-0.0041	-0.0023	-0.0022	0.0244	0.0239	0.0154	0.0153	-0.0008	-0.0009	-0.0006	-0.0010	0.0242	0.0239	0.0146	0.0146
	AH	0.0004	0.0029	0.0017	-0.0009	0.0570	0.0610	0.0351	0.0380	0.0006	-0.0023	-0.0004	-0.0013	0.0594	0.0583	0.0378	0.0381
	SGMM	-0.0834	-0.0925	-0.0356	-0.0421	0.0895	0.0993	0.0415	0.0483	-0.0118	-0.0141	-0.0067	-0.0078	0.0360	0.0369	0.0231	0.0240
	EGMM1	0.0360	0.1510	0.0162	0.0941	0.0700	0.1741	0.0356	0.1110	-0.0267	-0.0789	-0.0129	-0.0429	0.0479	0.0940	0.0272	0.0563
	EGMM2	0.0080	0.0963	-0.0002	0.0486	0.0524	0.1256	0.0274	0.0667	-0.0159	-0.0545	-0.0070	-0.0279	0.0405	0.0727	0.0238	0.0415
	EGMM3	0.0668	0.1875	0.0361	0.1280	0.0921	0.2043	0.0513	0.1416	-0.0374	-0.0966	-0.0180	-0.0584	0.0548	0.1074	0.0310	0.0692
T = 70	OLS	0.1244	0.2498	0.1341	0.2740	0.1441	0.2593	0.1461	0.2786	-0.0705	-0.1351	-0.0765	-0.1463	0.0809	0.1402	0.0827	0.1484
	LSDV	-0.0241	-0.0243	-0.0245	-0.0245	0.0330	0.0329	0.0278	0.0282	-0.0032	-0.0033	-0.0036	-0.0035	0.0224	0.0226	0.0144	0.0139
	LSDVC	-0.0016	-0.0018	-0.0020	-0.0021	0.0229	0.0226	0.0136	0.0142	-0.0004	-0.0006	-0.0008	-0.0007	0.0217	0.0220	0.0137	0.0133
	AH	-0.0009	0.0023	-0.0020	0.0009	0.0543	0.0567	0.0337	0.0352	-0.0003	-0.0011	0.0025	-0.0011	0.0522	0.0565	0.0348	0.0354
	SGMM	-0.0817	-0.0862	-0.0356	-0.0382	0.0877	0.0920	0.0408	0.0439	-0.0127	-0.0121	-0.0052	-0.0072	0.0334	0.0352	0.0206	0.0226
	EGMM1	0.0398	0.1469	0.0164	0.0985	0.0739	0.1707	0.0363	0.1162	-0.0292	-0.0764	-0.0131	-0.0453	0.0476	0.0923	0.0267	0.0592
	EGMM2	0.0136	0.0966	0.0009	0.0531	0.0562	0.1269	0.0268	0.0714	-0.0180	-0.0544	-0.0071	-0.0286	0.0405	0.0742	0.0229	0.0421
	EGMM3	0.0713	0.1848	0.0371	0.1329	0.0976	0.2019	0.0530	0.1469	-0.0394	-0.0951	-0.0186	-0.0607	0.0556	0.1067	0.0314	0.0720
T = 80	OLS	0.1187	0.2513	0.1330	0.2719	0.1376	0.2607	0.1437	0.2765	-0.0681	-0.1350	-0.0755	-0.1449	0.0789	0.1400	0.0814	0.1470
	LSDV	-0.0206	-0.0225	-0.0207	-0.0207	0.0283	0.0307	0.0242	0.0240	-0.0032	-0.0030	-0.0030	-0.0032	0.0201	0.0210	0.0128	0.0131
	LSDVC	-0.0009	-0.0028	-0.0009	-0.0009	0.0197	0.0214	0.0129	0.0124	-0.0007	-0.0005	-0.0005	-0.0007	0.0196	0.0204	0.0123	0.0125
	AH	-0.0008	-0.0003	0.0015	0.0025	0.0482	0.0517	0.0310	0.0324	-0.0010	-0.0006	-0.0017	-0.0012	0.0503	0.0505	0.0312	0.0340
	SGMM	-0.0799	-0.0864	-0.0343	-0.0364	0.0848	0.0918	0.0389	0.0412	-0.0132	-0.0119	-0.0060	-0.0062	0.0322	0.0330	0.0188	0.0204
	EGMM1	0.0349	0.1483	0.0162	0.0954	0.0678	0.1720	0.0331	0.1131	-0.0280	-0.0765	-0.0130	-0.0432	0.0461	0.0918	0.0258	0.0572
	EGMM2	0.0118	0.0971	0.0013	0.0515	0.0519	0.1260	0.0250	0.0695	-0.0179	-0.0542	-0.0068	-0.0269	0.0394	0.0727	0.0218	0.0398
	EGMM3	0.0670	0.1865	0.0370	0.1302	0.0918	0.2035	0.0506	0.1441	-0.0378	-0.0950	-0.0182	-0.0586	0.0541	0.1063	0.0304	0.0695