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Conference Paper

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Beiträge zur Jahrestagung des Vereins für Socialpolitik 2010: Ökonomie der Familie - Session: Panel Data Models, No. C15-V4

Provided in Cooperation with:

Verein für Socialpolitik / German Economic Association

Suggested Citation: Mitze, Timo (2010) : Dynamic Simultaneous Equations and Panel Data: Small Sample Properties and Regional Factor Demand Modelling for Policy Analysis, Beiträge zur Jahrestagung des Vereins für Socialpolitik 2010: Ökonomie der Familie - Session: Panel Data Models, No. C15-V4, Verein für Socialpolitik, Frankfurt a. M.

This Version is available at:

<https://hdl.handle.net/10419/37302>

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Dynamic Simultaneous Equations and Panel Data: Small Sample Properties and Regional Factor Demand Modelling for Policy Analysis

Timo Mitze*

First Version: March 2008, this version: February 2010
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Abstract

The superiority of full information approaches when estimating a system of equation is well known for large samples. However, less is known about the small sample properties of these estimators relative to limited information approaches. This is especially true for the context of Panel data although they are meanwhile a standard tool in estimating static and dynamic economic processes. Here only extensive Monte Carlo simulation evidence is given for single equation models. We expand the scope of Monte Carlo simulation evidence to system estimation. We especially aim to contribute to the methodological debate about appropriate dynamic panel data estimators beside standard - large N , small T - panel data assumptions. Since frequently used dynamic panel data models in 'first differences' have shown a poor empirical performance in these circumstances, we put a special emphasis on appropriate estimators with variables in levels based on Hausman-Taylor (1981) type estimator. We compare the model's performance in terms common evaluation criteria (such as bias and root mean square error) relative to various alternative specifications including the Anderson & Hsiao (1981) IV, the Arellano & Bond (1991) and Blundell & Bond (1998) GMM estimators.

Building upon the small sample simulation evidence, the paper then applies a simultaneous equation approach to analyse the effects of regional equalization policy instruments on regional economic output and endogeneized private and public factor demand equations for Germany. By doing so we are able to identify the direct and indirect policy channels of regional equalization schemes, which are often left unidentified in single equation estimations. To give an example, though our empirical analysis strongly confirms recent findings of a negative direct output effect of the German interstate/federal fiscal equalization transfer scheme (Länderfinanzausgleich) via its 'horizontal' (state-to-state) element, the additional analysis of the structural factor input equations reveals, that the 'vertical' (federal-to-state) transfer element contributes positively to the public sector investment rate. And the latter in turn is estimated to have a positive effect on regional output as well. Similarly we search for direct and indirect effects of the private sector investment promotion schemes as well as active labour market spendings.

JEL-Classification: C33, H54, R11

Keywords: Dynamic Panel Data, Simultaneous Equations, Economic growth, Regional Policy

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1 Introduction

This paper seeks to analyse the appropriateness of different dynamic Panel data models in estimating small simultaneous equation systems. The notion of simultaneity among variables arises for many economic relations. Having a specific application in mind we are especially interested in modelling a system of output growth and convergence together with endogenized factor demand equations. To do so we therefore specify different dynamic model representations and judge among them on the grounds of a Monte Carlo simulation exercise for small samples. In doing so we particularly aim to bridge the gap between two strands of panel econometric literature: 1.) simultaneous equations with panel data (see e.g. Cornwell et al. 1992, Baltagi, 2005), 2.) dynamic panel data models (see e.g. Arellano, 2003). Whereas the former approach is typically restricted to static models, the literature on dynamic panel data models merely focuses on single equation estimation. Throughout the paper we aim to match both strands of the literature starting from the static simultaneous equation panel data model and search for concepts along the literature on dynamic estimators to augment the static SEM approach.

Standard dynamic panel data models are typically transform data in first differences to control for a correlation of the lagged endogenous regressor and the composed error term. However, in a growth model context the difference estimators have typically shown a poor empirical performance (see e.g. Bond et al. 2001) in particular due to the 'weak instruments problem'. Building up on orthogonality conditions (instrument sets) of newly derived estimators in the dynamic panel data field, we thus aim to specify an estimator in levels rather than first differences. We show how the static simultaneous equations models with strictly exogenous regressors (e.g. Hausman-Taylor, 1981, Amemiya-Macurdy, 1986, or Breusch et al., 1989) may be augmented by appropriate instruments for the lagged endogenous variable stemming from both - the field of static as well as dynamic modelling approaches. We compare the performance of various estimators in a Monte Carlo simulation exercise.

In an empirical application we then estimate dynamic simultaneous equation modelling with panel data to assess the role of regional equalization/support policies for the regional growth and convergence process among German states (*Bundesländer*). Different from using commonly applied single equation 'Barro'-type convergence equations (see e.g. Scheufele & Ludwig, 2009, for a recent survey on German state level convergence) we explicitly set up a system of equations in order to account more appropriately for the possible endogeneity of right hand side regressors in the output (growth) equation. Compared to the single-equation approach the system estimation is able to spell out feed-back simultaneities among the endogenous variables specified in the system and identify the direct/indirect effects of regional equalization payments on output (per employee) and its factor inputs. The latter inputs include the private and public sector investment rates, human capital and employment growth.

The remainder of the paper is organised as follows: Section 2 starts with a short description of different dynamic panel data models in a simultaneous equation setting. The section puts a special emphasis on the derivation of dynamic versions for static simultaneous equation error component models based on the familiar Hausman-Taylor type (1981, thereafter HT) and related estimators. Section 3 presents a small Monte Carlo simulation study for the dynamic simultaneous equation panel data models in focus since there is little reference in the literature for this type of estimators. For the empirical application in section 4 we briefly outline the human and public capital augmented Solow growth model and discuss how the factor inputs of the underlying production function can be endogenized by appropriate structural equations. Section 5 reviews the major equalization/support instruments that are used in the German

regional policy context and describes in how far they are included in the model as additional exogenous regressors for both the factor input and output growth equations. This section also sketches earlier empirical findings for the macroeconomic impact of regional equalization schemes. Section 6 discusses data issues including the time-series properties of the variables in focus. For our empirical application with respect to regional equalization transfer schemes in a growth system section 7 reports the estimation results and computes dynamic interim and long-run multipliers to analyse the effects on the endogenous variables with respect to exogenous (policy) changes. Section 8 finally concludes.

2 Dynamic Panel Data Models and Simultaneous Equations

As outlined above our aim is to estimate a system of dynamic simultaneous equations with error components in each equation. The model may take either reflect a system of structural equations or a more flexible VAR approach (with potentially additional exogenous regressors such as typically assumed in a VARX context). The n -th structural equation of the system can be written in the following general form

$$y_{i,t} = \alpha + \sum_{j=0}^l \gamma_j' Y_{i,t-j} + \sum_{j=0}^k \beta_j' X_{i,t-j} + u_{i,t}, \quad \text{with: } u_{i,t} = \mu_i + \nu_{i,t}, \quad (1)$$

for $i = 1, \dots, N$ (cross-sectional dimension) and $t = 1, \dots, T$ (time dimension). $y_{i,t}$ is the endogenous variable and Y_i is a vector of current and lagged endogenous explanatory variables of the system including the (one-period) lagged endogenous variable of the respective equation. X_i a vector of explanatory time-varying and time invariant regressors, $u_{i,t}$ is the combined error term, where $u_{i,t}$ is composed of the two error components μ_i as the unobservable individual effects and ν_i is the remainder error term. Both μ_i and ν_i are assumed to be i.i.d. residuals with standard normality assumptions. In terms of orthogonality conditions these assumptions are given as follows:

$$\begin{aligned} E(\nu_{it}\nu_{js}) &= 0, \quad \text{for either } i \neq j \text{ or } t \neq s, \text{ or both} \\ E(\mu_i\mu_j) &= 0, \quad \text{for } i \neq j \\ E(\mu_i\nu_{jt}) &= 0, \quad \forall i, j, t \end{aligned} \quad (2)$$

The first two assumptions state that the homoscedastic error terms are mutually uncorrelated over time and across cross-sections. Furthermore the unobserved individual heterogeneity is random and uncorrelated between individuals. The third assumption rules out any correlation between the individual effects and the remainder disturbance term (that is μ_i is exogenous).

As already sketched above, there are broadly two strands of literature from which we can benefit for the composition of appropriate estimators for the model in eq.(6). However, until now only little effort has been made to link these subfields. In the following we will first discuss the main concepts of each strand of literature and then propose a unifying framework.

2.1 Dynamic Panel data models and Small Sample Performance

There are numerous contributions in the recent literature with respect to the single equation estimation of the dynamic model of eq.(6), which especially deal with the problem introduced by the inclusion of a lagged dependent variable in the estimation equation and its built-in correlation with the individual effect: That is, since y_{it} is also a function of μ_i , $y_{i,t-1}$ is a function of μ_i and thus $y_{i,t-1}$ as right-hand side regressor in eq.(6) is correlated with the error term. Even in the absence of serial correlation of ν_{it} this renders OLS, FEM and REM models biased and inconsistent (see e.g. Nickel, 1981, Sevestre & Trogon, 1985 or Baltagi, 2005, for an overview).

The most widely applied approaches of dealing with this kind of endogeneity typically start with first differencing (FD) equation (6) to get rid of μ_i and then estimate the model by instrumental variable (IV) techniques. The advantage of the FD transformation is that this form of data transformation does not invoke the inconsistency problem associated with the standard FEM or REM estimation (see e.g. Baltagi, 2005). Anderson & Hsiao (1982) were among the first to propose an estimator for the transformed FD model of eq.(6):¹

$$(y_{it} - y_{i,t-1}) = \alpha(y_{i,t-1} - y_{i,t-2}) + \sum_{j=1}^k \beta_j (X_{i,t-j} - X_{i,t-j+1}) + (u_{it} - u_{i,t-1}), \quad (3)$$

where $(u_{it} - u_{i,t-1}) = (\nu_{it} - \nu_{i,t-1})$ since $(\mu_i - \mu_i) = 0$. As a result of first differencing the unobservable individual effect has been eliminated from the model. However, there appears the problem that the error term $(\nu_{it} - \nu_{i,t-1})$ is correlated with $(y_{i,t-1} - y_{i,t-2})$ and thus the latter needs to be estimated by appropriate instruments which are uncorrelated with the error term. Anderson & Hsiao recommend to use lagged variables, either the lagged observation $y_{i,t-2}$ or the lagged difference $(y_{i,t-2} - y_{i,t-3})$ as instruments for $(y_{i,t-1} - y_{i,t-2})$. These IVs are correlated with the explanatory variable, but not with the error term. Arellano (1989) compares the two alternatives and recommends $y_{i,t-2}$ rather than the lagged differences as instruments since they have shown a superior empirical performance. The respective orthogonality conditions for this approach can be stated as:

$$E(y_{i,t-2} \Delta u_{i,t}) = 0 \quad \text{or alternatively:} \quad E(\Delta y_{i,t-2} \Delta u_{i,t}) = 0, \quad (4)$$

where Δ is the difference operator defined as $\Delta u_{i,t} = u_{i,t} - u_{i,t-1}$. The AH model can be estimated for $t = 3, \dots, T$ due to the construction of the instruments. Subsequently, refined instrument sets for the estimation of eq.(9) have been proposed in the literature: Trying to improve the small sample behaviour of the AH estimator Sevestre & Trognon (1995) propose a more efficient FD estimator which is based on a GLS transformation of eq.(8).² Searching for additional orthogonality conditions Arellano & Bond (1991) propose an GMM estimator, which makes use of all lagged endogenous variables - rather than just $y_{i,t-2}$ or $\Delta y_{i,t-2}$ - of the form:³

¹In the stylized presentation for sake of simplicity we skip the vector of endogenous explanatory variables Y except for the equation's own (one-period) lagged value since it is as a special characteristics of a Simultaneous Equation Model (SEM) and can easily added to the system.

²Since this GLS transformation leads to disturbances that are linear combinations of the $u_{i,t}$'s, the only valid instruments for $\Delta y_{i,t-1}$ are current and lagged values of ΔX .

³The use of GMM in DPD models was introduced by Holtz-Eakin et al. (1988), who propose a way to use 'uncollapsed' IV sets.

$$E(y_{i,t-\rho}\Delta u_{i,t}) = 0 \quad \text{for all } \rho = 2, \dots, t-1. \quad (5)$$

Eq.(10) is also called the 'standard moment condition' and is widely used in empirical estimation. However, one general drawback of dynamic model estimators in first differences is their poor empirical performance especially in a growth model framework (see Munnell, 1992, and Holtz-Eakin, 1994, for poor empirical estimates of a production function in FD, Bond et al. (2001) for growth equation estimates). Bond et al. (2001) argue that first difference IV/GMM estimators can be poorly behaved, since lagged levels of the time series provide only 'weak instruments' for sub-sequent first-differences.

In response to this critique a second generation dynamic panel data models has been developed which also makes use of appropriate orthogonality conditions (in linear form) for the equation in levels (see e.g. Arellano & Bover, 1995, Ahn & Schmidt, 1995, and Blundell & Bond, 1998) as:⁴

$$E(\Delta y_{i,t-1}u_{i,t}) = 0 \quad \text{for } t=3,\dots,T. \quad (6)$$

Thus, rather than using lagged levels of variables for equations in first difference as in the FD estimators, we get an orthogonality condition for the model in level that uses instruments in first differences. Eq. (11) is also called the 'stationarity moment condition'.⁵ Blundell & Bond (1998) propose a GMM estimator that uses jointly both the standard and stationarity moment conditions. This latter approach is typically labelled 'system' GMM as a combination of 'level' and 'difference' IV/GMM. Though labelled as 'system' GMM, this estimator treats the data system as a single-equation problem since the same linear functional relationship is believed to apply in both the transformed and untransformed variables (see e.g. Roodman, 2006).

However, the empirical application of the more sophisticated Arellano & Bond (1991) or Blundell & Bond (1998) type GMM estimators does not come without extra costs either: In simulation studies Kiviet (1995), Judson & Owen (1996), Harris & Matyas (1996), Hayakawa (2005) and Soto (2007) among others have shown that the gains in efficiency terms of moving from parsimonious models to more complex representations with larger instrument sets (orthogonality conditions) is rather marginal in panel data settings with increasing T . That is, the GMM estimators of Arellano & Bond, Arellano & Bover, Ahn & Schmidt and Blundell & Bond are typically designed for panel data sets with large N and small T . According to Judson & Owen (1996) the associated loss in efficiency of instrument reduction from more advanced GMM techniques to the standard Anderson & Hsiao (1981) estimator is negligible for large T (approximately $T \geq 10$), while at the same time the 'many instruments problem' and computational difficulties associated with the large instrument sets are avoided.⁶

Soto (2007) runs a simulation experiment to compare first difference, level and system GMM estimators

⁴The original form in Ahn & Schmidt (1995) is $E(\Delta y_{i,t-1}u_{i,T}) = 0$ for $t = 3, \dots, T$ derived from a set of non-linear moment conditions. Blundell & Bond (1998) rewrote it as in (11) for convenience. The latter moment condition is also proposed in Arellano & Bover (1995)

⁵That is because for eq.(11) to be valid we need an additional stationarity assumption concerning the initial values $y_{i,1}$. Typically $y_{i,1} = \mu/(1-\alpha) + w_{i,1}$ is considered as an initial condition for making $y_{i,t}$ mean-stationary, with assumptions on the disturbance $w_{i,1}$ as $E(\mu_i w_{i,1}) = 0$ and $E(w_{i,1}\nu_{i,t}) = 0$.

⁶Blundell & Bond (1998) them self argue that their GMM estimator is only appropriate for small T large N settings. For an overview of the literature on the 'many instruments problem' see e.g. Hayakawa (2005).

in settings where N is small compared to T (e.g. $N = 35, T = 12$, which comes much closer to the empirical setup in this study compared to the typical large N , small T assumption). His results show in terms of RMSE and standard deviation that on average the empirical fit of the first difference estimators is much lower compared to level and system counterparts. Though the latter estimator shows the best overall performance, the relative advantage to the level GMM estimator is rather marginal. If additionally the model is characterized by a high level of persistence (as it is typically the case in economic growth studies) the two estimators show an almost equal empirical performance. Similarly, comparing first differences, level and system GMM estimators Hayakawa (2005) even finds that the system estimator has a more severe downward bias than the level estimator, if the variance of the individual effects (σ_μ) is smaller than the variance of the remainder error term (σ_ν). That is, for many regions of the α -coefficient of the lagged dependent variable (especially moderate and high value) and a $(\frac{\sigma_\mu}{\sigma_\nu}) = 0,25$ the level estimator displays the smallest bias among the estimators. This result indicates that the fact that the system estimator is a weighted sum of the FD and level estimator becomes a disadvantage of particular combinations for $(\frac{\sigma_\mu}{\sigma_\nu}) = 0,25$ and moderate high regions of α .

Thus, for our panel data set, which we will apply in the second part of the paper and which has a dimension of $N = 16$ and $T = 10$, it might be a fruitful approach to start with a more parsimonious level estimator, especially since in a simultaneous equation setting the 'many instruments problem' may be very severe. A promising starting point for doing so is proposed by Harris & Matyas (1996) as well as Harris et al. (1996), who derive consistent generalizations of familiar static error components (single equation) models to the dynamic panel data case. These models comprise IV estimators proposed by Hausman-Taylor (1981), Amemiya & Macurdy (1986), Breusch et al. (1989). Another advantage of starting from this modelling perspective to setup dynamic simultaneous equation models is that for the static case there is a bulk of literature dealing with simultaneity, whereas contributions (both theoretical as well as empirical) in a dynamic context are rather spare. Among the few exceptions is a theoretical contribution by Ben Jedidia (1994), who proposes as system estimator of the Ahn & Schmidt (1995) single equation estimator.⁷ Another system estimator which as recently been applied in a series of papers by Driffield and associates is a FD-3SLS estimator, which generalizes the Anderson & Hsiao (1981) type estimator to the system case (see e.g. Driffield & Girma, 2003, Driffield & Taylor (2006) as well as Driffield & De Propris, 2006). Finally, Kimhi & Rekah (2005) apply an Arellano & Bond (1991) type estimator for a two equation system that explicitly accounts endogeneity and predeterminedness of right-hand side regressors in a limited information approach.⁸

2.2 Static simultaneous equation models with panel data

Theoretical and empirical contributions to static case simultaneous equation estimators with panel data structure are much more common and for instance given by Baltagi (1980, 1981 & 2005), Baltagi & Chang (1994, 2000), Prucha (1984), Hsiao (1986), Balestra & Krishnakumar (1987), Krishnakumar (1988), Bjorn & Krishnakumar (2007), Cornwell et al. (1992) as well as Park (2005). Among the standard estimators in empirical application are Baltagi's (1980 & 1981) EC-SUR and EC-3SLS, which are extensions of

⁷A short summary of this model is given in Krishnakumar (1995).

⁸Also, starting from a time-series perspective Binder et al. (2005) derive different Panel VAR models and evaluate them in a Monte Carlo simulation exercise.

the random effects model (REM) for the system case. The use of instrumental variables in the model is necessary for the case that we have to deal with endogeneity of right-hand side regressors. More general approaches in this field - which comprise the EC-SUR and EC-3SLS as special cases - are system extensions of the Hausman-Taylor (1981) type single equation estimators: HT-SUR and HT-3SLS (a convenient overview is given in Cornwell et al., 1992, Ahn & Schmidt, 1999, as well as Park, 2005 among others).

We thus start with a short description of the static system estimators and then propose different methods, how these estimators can be expanded to the dynamic case by appropriate orthogonality conditions (instrument choice). The basic approach to these type of models is to first transform the model into a spherical one by a GLS correction (taking into account both error components either for a block diagonal or full covariance matrix) and then using appropriate instruments to estimate the model by limited or full information IV methods (2SLS or 3SLS respectively). The HT model specification starts with a standard (one way) error component model such as eq.(6), where the lagged endogenous variables is excluded (static case).

Additionally, the vector of explanatory variables X is separated into right-hand side regressors in the model that are treated as either (doubly) exogenous (that is both uncorrelated with the unobserved individual effects and the remainder error term) or singly exogenous as being correlated with μ_i . Further, a distinction is made between time-varying and time invariant explanatory variables. Following HT we define the sub-vector of time-varying variables as X and the sub-vector of time invariant variables Z . Taking into account the distinction between doubly and singly exogenous variables we can split each sub-vector into two sub-vectors such as $X = [X1, X2]$ and $Z = [Z1, Z2]$, where $X1$ and $Z1$ are doubly exogenous with respect to μ and ν , while $X2$ and $Z2$ are treated as singly exogenous (correlated with μ). The full augmented model can be written in the following form:

$$y_{it} = \alpha + \beta'_1 X1_{it} + \beta'_2 X2_{it} + \gamma'_1 Z1_i + \gamma'_2 Z2_i + u_{it}, \quad (7)$$

where again the unobservable individual effects are treated as random with ($u_{it} = \mu_{ij} + \nu_{ijt}$). The presence of $X2$ and $Z2$ would be a severe cause for biased inference in the standard REM approach. The underlying orthogonality conditions of the HT model are:

$$\begin{aligned} E(X1_{it}\mu_j) &= 0, \quad \forall i, j, t \\ E(X1_{it}\nu_{js}) &= 0, \quad \forall i, j, t, s \\ E(X2_{it}\nu_{js}) &= 0, \quad \forall i, j, t, s \\ E(Z1_i\mu_j) &= 0, \quad \forall i, j \\ E(Z1_i\nu_{js}) &= 0, \quad \forall i, j, s \\ E(Z2_i\nu_{js}) &= 0, \quad \forall i, j, s \end{aligned} \quad (8)$$

The main idea of the HT model is to use instrumental variable methods to circumvent the endogeneity problem of $X2$ and $Z2$. Thereby the strictly exogenous time-variant variables ($X1$) are used as instruments for estimating time invariant singly exogenous coefficients ($Z2$), where group means of $X1$ are used to instrument $Z2$. Deviations from individual means of $X1$ and $X2$ are used as instruments for $X1$ and $X2$

(in the logic of the fixed effect (FEM) or within group estimator), while $Z1$ are used as their own (strictly exogenous) instruments. The HT strategy thus makes use of information already contained in the model to instrument $X2$ and $Z2$ and does not rely on other external IVs.

Amemiya & Macurdy (1986) propose an extension to the HT model based on the assumption that the $X1$ variables are doubly exogenous and thus all past, present and future values become valid instruments. Therefore, instead of just using group means of the time-varying variables $X1$, the Amemiya & Macurdy estimator extends the instrument set to include the vector $X1^*$, which includes T time invariant instruments for each time period t within the estimation period according to

$$X1^* = \begin{bmatrix} X1_{1,t} & X1_{1,t+1} & \cdots & X1_{1T} \\ X1_{2,t} & X1_{2,t+1} & \cdots & X1_{2T} \\ \vdots & \vdots & & \vdots \\ X1_{N,t} & X1_{N,t+1} & \cdots & X1_{NT} \end{bmatrix} \otimes e_T, \quad (9)$$

where e_T is an $T \times 1$ vector of ones.

Turning to the case of simultaneous equations some further aspects have to be taken into account. First, different from the single-equation case the right-hand side of eq.(11) includes a vector of endogenous explanatory variables $Y_{i,t}$. The main difference to the $X_{i,t}$ and Z_i variables is that $Y_{i,t}$ are correlated with the statistical noise $\nu_{i,t}$ and the unobservable individual effects $\mu_{i,t}$. Recalling the singly an doubly exogenous variables introduced above for the $Y_{i,t}$ variables we now define a further category - endogenous regressors. Endogeneity is defined as a correlation of a variable with both error components. The motivation for this three-type distinction is as follows: The structural model has statistical noise and an individual effect in every structural equation. In computing its reduced form each reduced form equation will have an individual effect which is a linear combination of the individual effects in the structural equations. As Cornwell et al. (1992) note, the solution for every endogenous variable will therefore in general involve every structural error and also the individual effect from every equation. The nature of this solution implies that every endogenous variable should be correlated with every structural error and hence also with the individual effects. The importance of this argument is that there cannot be any endogenous variable correlated with the remainder error term but not with the individual effect.

Taking into account the vector of endogenous explanatory variables $Y_{i,t}$ we can write the n^{th} structural equation of the system according to eq.(11) as:

$$\begin{aligned} y_n &= R_n \xi_n + u_n \\ u_n &= \mu_n + \nu_n, \end{aligned} \quad (10)$$

where n denotes the n^{th} structural equation of the system with $n = 1, \dots, N$, $R_n = (Y_n, X_n, Z_n)$ and $\xi = (\delta', \beta', \gamma')$, where δ' is a coefficient vector for Y_n . We can then stack the equations given in eq. (15) into the form usual considered in a system (SUR or 3SLS) context as:

$$y = R\xi + u, \quad (11)$$

where $y' = (y'_1, \dots, y'_N)$ and similar for ξ and u . R is defined as

$$R = \begin{bmatrix} R_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & R_N \end{bmatrix} \quad (12)$$

As in the single equation model we assume that both μ and ν are i.i.d. errors with the zero mean and covariance matrices for the error components as $[\sigma_{\mu(j,l)}^2]$ (with $j = 1, \dots, N$ and $l = 1, \dots, N$) for the unobserved individual effects, $\Sigma_\nu = [\sigma_{\nu(j,l)}^2]$ for the remainder error term respectively.

For estimation one has to transform the system of equations in (16) by $\Omega^{-1/2}$ so that the error is whitened, where $\Omega = E(uu')$ is the variance-covariance for the system of equations consisting of the cross-equation variance components according to:

$$\Omega^{-1/2} = (\Sigma_\nu + T\Sigma_\mu)^{-1/2} \otimes P_v + \Sigma_\nu^{-1/2} \otimes Q_v, \quad (13)$$

where Q_v is an operator transforming a variable into its deviations from group means, while P_v produces group means of a variable. P_v is defined as $I_N \otimes \bar{J}_T$, where I_N is an identity matrix of dimension N and $\bar{J}_T = J_T/T$ and J_T is an (TxT) matrix of ones. Q_v is defined as $I_{NT} - P_v$, where I_{NT} is an identity matrix of dimension NT . Kinal & Lahiri (1990) suggest obtaining the Cholesky decomposition of Σ_ν and Σ_μ to reduce the computation and simplify the transformation of the system. To do so we thus need consistent estimators of σ_μ^2 and σ_ν^2 , these are typically based on untransformed 2sls estimates of the respective modelling approach (e.g. HT or AM, for further details see e.g. Baltagi, 2005). After having whitened the error terms in the model we can use 3SLS to the transformed models using all relevant instrument variables based on the singly and doubly exogenous variables to estimate all parameters of the system.

2.3 Synthesis to Dynamic Simultaneous Equation Panel Data Models

Having briefly reviewed system estimators for the static case, these models can now be generalized to the dynamic setting. Harris & Matyas (1996) argue that for dynamic panel data models the lagged dependent variable $y_{i,t-1}$ can be treated as predetermined and thus in analogy to the $X2$ variables, that is it is singly exogenous with respect to the error component μ_i . The authors propose to use lagged deviations from group means from $X1$ as $Q_v X1_{i,t-1}$ as well as lagged group means $P_v X1_{i,t-1}$ as instruments for $y_{i,t-1}$. In the Amemiya-Macurdy case additionally to the $Q_v X_{i,t-1}$ the vector $X1^*$ has to be augmented to include lags of $X1_{t-1}^*$ (where the subscript D indicates the augmented Instrument matrix for the dynamic case) as

$$X1_D^* = \begin{bmatrix} X1_{1,t-1} & X1_{1,t} & X1_{1,t+1} & \cdots & X1_{1T} \\ X1_{2,t-1} & X1_{2,t} & X1_{2,t+1} & \cdots & X1_{2T} \\ \vdots & \vdots & \vdots & & \vdots \\ X1_{N,t-1} & X1_{N,t} & X1_{N,t+1} & \cdots & X1_{NT} \end{bmatrix} \otimes e_T. \quad (14)$$

A further extension to the instrument set is proposed by Ahn & Schmidt (1995): Given the strict exogeneity of $X1$ (and $Z1$ analogously) with respect to $u_{i,t}$, Ahn & Schmidt (1995) demonstrate that there are many more instruments in the space spanned by Q_v in addition to $Q_v X1$ that help to explain the regressor ($Q_v y_{t-1}$). The authors propose a vector of instruments defined as $X1^{**}$, where

$$X1^{**} = Q_v \left[\begin{array}{cccccc} X1_{1,t-j} & \cdots & X1_{1,t} & X1_{1,t+1} & \cdots & X1_{1T} \\ X1_{2,t-j} & \cdots & X1_{2,t} & X1_{2,t+1} & \cdots & X1_{2T} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ X1_{N,t-j} & \cdots & X1_{N,t} & X1_{N,t+1} & \cdots & X1_{NT} \end{array} \right] \otimes I_T. \quad (15)$$

This vector of instruments can be interpreted as using all leads and lags of variables $X1$ in its deviations from group means. An alternative interpretation of this instrument set can be given, if we make use of the fact that first differences and deviations from means preserve the same information in the data. Making use of this information Ahn & Schmidt (1995) rewrite the instrument set $X1^{**}$ as

$$\begin{aligned} X1^{**} &\stackrel{P}{=} \left[\begin{array}{cccccc} X1_{1,t-1} & X1_{1,t} & X1_{1,t+1} & \cdots & X1_{1T} \\ X1_{2,t-1} & X1_{2,t} & X1_{2,t+1} & \cdots & X1_{2T} \\ \vdots & \vdots & \vdots & & \vdots \\ X1_{N,t-1} & X1_{N,t} & X1_{N,t+1} & \cdots & X1_{NT} \end{array} \right] \otimes Q \\ &= \left[\begin{array}{cccccc} X1_{1,t-1} & X1_{1,t} & X1_{1,t+1} & \cdots & X1_{1T} \\ X1_{2,t-1} & X1_{2,t} & X1_{2,t+1} & \cdots & X1_{2T} \\ \vdots & \vdots & \vdots & & \vdots \\ X1_{N,t-1} & X1_{N,t} & X1_{N,t+1} & \cdots & X1_{NT} \end{array} \right] \otimes L \end{aligned} \quad (16)$$

where L is a matrix operator that performs the first difference transformation to $X1$ and the ' $\stackrel{P}{=}$ ' relationship between to matrices means that they yield the same projections. Thus, the vector of instruments can be alternatively interpreted as using all leads and lags of variables $X1$ in its first differences rather than deviations from group means.⁹ Focusing on lagged values, the proposal by Ahn & Schmidt (1995) includes all lags and not only the first as proposed by Harris & Matyas (1996). The overall set of instruments from $X1$ is thus $[X1^{**}, X1^*]$. However, as in the single equation dynamic panel data model, the 'many instruments problem' may be in order here, so that in most cases we restrict the lag length to 1 and follow the suggestion of Harris & Matyas (1996).

We will classify the two groups of instruments based on deviations of group means and first differences as $IV\Delta X$ and $IVQX$. Especially for the latter Kiviet (1995) found remarkably good model properties both in terms of bias and efficiency when performing model comparison among different (single equation) dynamic panel data estimators. Kiviet (1995) shows that $IVQX$ is virtually unbiased and efficient, that

⁹In the following we primary make use of the 'collapsed' interpretation of the GMM-style instrument set proposed by Ahn & Schmidt (1999). The total number of GMM-style $X1^{**}$ instruments is $T(T-1)$.

is it beats the Arellano & Bond (1991) GMM type and Anderson & Hsiao IV-type estimator for all of the Monte Carlo simulation designs. Comparing the efficiency of the closely related (restricted) EC-3SLS estimator in a dynamic setup with no additional instrument for $t - 1$, Haque et al. (1993) also find that this level estimator is more efficient than the Arellano & Bond (1991) GMM first difference counterpart.

So far we have only derived instrumental variables based on the strictly exogenous variables to better explain $y_{i,t-1}$. However, another way of exploiting additional orthogonality conditions would be to utilize a combination of moment conditions from the dynamic panel data literature and the HT type models presented above. Since the HT model is typically estimated in levels, a straightforward starting point would be to make use of the stationarity moment condition in eq.(11) as $E(\Delta y_{i,t-1} u_{i,t}) = 0$ for $t=3, \dots, T$. This orthogonality condition can be used to extend the instruments set of the different HT/AM estimators.¹⁰ For the HT models we focus on the 'collapsed' version of the IV set. This leads to the following sets of instrument for our dynamic HT model (for convenience assuming that all exogenous variables are time-varying and strictly exogenous - thus $X1$; additionally we focus only on one lagged value for the exogenous and predetermined variables) :

- $HT1 = (Q_v X1_{i,t}, Q_v X1_{i,t-1}, P_v X1_{i,t}, P_v X1_{i,t-1})$,
- $AM1 = (Q_v X1_{i,t}, Q_v X1_{i,t-1}, X_{Di}^*)$,
- $HT2 = (Q_v X1_{i,t}, Q_v X1_{i,t-1}, P_v X1_{i,t}, P_v X1_{i,t-1}, \Delta Y_{i,t-1})$,
- $AM2 = (Q_v X1_{i,t}, Q_v X1_{i,t-1}, X_{Di}^*, \Delta Y_{i,t-1})$,
- $HT3 = (\Delta X1_{i,t}, \Delta X1_{i,t-1}, P_v X1_{i,t}, P_v X1_{i,t-1}, \Delta Y_{i,t-1})$,
- $AM3 = (\Delta X1_{i,t}, \Delta X1_{i,t-1}, X_{Di}^*, \Delta Y_{i,t-1})$,

where $\Delta Y_{i,t-1}$ is the entire set of predetermined endogenous variables of the system, $X1$ captures all exogenous variables. Following Cornwell et al. (1992) and Ahn & Schmidt (1999) we implicitly assume that the same instruments are available for each structural equation. A final aspect worth noting is that in the static case under the homoscedasticity assumption the asymptotic equivalence between 3SLS and GMM holds. However, Ahn & Schmidt (1999) show that this is not the case for the dynamic model using the full orthogonality conditions, in particular eq.(10). For the full argument see Ahn & Schmidt (1999). Thus, using a GMM framework could potentially bring additional gains in efficiency, however at the same time the 'many instruments problem' may be in order.

3 Monte Carlo Simulation Exercise

Before we turn to the empirical application of the growth model outlined in section 2, this section serves to perform some preliminary Monte Carlo simulation experiments for a two equation dynamic simultaneous equation model with error components. As described above, though there is a vast literature on monte carlo simulations for DPD estimators in a single equation context, less evidence is known for the multiple

¹⁰Ahn & Schmidt (1995) similarly propose a combination of the standard orthogonality condition with the orthogonality conditions of the HT- and AM-type estimators for the single equation case

equation case. In the following we draw on the simulation setup of Matyas & Lovrics (1990), using a 2-equation model with the endogenous variables $y1$ and $y2$ of the following form:

$$y1_{i,t} = \alpha_0 + \alpha_1 y2_{i,t} + \alpha_2 y1_{i,t-1} + \alpha_3 x1_{i,t} + \mu1_i + \nu1_{i,t}, \quad (17)$$

$$y2_{i,t} = \beta_0 + \beta_1 y1_{i,t} + \beta_2 x2_{i,t} + \beta_3 x3_{i,t} + \mu2_i + \nu2_{i,t}, \quad (18)$$

where exogenous regressors $x1, x2, x3$ are generated by the following DGP:

$$x1_{i,t} = \rho_1 x1_{i,t-1} + \psi1_{i,t} \quad (19)$$

$$x2_{i,t} = \rho_2 x2_{i,t-1} + \psi2_{i,t} \quad (20)$$

$$x3_{i,t} = \rho_3 x3_{i,t-1} + \psi3_{i,t} \quad (21)$$

In this setup special attention has to be given to the proper specification of the various error terms in the equations for the endogenous and exogenous variables. Here we make the following assumptions (mostly) in line with the recent mainstream body of Monte Carlo simulation work:

$$\nu1_{i,t} \sim N(0, \sigma_{\nu1}^2) \quad (22)$$

$$\nu2_{i,t} \sim N(0, \sigma_{\nu2}^2) \quad (23)$$

$$\mu1_{i,t} \sim N_2(0, \Sigma_\mu) \quad (24)$$

$$\mu2_{i,t} \sim N_2(0, \Sigma_\mu) \quad (25)$$

$$\psi1_{i,t} \sim N(0, \sigma_{\psi1}^2) \quad (26)$$

$$\psi2_{i,t} \sim N(0, \sigma_{\psi2}^2) \quad (27)$$

$$\psi3_{i,t} \sim N(0, \sigma_{\psi3}^2) \quad (28)$$

As in Arellano & Bond (1991) we use $\sigma_{\nu1}^2$ and $\sigma_{\nu2}^2$ as normalization parameter which we set equal to 1. Different from the time varying error term ν we model the unobservable individual effects μ as multivariate normally distributed to test whether a full information approach may enhance the estimator efficiency. The general distribution function for a set of p variables is denoted $N_p(a, \Sigma)$, where a is a $(p \times 1)$ vector of means and Σ is the $(p \times p)$ covariance matrix of the variables (see also Mooney, 1997). We specify μ as multivariate normally distributed with zero mean and variance-covariance matrix according to

$$\Sigma_\mu = \begin{bmatrix} 1 & 0,5 \\ 0,5 & 1 \end{bmatrix} \quad (29)$$

Throughout the Monte Carlo simulation experiment we also define a load factor ξ determining the ratio of the two error components as $\xi = \frac{\sigma_\mu}{\sigma_\nu}$. This gives us the opportunity to test for the estimators' performance for different error component weighting schemes (as found e.g. in Hayakawa, 2005). While we keep some parameters constant ($\sigma_{\psi_i} = 0,9$; $\rho_i = 0,5$; $\beta_i = 0,5$), we modify the following parameters during the exercise: $\alpha_2 = (0,8; 0,5)$, which then also varies $\alpha_{1,3} = (1 - \alpha_2)$; $\xi = (4; 1; 0,5)$; $N = (15; 25; 50; 100)$ and $T = (5; 10; 15)$. With respect to the initial observations we proceed as follows: $y_{0,i} = 0$ and $x_{0,i} = 1/(1-\rho)$.

In line with Arellano-Bond (1991), for the DGP we set $T = T + 10$ and cut off the first 10 cross-sections so that the actual samples contain NT observations. The total number of repetitions is set to 1000, where we keep the observations on x_i fixed over replications

For estimator comparison we compute various common evaluation criteria as *bias*, *std.dev.*, *rmse*, *NOMAD* and *NORMADSQD*, where the latter are (normalized) evaluation criteria averaged over all estimated model parameters. That is the NOMAD (normalized mean absolute deviation) computes the absolute deviation of each parameter estimate from the true parameter, normalizing it by the true parameter and averaging it over all parameters and replications considered. The NORMSQD computes the mse for each parameter, normalizing it by the square of the true parameter, averaging it over all parameters and taking its square root (for details see Baltagi & Li, 2000). We compute results of Anderson-Hsiao (1982), Arellano-Bond (1991), Blundell-Bond (1998) estimators and *HT1* to *HT3* as defined above.

At this stage of research we predominantly focus on limited information methods in line with Matyas & Lovrics (1990), this means that we apply the same set of system IVs denoted as Z^S for both equations using $X1_{t,i}, \dots, X3_{t,i}$; $X1_{t-1,i}, \dots, X3_{t-1,i}$ and $Y1_{t-1,i}, \dots, Y1_{t-n,i}$ but do not account for cross-equation residual correlations.¹¹ For the rival estimators of the HT-specifications we use the following data transformations:

- AH: $(\Delta X1_{t,i}, \dots, \Delta X3_{t,i}); (\Delta X1_{t-1,i}, \dots, \Delta X3_{t-1,i}); Y1_{t-2,i}$
- AB: $(\Delta X1_{t,i}, \dots, \Delta X3_{t,i}); (\Delta X1_{t-1,i}, \dots, \Delta X3_{t-1,i}); (Y1_{t-2,i}, \dots, Y1_{t-n,i})$
- BB1: *Level*: $(X1_{t,i}, \dots, X3_{t,i}); (X1_{t-1,i}, \dots, X3_{t-1,i}); \Delta Y1_{t-1,i}$; *Diff*: as AH
- BB2: *Level*: $(X1_{t,i}, \dots, X3_{t,i}); (X1_{t-1,i}, \dots, X3_{t-1,i}); (\Delta Y1_{t-1,i}, \dots, \Delta Y1_{t-n,i})$; *Diff*: as AB

For the GMM estimators we use an efficient two-step approach including the Windmeijer (2005) small sample correction to make the competition for the HT-specifications as tough as possible.¹² In the case of full information estimation we specify the optimal weighting matrix V^S for the whole system as:

$$V_N^S = N^{-1} \sum_{i=1}^N Z_i^{S'} \hat{u}_i^S \hat{u}_i^{S'} Z_i^S \quad (30)$$

where u_i is estimated from a consistent 1.stage regression (such as 2SLS), Z_i^S is the instrument matrix for the whole system.

Turning to the results, figure 1 to 8 first report the Monte Carlo results with respect to the autoregressive parameter for the endogenous variable in eq.(23) which is given a prominent role in single equation Monte Carlo study comparisons. Thereby, our simulation results merely confirm the results given so far: As figure 1 shows for the standard large N , small T setting the two-step efficient Blundell-Bond (1998) estimators perform best in terms of bias from the true α_2 -value. The box plots in figure 1 show that the mean of the two BB estimators are very close to the true value of 0,8 with a small standard deviation. The HT specifications also work well with the HT2 and HT3 being slightly downward biased. The figure

¹¹An extension to run Monte Carlo simulations based on full information methods for the various estimators is currently ongoing. However, some first results are presented here of a restricted set of simulation parameters. At this stage we also ignore AM-type estimators.

¹²For the estimation we use the *ivreg2* (see Baum et al., 2003) and *xtabond2* (see Roodman, 2006) Stata routines.

also confirms the poor performance of FD estimators (both AH and AB) typically found in simulation work. In figure 2 we now keep the number of cross-sections fixed, but augment the time period to $T = 10$. The results show that though the BB2 still has the smallest bias on average, the BB1 specification is outperformed by the HT1-HT3 models. The performance of the FD estimators is somewhat better for longer time periods, however they are still the less accurate estimators for the true α_2 coefficient.

[Figure 1 and Figure 2 about here]

If we now reduce the number of cross-sections to $N = 10$ we offset the standard panel data assumptions and move on to two-sided small sample panels in which the time dimension of the panel is not that short and the cross-section dimension not that large. The results in figure 3 show that for these settings the HT specifications on average slightly outperform both BB estimators. This impression is also supported if we relax the assumption of an equal weight of the two error components. For a load factor of $\xi = 4$ in figure 4 the HT2 specification works best. In figure 5 and 6 we finally reduce the degree of persistence in the autoregressive coefficient to $\alpha_2 = 0,5$. Here the results show that the BB estimator break down for different load factors, while the HT2 specification works best. Thus, in non-standard panel settings the HT-IV estimators seem to be more accurate than their GMM rivals, which may suffer from a substantial weak instrumentation bias.

[Figure 3 to Figure 8 about here]

In our system context, not only the bias of single coefficient estimates but also the overall performance of the various estimators is of special importance. Figure 9 to 15 therefore report the NORMSQD values for the various estimators. In the standard large N , small T setting the Blundell-Bond estimators are most efficient. However, this dominance changes with increasing time period and smaller cross section dimension. Especially for settings with less persistence in the lagged endogenous variable and a high load factor (figure 15). Here the HT specification perform far better than the BB as well as FD estimators.

Figure 16 to 19 show the performance of the (absolute) bias and RMSE for β_2 as well as the overall performance criteria NOMAD and NORMSQD for different settings of the cross section dimension of the panel data. The general tendency in all figures shows that the estimators' performance increases with a higher cross-section dimension. Accumulating the different cross-section cases for the different estimators, the figures show that the HT specifications (in particular the HT2 version) perform best. Interestingly the BB specification come close to the HT results with respect to (absolute) bias for α_2 and overall NOMAD, while they are sensitive to outliers as the RMSE for α_2 and overall NORMSQD criteria show. With respect to the latter the BB estimators are even outperformed by simple FD-IV rival estimators.¹³ In the next section we now turn to an empirical application for the different dynamic simultaneous equation panel data models.

[Figure 9 - Figure 19 about here]

¹³Standard Monte Carlo simulation results for $N = (25, 100)$ and $T = (5, 10)$ are given in table A.1 to table A.6. Other results can be obtained from the author upon request.

Finally, also some preliminary simulation results are given for full information estimation. As figure 20 shows the results for $N = 25$ and $T = 10$ are rather mixed with no clear efficiency gains based on the full information approach. However, further simulation runs with varying settings for the cross-section and time-dimension of the panel data are necessary to give a complete picture of the relative efficiency of full versus limited estimation in the context of panel data.

[Figure 20 about here]

4 Modelling Output (Growth) and Factor Demand Equations for Policy Analysis

At the core of our modelling system we use a human and public capital augmented neoclassical Solow growth model in its standard empirical growth formulation (see e.g. Barro & Sala-i-Martin, 1991/1995, for the standard two-factor production function or Gondl, 2001, and Lall & Yilmaz, 2001, for its human and public capital generalization) as:

$$\begin{aligned} \log(y_{i,t}) - \log(y_{i,t-1}) = & \alpha - \beta \log(y_{i,t-1}) + \sum_{j=0}^1 \gamma_j \log(inv_{i,t-j}) \\ & + \sum_{j=0}^1 \delta_j \log(pub_{i,t-j}) + \sum_{j=0}^1 \phi_j \log(hc_{i,t-j}) \\ & + \sum_{j=0}^1 \omega_j \log(n + g + \delta)_{i,t-j} + \Psi' \mathbf{Z} + u_{i,t}, \end{aligned} \quad (31)$$

where $i = 1, \dots, N$ is the cross-sectional dimension and $t = 1, \dots, T$ is the time dimension. The dependent variable y_{it} is defined as output per employee for region i and time period t , $y_{i,t-1}$ is the one-period lagged observation. Next to its own lagged value we include current and (one-period) lagged values of the following factor inputs as right-hand side regressors: inv is the private sector investment rate, pub is the public sector investment rate, hc is a measure for human capital, n is the labour force growth rate, g and δ are exogenous technical change and depreciation (the later two variables are capped to 0,05 as standard in the related literature). \mathbf{Z} is a vector of further exogenous output growth determinants including regional equalization policies, u_{it} is the error term and $\alpha, \beta, \gamma, \delta, \phi, \omega$ are coefficient, Ψ is a coefficient vector.

Eq.(1) can be equivalently rewritten as a dynamic panel data model in levels with output per employee for region i in period t as dependent variable (see e.g. Gondl, 2001):

$$\begin{aligned} \log(y_{i,t}) = & \alpha + \theta \log(y_{i,t-1}) + \sum_{j=0}^1 \gamma_j \log(inv_{i,t-j}) \\ & + \sum_{j=0}^1 \delta_j \log(pub_{i,t-j}) + \sum_{j=0}^1 \phi_j \log(hc_{i,t-j}) \end{aligned} \quad (32)$$

$$+ \sum_{j=0}^1 \omega_j \log(n + g + \delta)_{i,t-j} + \Psi' \mathbf{Z} + u_{i,t},$$

with $\theta = (1 - \beta)$. In empirical estimation we will use eq.(2) and additionally add structural equations for the various factor inputs [*inv*, *pub*, $(n + g + \delta)$, *hc*] based on theoretical motives. In principle we will build up dynamic specification for the various factor demands in a rather ad-hoc fashion somewhat related to the Nadiri & Rosen (1974) type factor demand system (or also labeled second generation dynamic factor demand model; for a recent overview of different approaches to factor demand modelling see e.g. Larsson, 2004, Morana, 2007).

By account for the endogeneity of the factor inputs we are able to explicitly channel the relationship between regional policies and the arguments of the production function in a structural manner. Some of the likely gains associated with this system approach compared to the single equation estimation are as follows:¹⁴ First, the role of the policy variables in the system can be interpreted more meaningful: That is, the indirect effects of regional policies on the production function are modelled via the endogenized factor inputs and so the policy variables in the growth equation are left to determine the effect on total factor productivity solely. Second, by addressing potential r.h.s. regressor endogeneity and cross-equation residual correlation, this setup generally results in consistent and more efficient parameter estimates compared to the single equation approach. By using appropriate instrumental variables for endogenous right-hand side variables in the system approach, the single parameters will be estimated consistently (see e.g. Bond et al., 2001, with an explicit reference to growth model estimates), further the system approach will lead to more efficient results especially if there is a non-zero covariance matrix of the error terms (see e.g. Greene, 2003).

In extension to eq.(1)/(2) we can thus write the resulting 5-equation system compactly in a partial adjustment framework as a restricted version of the more general ARDL(p, q_1, \dots, q_n) or in the system case VARX-form:¹⁵

$$\begin{aligned} y_{i,t}^* &= f_1(inv_{i,t}^*, pub_{i,t}^*, [n + g + \delta]_{i,t}^*, hc_{i,t}^*, \mathbf{Z}) + u_1, \\ inv_{i,t}^* &= f_2(y_{i,t}^*, pub_{i,t}^*, [n + g + \delta]_{i,t}^*, hc_{i,t}^*, \mathbf{Z}) + u_2, \\ pub_{i,t}^* &= f_3(y_{i,t}^*, inv_{i,t}^*, [n + g + \delta]_{i,t}^*, hc_{i,t}^*, \mathbf{Z}) + u_3, \\ (n + g + \delta)_{i,t}^* &= f_4(y_{i,t}^*, inv_{i,t}^*, pub_{i,t}^*, hc_{i,t}^*, \mathbf{Z}) + u_4, \\ hc_{i,t}^* &= f_5(y_{i,t}^*, inv_{i,t}^*, pub_{i,t}^*, [n + g + \delta]_{i,t}^*, \mathbf{Z}) + u_5, \end{aligned} \tag{33}$$

where $'^*$ denote the equilibrium level for a variable x . This equilibrium level is assumed to be connected to actual current and past observations of x according to:

¹⁴See e.g. Ulubasoglu & Doucouliagos (2004) for a further discussion.

¹⁵For details how the partial adjustment model can be derived as a restricted form of the more general ARDL(p, q_1, \dots, q_n)-model (where p denotes the number of own lags for the endogenous variable in the estimated equation and q is the lag length of the respective n exogenous variables) see e.g. Smith & Fuentes (2004).

$$\log(x_{i,t}) - \log(x_{i,t-1}) = \eta \log(x_{i,t}^*) - \eta \log(x_{i,t-1}) \quad (34)$$

and solving for $x_{i,t}^*$ yields:

$$\log(x_{i,t}^*) = \frac{1}{\eta} \log(x_{i,t}) + \log(x_{i,t-1}), \quad (35)$$

where η can be interpreted as the speed of adjustment parameter for variable x . Substituting this equation for each $x_{i,t}^*$ in the equation system of (3) yields for each equation a relationship for estimation with only observable variables, since each equilibrium value is substituted by current and one-period lagged observed values for the respective variable. In the empirical estimation we will judge on theoretical and econometric grounds which of current and lagged variables out of this 'pool' will be included in the final regression output for each equation of the system in (3). Typically we start from a more general model and test down by excluding insignificant variables.

5 Regional Equalization Policy Instruments

A prominent role in the design of the empirical model of the equation system in eq.(3) is given to regional equalization policy instruments included in the vector of exogenous explanatory variables \mathbf{Z} . We will focus on three of the major policy schemes in the actual institutional setup of German regional policy: 1.) the federal/interstate fiscal equalization transfer scheme (*Laenderfinanzausgleich*, thereafter LFA), 2.) the joint federal/state government program 'Improvement of Regional Economic Structures' (*Gemeinschaftsaufgabe "Verbesserung der regionalen Wirtschaftsstruktur"*, thereafter GRW), as well as 3.) instruments of the active labour market policy (thereafter ALMP).¹⁶ Especially, the LFA is a matter of heavy debate both at the political as well as academic level.¹⁷ A central question arising in this controversy is whether those transfers associated with the LFA are effective in fostering growth in the relatively poor recipient regions and thus support the central goal of income convergence among German states. In the latter sense equalization payments of the LFA are seen as an 'allocative' policy instrument, where positive macroeconomic effects are likewise associated with spillovers of public (infrastructure) investments as well as scale effects in the production of public goods (for a summary see e.g. Kellermann, 1998). The two central layers of the LFA comprise a horizontal reallocation between different units of the same administrative level (states) as well as transfers stemming from vertical linkages between the federal government and the states. The LFA targets the level of regional tax revenues, where equalization is achieved through a combination of horizontal and vertical transfer payments which both serve as to subsidize low revenue states to fill the gap between a state's actual revenues relative to a population weighted average level of tax revenues across states. Since most tax categories can be directly related to the economic output performance of a region, the LFA can be interpreted as equalization transfers from regions with high income to low income regions (in terms of GDP per capita).

In the recent literature contrasting arguments can be found with respect to the likely macroeconomic

¹⁶A detailed description of the institutional setup of these instruments is given in Alecke et al., 2006.

¹⁷The latter is in particular due to the large transfer amounts for the East German states ("*Aufbau Ost*") which are nested within the overall transfer scheme.

effects of federal transfer payments such as the LFA - either in favour of promoting per capita income convergence or against it. A typical argument from the latter point of view is that equalization transfers may result in persistent 'transfer dependency', where poor net recipient regions have little incentives to boost their revenue base. On the contrary, transfers can also be seen as a form of public capital which in turn may help to foster the productivity of private capital stock and thus also output growth. For the magnitude of this public capital growth channel the share of investive spending items relative to total net transfers is relevant: The higher the share of investive (or supply side) spendings relative to total transfers, the stronger we expect the impulse of the LFA on the regional growth pattern. Focusing on net transfers to the East German states Bradley et al. (2006) show that these transfers may have a significant impact on the aggregate development pattern. However, the results are based on simulation experiment using a one-region macromodel for East Germany. In this modelling framework the federal transfers are necessarily exogenous and do not affect parameters such as the tax rate, which in turn may lower the economic growth rate (see e.g. Gondl, 2001). A more appropriate setup to test for the overall growth effect of transfers on the economy in focus would therefore be to include all (donor and recipient) states in a joined estimation setup.

Previous empirical contributions of this kind have shown mixed results: For Canada Kaufman et al. (1997) find a significant positive influence of net transfer payments on the regional growth and convergence process of its provinces. On the contrary, studies based on German data mainly reveal a negative relationship between LFA transfers and regional economic growth: Baretta (2001) uses data for 10 West German states (excluding Berlin) between 1970 and 1997, Berthold et al. (2001) expand the approach to a panel of all 16 German states using a shorter observation period between 1991 and 1998. Both studies find a significant negative relationship between the elements of the LFA and the regional growth process in Germany. Starting from a theoretical model of the LFA, Baretta (2001) derives two proxy variables measuring the effect of LFA payments on regional growth: 1.) the marginal absorption of additional regional tax revenues due to the LFA, 2.) the average tax revenue relevant for the LFA in all other regions excluding i . The first variable is assumed to have a negative effect on growth, while for the latter - measuring the absolute financial mass of the LFA - the effect is a priori not that clear. For details see Baretta (2001) or Baretta et al. (2000).

In the empirical estimation Baretta (2001) found a negative absorption effect of the LFA on growth, while the overall financial mass was tested insignificantly. The main conceptual problem of the approach of Baretta (2001) is that the productive character of LFA transfers in terms of public capital as input for the regional production function is not appropriately captured in the two proxy variables. Thus, Berthold et al. (2001) use a more direct way and take net transfers disaggregated by horizontal and vertical payment flows. However, as Baretta (2001) points out, the main methodological critique of this study is that the estimation approach does not appropriately account of a possible endogeneity of LFA transfers relative to economic growth. Finally, Alecke et al. (2006) use a 'Barro'-type convergence equation to test for output effects on a panel on all 16 German states for the most recent sample period between 1994-2003. Their results do not support any causal relationship between LFA payments and regional economic growth.

The joint federal/state government programme 'Improvement of Regional Economic Structures' (Gemeinschaftsaufgabe "Verbesserung der regionalen Wirtschaftsstruktur", GRW) comprises two major components: The first pillar of the programme serves as an regional investment support scheme for the private sector. The second pillar aims at providing public infrastructure to subsidized regions, where the infra-

structure projects are closely related to the private sector business activity and do not comprise basic or household related infrastructure. There is a broad empirical literature analysing the impact of various investment incentives on an economy's investment and growth path (for a literature overview see e.g. Gondl, 2001). Macroeconomic evaluations of the German GRW are conducted by Schalk & Untiedt (2000), Gerling (2002), Blien et al. (2003a&b), Eckey & Kosfeld (2004) as well as Alecke et al. (2006).

Schalk & Untiedt (2000) estimate the impact of regional investment incentives on investment activity and growth via its effect on the regional user costs of capital.¹⁸ The latter variable reflects the compound effect of all tax instruments including the GRW items investment bonus, investment grants and depreciation allowances, which subsequently reduce the total tax burden and thus in turn the user costs of capital. The estimation results for West German districts shows that investment and output react positively to a reduction in the user costs of capital. However as Gondl (2001) argues, one drawback of the user cost of capital approach is that the compound measure of various tax instruments cannot give an insight as to the role of the single tax and GRW instruments in the total effect. Alecke et al. (2006) use a more direct estimation method by adding GRW payment flows in an augmented growth regression and find analogously that the GRW funds spent in the observation period contributed to higher interregional capital mobility and higher per capita income in the receiving regions. Eckey & Kosfeld (2004) find a positive effect of the GRW only in the subsidized regions, while the effect in the non-subsidized regions is negative. According to the authors the GRW on average has thus only very marginal positive growth effects. Finally, focusing on labour market effects in East German regions Blien et al. (2003a&b) find a positive employment effect of the GRW.

The latter study of Blien et al. (2003a&b) additionally integrates the macro impact analysis of the GRW together with an assessment of instruments of the active labour market policy in East Germany. With respect to the latter Blien et al. (2003a&b) find equivalently positive employment effects. However, this result contrasts the bulk of recent studies on the macroeconomic effects of the active labour market policy (ALMP) in Germany: Fertig et al. (2002), Hujer et al. (2002) as well as Hagen (2003) find at most partially positive employment effects. While Fertig et al. argue that direct employment support instruments (ABM, SAM) even have an adverse on the reduction of the unemployment rate and only qualification scheme result in positive employment effects, Hujer et al. support the later effect only for West German regions with insignificant effects for East Germany. According to Hagen (2003) no one of the ALMP instruments has persistent effects on employment. Focusing on the impact of regional ALMP spending programs on output growth Alecke et al. (2006) do not find any statistically significant effect either.

6 Database and Variable Description

Before we start estimating different panel data models, we briefly describe the underlying dataset. For the empirical estimation we use a panel data set for the 16 German states between 1995 and 2004 (160 observation). The sample period is chosen to allow for an appropriate lag length (observations typically start in 1991). All variables are denoted in real terms. If is no specific price series is available, the GDP deflator is used. We have constructed different ratios or composite indicators for the respective variables,

¹⁸A similar approach is also followed by Gerling (2002).

a detailed description of the variables and source is given in table 1. Finally, since the data to be used in estimation consist of macroeconomic time series the (non)-stationarity of the data - and thus spurious regression - may be an issue. We therefore present unit panel root tests for the five endogenous variables in table 2 (using the test proposed by Levin-Lin-Chu, 2002, and Im-Pesaran-Shin, 1997). We compute four different alternatives: 1.) no lag, no trend; 2.) no lag, trend; 3.) lag(1), no trend; 4.) lag(1), trend. We apply the tests both to the variable in levels as well as first differences.

Turning to the results, interestingly, for output per employee in levels both test statistics reject the null hypothesis of non-stationarity for all four variants, though the variable is typically assumed I(1). One likely explanation for this result is the relatively short sample period with a low growth performance on average. Although employment growth is overwhelmingly tested to pass the null of non-stationarity, for private and public investment as well as human capital only about half of the variants of the test statistics turn out significant in favor of against non-stationarity in the data (all in levels).¹⁹ Taking together the empirical evidence for the level variables as our major focus throughout the analysis, we finally choose a pragmatic approach and follow the related literature (see e.g. Haque et al., 1993) assuming that - since we are broadly using per capita values and/or flow/stock-ratios and get somewhat supportive test results - the underlying variables can be treated as stationary (or for the case of I(1) we will assume based on theoretical grounds that the variables in the respective equation are cointegrated without explicitly testing) even though some caveats may apply.

[Table 1 about here]

[Table 2 about here]

7 Empirical Results and Multiplier Analysis

In the empirical application of the above specified 5-equation growth system we compare the results of the HT and AM estimates with the empirical performance of the most common alternative dynamic panel data approaches in the literature, that is the Anderson & Hsiao IV and Arellano & Bond GMM estimators in first differences as well as the Blundell & Bond system GMM estimator.²⁰ Thereby the AH model and the BB1 GMM model use only current and one period lagged and 'collapsed' instruments for both the exogenous and predetermined variables in line with the HT models. The AB and BB2 estimator use GMM style 'all lags' instruments for the predetermined variables which by far exceed their collapsed counterparts. The BB1 model is especially designed to test for the validity of the standard moment condition when moving from the HT level to the system estimator. The AB and BB2 models can be used to check for the relevance of the 'many instruments problem'.

We start with a limited information approach, which accounts for the endogenous variables of the system by appropriate IVs (orthogonality conditions) but ignores cross equations residual correlations

¹⁹The first difference transformation almost exclusively passes the unit root tests.

²⁰For estimation we use the *ivreg2* and *xtabond2* Stata-routines provided by Baum et al. (2003) and Roodman (2006) respectively.

(full information approach). The estimation results for the five equations are given in table 9 to table 13.²¹ First, we concentrate on the technical comparison of the various estimators. Having identified the most appropriate representation in a second step we then turn to a discuss and interpretation of the impacts of regional equalization schemes on regional output and factor demand.

[Table 9 - Table 13 about here]

For the model comparison we employ a broad set of postestimation tests to check for the appropriateness of the respective representation. These test includes the Pagan-Hall (1983) test for heteroscedasticity in IV regression residuals, the Arellano-Bond (1991) test for autocorrelation in the error terms and the Anderson canonical correlation LR test for instrument appropriateness. For the level and system estimator we also calculate the C-statistics ('diff-in-Sargan') in order to check whether the use of additional instruments in various estimators is valid. Under the null hypothesis of the C-statistic that both the smaller set of instruments and the additional ones are valid, the C-statistic is distributed as χ^2 with degrees of freedom according to the additional instruments tested. For the HT models we also report the GLS transformation factor ($\hat{\theta}$) based on σ_μ and σ_μ (under the assumption of a block-diagonal covariance matrix). The ratio of the two error components may give a further indication whether the system or level estimator may be more biased according to Hayakawa's (2005) results, whose results are also confirmed by our system Monte Carlo simulations in section 6. We also report the total number of instruments used in each model finally compute the Root Mean Square Error (RMSE) to judge among the predictive performance of the various estimators as a relative efficiency indicator.

Turning to the regression results the HT1-HT3 level and BB1-BB2 estimators on average clearly outperform the FD model for all equations. Starting with the central output equation (table 9) here the HT2 model show the smallest RMSE followed by the other HT, BB and AH model. For the AB-GMM estimator the RMSE is significantly worse though the model uses by far more instruments than the first difference counterpart AH-2sls. Also for the BB2 estimator the use of additional instruments (205 compared to 42 in BB1) does not result in improved RMSE values.

For the HT2 and HT3 model the null hypothesis of C-statistic, which tests for the additional instruments based on the stationary moment condition $E(\Delta y_{i,t-1} u_{i,t}) = 0$, cannot be rejected for reasonable confidence levels. Thus, both the augmented HT2 and HT3 models' instrument sets are valid. On the contrary for the BB1-GMM models the use of the lagged levels of predetermined endogenous variables in the difference equation as valid instruments is strongly rejected. Additionally, for the output model the ratio $\frac{\sigma_\mu}{\sigma_\mu}$ is much below unity when deriving the GLS correction factor $\hat{\theta}$. Taking Hayakawa (2005) and our Monte Carlo results as a guideline, this would favors the level estimator since the system counterpart could be severely biased - a result which is mirrored in our estimation output. Furthermore, all models tested pass the Pagan & Hall (1983) heteroscedasticity test and the Arellano & Bond (1991) autocorrelation test.²² The AH-2SLS model fails to pass the Anderson canonical correlation LR test which is another hint that there may be a 'weak instrument problem' in these specifications.

In terms of model comparisons the other equations of the system reveal quite similar results: In all

²¹Since HT- and AM-model resulted in almost the same parameter estimates, we skip the AM output here. Results can be obtained upon request.

²²We have tested for AR(2) in the FD estimators and AR(1) in the level estimators.

equations the ratio $\frac{\sigma_\mu}{\sigma_\mu}$ is around 0,25 and the coefficient of the lagged endogenous variable shows moderate high values. Taken together this result with the C-statistic, which rejects the use of the standard moment condition jointly with the level specification, and the RMSE criterion which is again best for the HT level models, we may conclude that the system estimator is not superior to the level estimator in our estimation setup. Moreover, in concordance with earlier research FD estimator show a significant 'weak instrument problem, e.g. the AH model persistently fails to pass the Anderson canonical correlation LR test. For most models heteroscedasticity and autocorrelation of the residuals is no problem. With respect to the HT models the C-statistic also justifies the use of augmented instruments derived from the HT literature together with the stationarity moment condition. As Kiviet (1995) found for the single equation case, also for the system specification thereby the $IVQX$ (HT2) performs slightly better than the $IV\Delta X$ (HT3). This also mirrors our Monte Carlo findings in section 6.

For our further modelling steps we thus focus on the HT2 model specification. First, in addition to the postestimation test conducted so far, we want to check for the appropriateness endogeneity classification and employ the Durbin-Wu-Hausman endogeneity test for all five equations. The null hypothesis of the DWH endogeneity test is that an ordinary least squares (OLS) estimator of the same equation would yield consistent estimates: that is, an endogeneity among the regressors would not have deleterious effects on OLS estimates. A rejection of the null indicates that endogenous regressors' effects on the estimates are meaningful, and instrumental variables techniques are required. The test results are given in table 14.

Table 14: Durbin-Wu-Hausman (DWH) endogeneity tests for HT2 specification

Equation	D.F.	χ^2 (p-value)
$\log(y_{i,t})$	5	10,25 (0,06)
$\log(inv_{i,t})$	3	0,89 (0,82)
$\log(pub_{i,t})$	5	10,54 (0,06)
$\log([n + g + \delta]_{i,t})$	5	29,59 (0,00)
$hc_{i,t}$	4	26,19 (0,00)

Note: A description of the Hausman m-statistic used for DWH is given in eq.(23). The test compares OLS and IV parameter estimates. We used the endog option implemented in the stata routine *ivreg2* to run the DWH test (see Baum et al., 2003).

The results generally support our ex-ante expectation that endogeneity is a matter in the growth system even if the null hypothesis of the DWH test cannot be rejected for the investment model. Second, we finally aim to further enhance the estimation efficiency by applying a full information (3SLS) approach. The likely benefit from this approach can be seen if we plot the residual correlation of the single equation estimates (based on the HT2 specification).

Table 15: Cross-equation correlation of σ_μ for HT2 specification

	$\log(y_{i,t})$	$\log(inv_{i,t})$	$\log(pub_{i,t})$	$\log([n+g+\delta]_{i,t})$	$hc_{i,t}$
$\log(y_{i,t})$	1,00				
$\log(inv_{i,t})$	-0,25*** (p=0,00)	1,00			
$\log(pub_{i,t})$	0,34*** (p=0,00)	-0,26*** (p=0,00)	1,00		
$\log([n+g+\delta]_{i,t})$	-0,08 (p=0,29)	0,13* (p=0,10)	0,15** (p=0,05)	1,00	
$hc_{i,t}$	-0,004 (p=0,93)	-0,06 (p=0,33)	0,02 (p=0,72)	0,48*** (p=0,00)	1,00

Note: ***, **, * = denote significance levels at the 1%, 5% and 10% level respectively.

Table 16: Cross-equation correlation of σ_ν for HT2 specification

	$\log(y_{i,t})$	$\log(inv_{i,t})$	$\log(pub_{i,t})$	$\log([n+g+\delta]_{i,t})$	$hc_{i,t}$
$\log(y_{i,t})$	1,00				
$\log(inv_{i,t})$	0,08 (p=0,26)	1,00			
$\log(pub_{i,t})$	-0,01 (p=0,86)	-0,07 (p=0,38)	1,00		
$\log([n+g+\delta]_{i,t})$	-0,13* (p=0,09)	-0,32*** (p=0,00)	0,05 (p=0,49)	1,00	
$hc_{i,t}$	0,18** (p=0,02)	0,13 (p=0,11)	-0,04 (p=0,63)	-0,02 (p=0,82)	1,00

Note: ***, **, * = denote significance levels at the 1%, 5% and 10% level respectively.

With respect to the unobservable individual effects (σ_μ) most of the cross-equation residual correlations in table 15 turn out to be statistically significant, while the results are mixed for the remainder error term σ_ν (see table 16). Thus, on average it seems very promising to switch to a full information approach using the unrestricted $\Omega^{-1/2}$ transformation as described in section 5. For the HT2 model the resulting HT2-3SLS estimates are shown in table 17.

[Table 17 about here]

To compare the 2SLS and 3SLS estimators with respect to estimation efficiency we employ the Hausman (1978) m -statistic, which is defined as:

$$m = \hat{q}'(\hat{Q} - \hat{V})^{-1}\hat{q}, \quad (36)$$

where $\hat{q} = \hat{\beta}_{3SLS} - \hat{\beta}_{2SLS}$ is the difference between the 3SLS and 2SLS estimators of the same parameter, \hat{Q} and \hat{V} denote consistent estimates of the asymptotic covariance matrices of $\hat{\beta}_{3SLS}$ and $\hat{\beta}_{2SLS}$ respectively. The m -statistic has a χ^2 distribution with degrees of freedom equal to the number

of parameter estimates. The underlying idea of the test is quite simple: Under the assumption that the 3SLS estimator is generally more efficient than the 2SLS estimator, we test whether the difference between the estimators is large, indicating that the more complex GLS transformation in the 3SLS case induced a misspecification in the model which renders it inconsistent. Thus, under the null hypothesis both estimators are consistent but only $\hat{\beta}_{3SLS}$ is efficient. Under the alternative hypothesis only $\hat{\beta}_{2SLS}$ is consistent.²³ The results of the Hausman m -statistics in table 17 show that for all equations the null hypothesis cannot be rejected for reasonable confidence levels (or even turns out to be negative), giving strong support for the 3SLS compared to the 2SLS results.

Hence, since the HT2-3SLS model is even more efficient than the 2SLS counterpart, a discussion of the estimation results seems most reasonable for this specification. As table 17 shows, the results show different simultaneities among the output and factor input variables. For the output equation we get a high level of persistence in the data. Surprisingly, the investment rate does not show a positive impact on output (growth), a result that is in line with related work by Gondl (2001) for a panel Southern European Regions and Paci & Pigliaru (1995) for Italian regions. For Germany the most likely explanation is that throughout our estimation period the investment rates in the East German states are still significantly higher, while there was almost no difference in regional growth (the latter is also reflected by the insignificant dummy variable East). However, the share of public investment relative to total government expenditure shows a significant positive effect on output. Employment growth and human capital are tested insignificant in the HT2-3SLS output equation. For the investment rate equation again public capital shows a positive effects as well as the human capital composite indicator. The estimated coefficient for the lagged endogenous variable is lower than in the output equation, the same also accounts for the public investment rate and employment growth equation.

As the estimation results shows, also the regional equalization policy instruments work through various direct and indirect channels on the regional economic development path. With respect to the direct effect on output per employee ($y_{i,t}$), the results mainly confirm previous research. That is, we find a negative in the horizontal (interstate) element of the LFA (in line with Baretta (2001), Berthold et al. (2001)). The vertical element is slightly positive but tested not significantly different from zero. On the contrary we get weak support for a positive output effects of the active labour market policy (ALMP), while the effect of the GRW is estimated negative. These qualitative results are also confirmed by the first step estimators (HT-2SLS and BB-GMM) and also reflect the recent literature discussed in section 3.

Going beyond the these direct effects, we additionally get evidence for some important indirect policy channels on factor inputs that are typically ignored in the empirical literature. That is for example, though the LFA is estimated to have a negative distortionary effect on output and also investment, we detect a significant positive effect of the vertical (federal) redistribution mechanism on public investive spendings. The latter in turn are estimated to have a positive effect on output per employee, so that the vertical LFA element also affects output positively through the public sector investment channel. Taking a closer look at the employment effect of the active labour market policy instruments we get rather evidence for a small negative cumulated effect of ALMP spendings on employment growth (different to total factor

²³By construction, if the 2SLS variance is larger than the 3SLS variance, the test statistic will be negative. Though the original test is not defined for negative values, here we will follow Schreiber (2007) and take the absolute value of the m -statistics as indicator for rejecting the null hypothesis of 3SLS efficiency.

productivity). In our analysis we also could not find much empirical support for positive investment effects of the investment promotion element of the GRW (only the FD estimator estimator find weak support for positive GRW infrastructure effects on the regional output, while the private investment scheme shows negative results for various estimators; also, only the HT2-2SLS model estimates positive employment growth effects of GRW infrastructure spendings). The main difference with respect to the positive effects typically found in the literature may be explained by the use of different regional scales. Empirical work on the GRW is typically conducted at at more narrow administrative units (districts or labour market regions). Thus, though there may be positive GRW effects for these smaller regional units, the effects may vanish when analysed from a macro-regional perspective.

So far, we have focused on discussing the estimation results within the structural form representation of the DSEM model. However, in order to fully analyse the marginal impact of changes in the exogenous (policy) determinants on the endogenous variables we have to transform our 5-equation system into the so-called reduced and final form subsequently (see e.g. Lütkepohl, 2005, Bardsen et al., 2005). Starting point for this transformation is the system written in matrix notation as:

$$BY_t + \Gamma X_t = U_t, \quad (37)$$

where Y_t is the vector endogenous variables, X_t is the vector of exogenous variables containing both predetermined (lagged) endogenous as well as current and lagged exogenous variables. B and Γ are the respective matrices of endogenous and predetermined variables parameters. The reduced form of the system is obtained by premultiplying eq.(37) with B^{-1} , where $\Pi = B^{-1}\Gamma$ containing the reduced form coefficients π_i which are in general nonlinear functions of the structural form parameters. The reduced form coefficients as partial derivatives of the endogenous variables with respect to the exogenous variables can be used to compute the so-called impact multiplier measuring an instantaneous effect on the endogenous variable based on an exogenous variable change in the same (first) period t . Additionally, in order to account for the total multiplier of the exogenous variable change also the dynamic nature of the system has to be taken into account. Hence, subsequent effects for the periods $t+1, t+2, \dots, t-n$ come through lagged dependent variables in form of time distributed (dynamic) interim multipliers, moving the system forward towards long-term equilibrium. The sum of the interim multipliers gives therefore the opportunity of evaluating the overall exogenous effects of a policy variable change on the five endogenous variables of the model (see also Bardsen et al., 2005, Glytsos, 2005).

The interim (or also called delayed) multipliers for the $t+1, t+2$ up to $t-n$ periods are calculated by partitioning the matrix Π into three submatrices: Π_1 containing only current exogenous variables, Π_2 with lagged exogenous variables and Π_3 with predetermined (lagged) endogenous variables. According to the final form of the model the interim multipliers are obtained as follows: For $t+1 = (\Pi_2 + \Pi_3 \times \Pi_1)$; $t+2 = \Pi_3(\Pi_2 + \Pi_3 \times \Pi_1)$; $t+3 = \Pi_3^2(\Pi_2 + \Pi_3 \times \Pi_1)$; $t+n = \Pi_3^{n-2}(\Pi_2 + \Pi_3 \times \Pi_1)$. Finally, the total multipliers are given by the matrix $\Pi_{LR_n} = \Pi_1 + \sum_{t=2}^{t=n} \Pi_3^{t-2}(\Pi_2 + \Pi_3 \times \Pi_1)$. For the structural form 3SLS regression output from table 17 we can now compute both direct impact and long run multiplier matrices of an (sustained one percentage) change of the system's exogenous variables on the endogenous ones (for the LR multiplier we set $n = 10$ and $n = 25$):

$$\Pi_1 = \begin{bmatrix} & LFA(h) & \log(GRW[inv]) & \log(ALMP) & LFA(v) & \log(unemp) \\ \log(y) & -0,061 & -0,02 & 0,031 & 0,002 & -0,007 \\ \log(inv) & -0,160 & 0 & 0,011 & 0,016 & -0,056 \\ \log(pub) & -0,017 & 0 & 0,048 & 0,072 & -0,258 \\ \log(n + g + d) & -0,129 & 0 & 0,368 & 0,013 & -1,985 \\ hc & -0,005 & 0 & 0,001 & 0,001 & -0,002 \end{bmatrix} \quad (38)$$

$$\Pi_{LR_{10}} = \begin{bmatrix} & LFA(h) & \log(GRW[inv]) & \log(ALMP) & LFA(v) & \log(unemp) \\ \log(y) & -0,546 & -0,161 & 0,227 & 0,084 & -0,104 \\ \log(inv) & -1,179 & 0 & -0,094 & 0,458 & -0,503 \\ \log(pub) & -0,495 & 0 & -0,179 & 0,559 & -0,429 \\ \log(n + g + d) & -0,146 & 0 & -0,358 & 0,097 & -0,047 \\ hc & -0,024 & 0 & -0,003 & 0,010 & -0,009 \end{bmatrix} \quad (39)$$

$$\Pi_{LR_{25}} = \begin{bmatrix} & LFA(h) & \log(GRW[inv]) & \log(ALMP) & LFA(v) & \log(unemp) \\ \log(y) & -1,191 & -0,289 & 0,292 & 0,334 & -0,156 \\ \log(inv) & -2,139 & 0 & -0,597 & 1,242 & -0,386 \\ \log(pub) & -1,144 & 0 & -0,565 & 1,120 & -0,272 \\ \log(n + g + d) & 0,003 & 0 & -0,352 & 0,031 & 0,049 \\ hc & -0,022 & 0 & -0,010 & 0,016 & 0,001 \end{bmatrix} \quad (40)$$

Additionally we compute the time distribution of the dynamic interim multipliers which are given in figure 21 for the net overall LFA effect (combining both horizontal and vertical effects) and disaggregated for each exogenous variable component in figure 22.²⁴ The results underline the qualitative discussion given for the structural form estimation results. That is, taking a look at the overall (net) LFA effect, we see from figure 21 that the primary effect on the public investment rate is positive, resulting in dynamic adjustment processes in the first 5 periods. Afterwards dynamic multiplier effects fade out rapidly.

On the contrary, the net LFA effect on private investment, employment growth and output is negative. While investment and employment effects fade out within the displayed time period ($n = 25$), the negative output adjustment process is observed to be of high persistence. This tendency can also be confirmed if we look at the disaggregated dynamic multiplier effects in figure 22 as well as the impact and long-run multiplier matrices in eq.(38) to eq.(40). The horizontal element of the LFA has a negative impact multiplier for all endogenous variables in the system (column 1 of the impact matrix in eq.(38)), which is the highest for public sector investment and employment growth. The long run effects after 10 years and 25 years (where most of the dynamic adjustment processes have been worked through the system) show

²⁴In figure 22 we skip the graphical presentation of the GRW since the latter only affects output.

that while the impact on employment growth is rather of a temporary manner, the long run impact on private investment is more persistent. Also, the negative long-run effect of an horizontal LFA increase on output and public sector investment rate are significantly higher than the initial impacts. According to the model specification there is almost no effect on changes of the horizontal LFA on human capital.

As discussed before the negative effect of the overall LFA transfer flows is partly offset by the positive short and long run impact of the vertical transfer payments on the endogenous variables (listed in column 2 of eq.(38) to eq.(40), as well as row 1 to 3 in figure 22). However, only for public sector investment shows a small positive net long run multiplier where the positive long run effect of vertical transfer payments offsets the negative long run impact of horizontal transfers. For output and the private sector investment the positive long run effects of vertical LFA transfers account only for about 15% to 40% of the negative horizontal transfer effect respectively. The long run impact of a change in active labour market transfer schemes is rather small with positive output and negative employment (growth) effects. However, as the dynamic multipliers in figure 22 show, the employment effects of ALMP changes rather fade out rapidly, while negative investment effects contrast positive output adjustment processes even for a longer time period (see row 3 in figure 22). The positive dynamic adjustment process of output with respect to ALMP fades out after around 25 periods (left graph in row 3 of figure 22).

To sum up, the most robust result is found with respect to the negative output effect of the LFA indicating that this transfer scheme is not an allocative policy instrument to foster the economic growth process in lagging regions, even though the vertical element has a positive stimulus on public sector investment. This confirms earlier empirical results, but also adds a new dimension to the discussion of the allocative effect of LFA transfers. The ALMP shows positive output effects but adverse effects for employment growth (even though the short run impact is positive) and investment rates, the GRW investment schemes do not show significant macro-regional effects on output or factor demand equations.

[Figure 21 and Figure 22 about here]

8 Conclusion

In this paper we have specified Dynamic Simultaneous Equation Error Models with panel data for the estimation of economic systems such our empirical application to the analyse of direct and indirect effects of regional equalization policy instruments on regional output (growth) and factor inputs. The aim of this paper was twofold: First, we tried put forward the methodological discussion about appropriate dynamic panel data estimators in the context of growth regressions with non-standard (large N , small T) panel data assumptions. Since frequently used dynamic models in 'first differences' have generally shown a poor empirical performance in these circumstances, we put a special emphasis on appropriate estimators which merely use levels of variables instead of first differences. We are doing so by using straightforward generalizations of familiar static panel data models with strictly exogenous variables based on the most commonly known Hausman-Taylor (1981) type estimator.

The rather new contribution of this paper to the field is to propose a Dynamic Simultaneous Equation Model with error-component structure as a synthesis of two separate subfields in panel econometrics: 1.) static simultaneous equation models for estimators with strictly exogenous variables on the one side, as

well as 2.)dynamic - but dominantly single equation - panel data (DPD) estimators on the other side. The combination of the two types of model elements allows to account both for potential endogeneity and cross-correlations among the residuals (system approach contribution) as well as for an appropriate handling of dynamic specifications and predetermined variables (DPD contribution). Basically, our modelling strategy is to search for appropriate orthogonality conditions (instrument sets) stemming from both subfield which can be combined for consistent and efficient system estimators. We have checked for the empirical performance somewhat new synthesis estimator we compare its performance to various competitors in the field including the Anderson & Hsiao (1981) IV, the Arellano & Bond (1991) GMM (both in first differences) and Blundell & Bond (1998) system GMM estimator - both on the grounds of a Monte Carlo simulation exercise as well as an empirical application. The Monte Carlo results thereby confirm the broad single equation evidence that (rather simple) IV estimators may be the better choice in non-standard panel data settings,

Taken together with the evidence from the empirical application, our analysis shows that the dynamic Hausman Taylor (HT) 3SLS system estimator is a consistent and efficient representation of the underlying system of output and factor demand equations for German NUTS1 regions. We thus rely on this model when discussing the various direct and indirect policy channels of regional equalization schemes which are often left unidentified in single equation estimations. To sum up, the most robust result is found with respect to the negative output effects of the horizontal LFA indicating that this transfer scheme is not an allocative policy instrument to foster the economic growth process in lagging regions, even though the vertical element has a positive stimulus on public sector investment. Calculating dynamic interim and long-run multipliers we could show that overall (net) LFA effect still remains negative. This result thus confirms recent findings in the empirical literature, but also adds a new dimension to the discussion of the allocative effect of (horizontal and vertical) LFA transfers. The active labour market policy (ALMP) shows positive output effects but adverse one for investment rates and employment growth, though the latter effects rapidly fade out as seen in the dynamic multiplier analysis. Finally, for the GRW investment promotion schemes do not find any significant macro-regional impact on the output equation or its factor inputs.

Future research effort should more carefully account for the following aspects: From a methodological point of view it has to be carefully analysed whether standard statistical inference is valid for the evaluation of the different estimators in the two-sided small panel setting or whether bootstrapped standard errors should be seen as a promising alternative (see e.g. Galiani & Gonzalez-Rocha, 2003, for a discussion in single equation settings). For the empirical application of an evaluation of regional equalization payments in a growth system for two of the three policy instruments analysed (namely ALMP and GRW) data on smaller regional units (NUTS2) are available. This data could be used in the outlined econometric model setup presented here to check for the robustness of the policy results, especially with respect to the GRW investment schemes.

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Figure 1: Monte Carlo simulation results for true $\alpha_2 = 0,8$ with $N = 100, T = 5, \xi = 1$

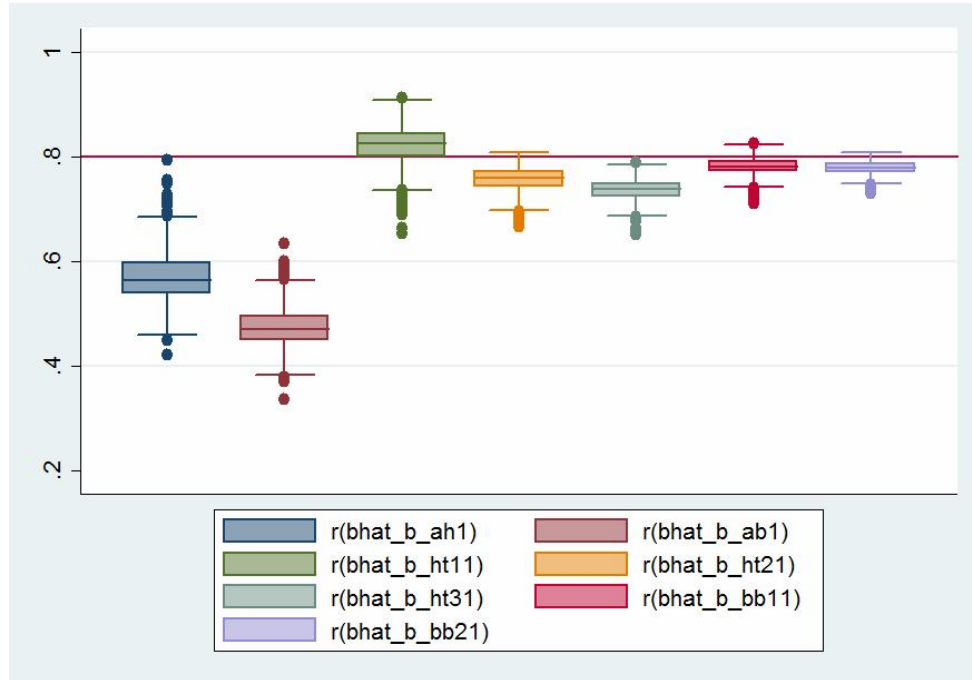


Figure 2: Monte Carlo simulation results for true $\alpha_2 = 0,8$ with $N = 100, T = 10, \xi = 1$

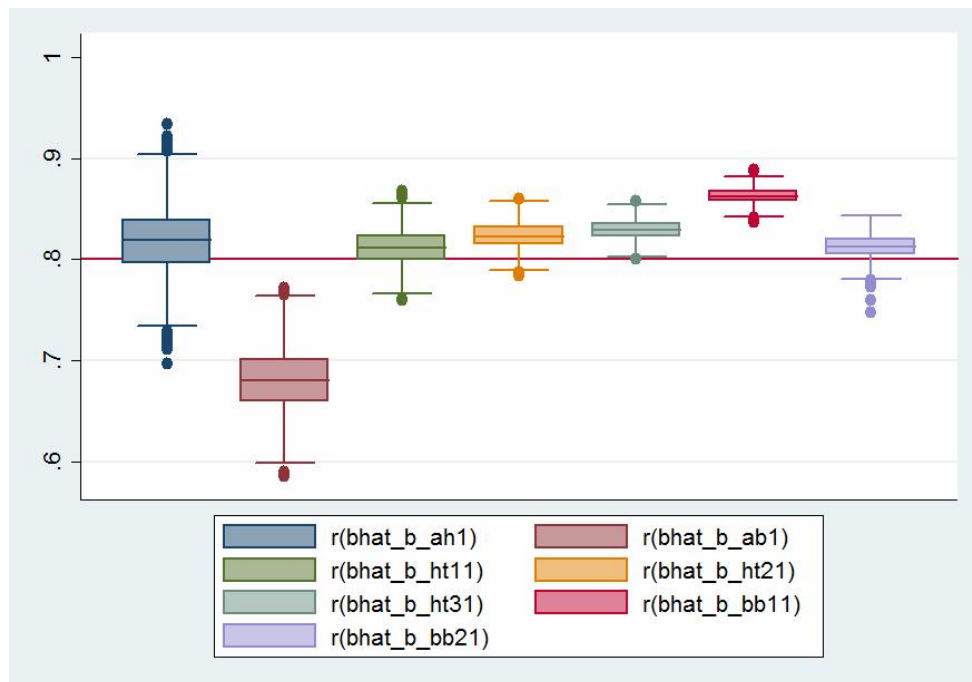


Figure 3: Monte Carlo simulation results for true $\alpha_2 = 0,8$ with $N = 25, T = 10, \xi = 1$

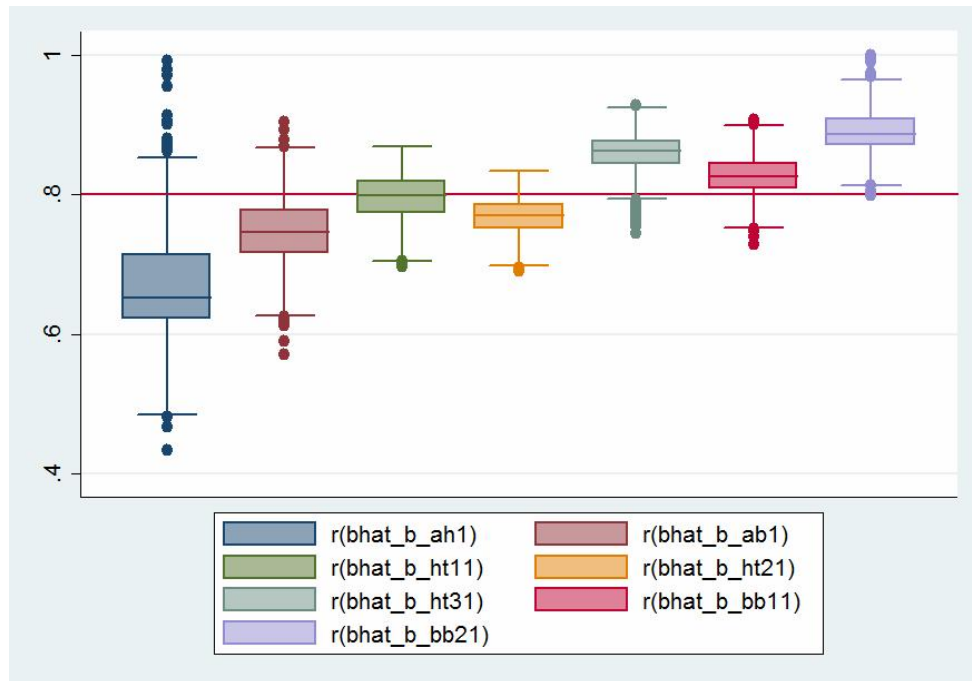


Figure 4: Monte Carlo simulation results for true $\alpha_2 = 0,8$ with $N = 25, T = 10, \xi = 4$

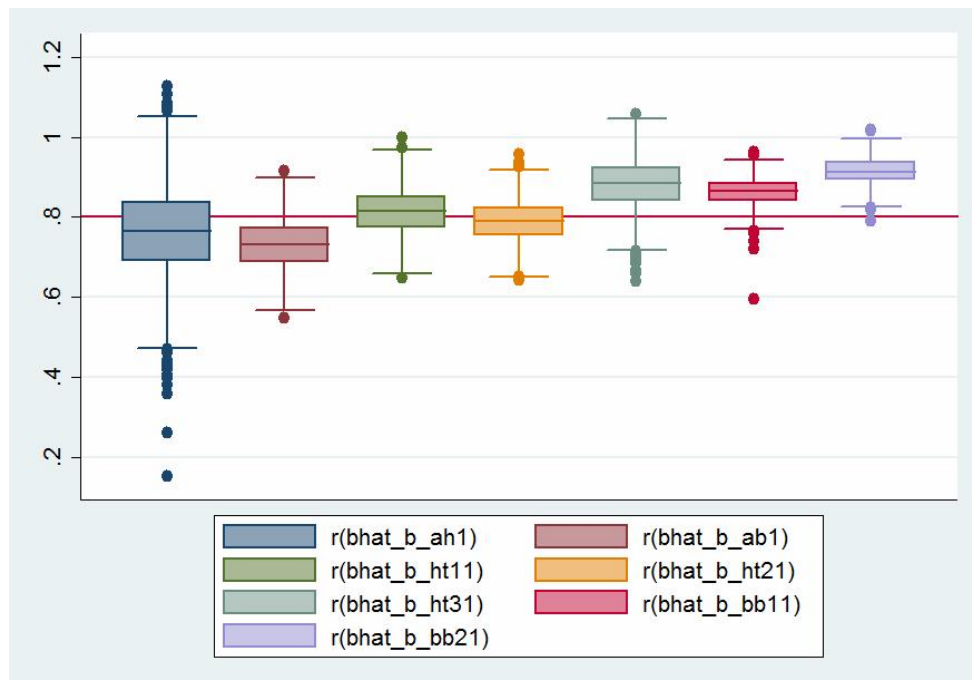


Figure 5: Monte Carlo simulation results for true $\alpha_2 = 0,8$ with $N = 25, T = 10, \xi = 0,5$

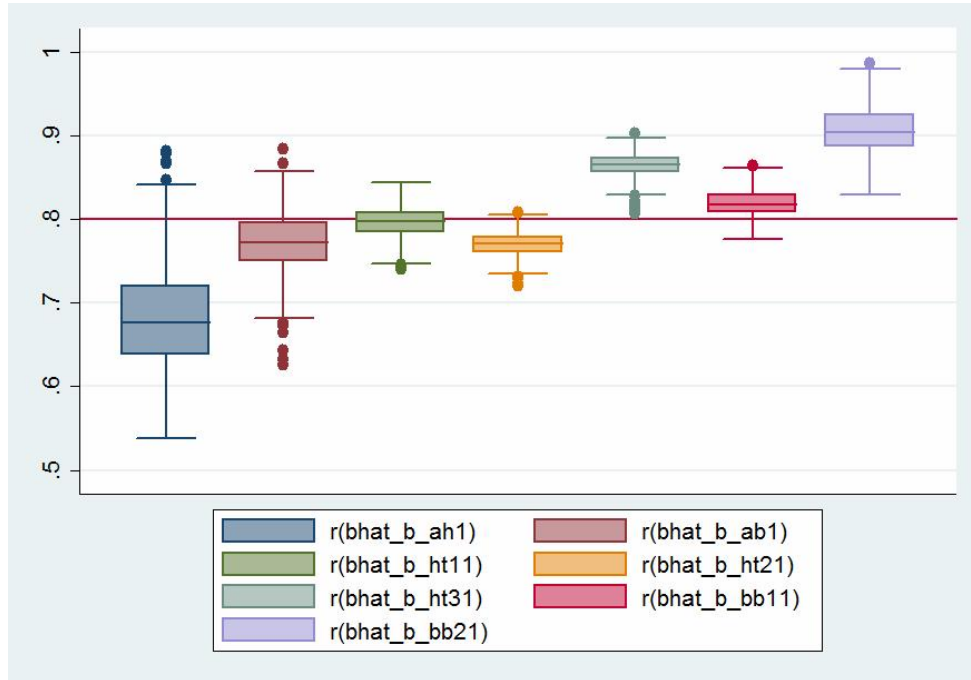


Figure 6: Monte Carlo simulation results for true $\alpha_2 = 0,5$ with $N = 25, T = 10, \xi = 1$

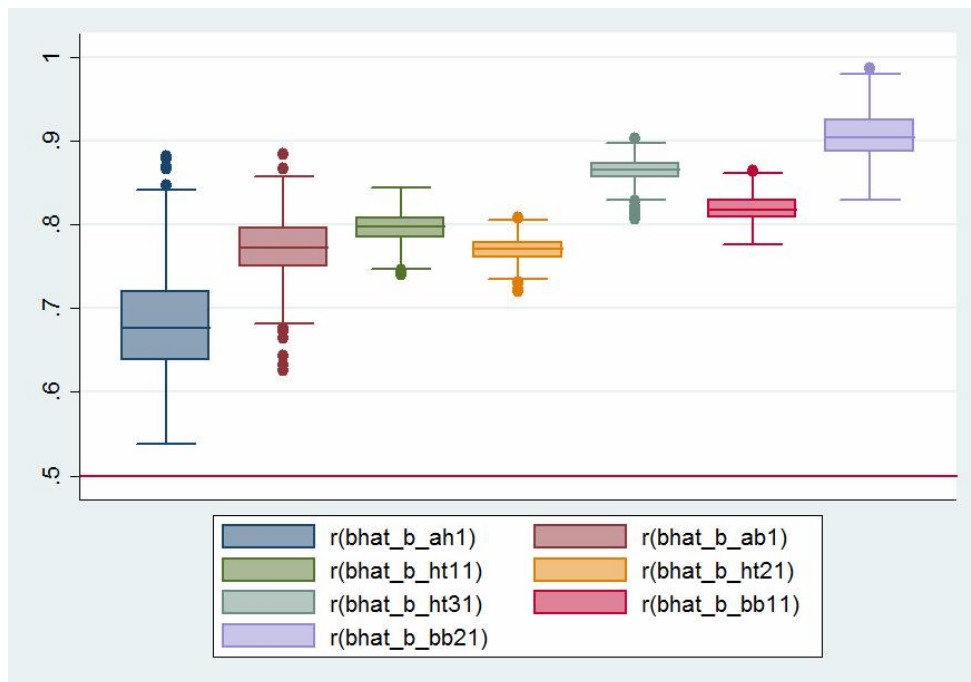


Figure 7: Monte Carlo simulation results for true $\alpha_2 = 0,5$ with $N = 25, T = 10, \xi = 0,5$

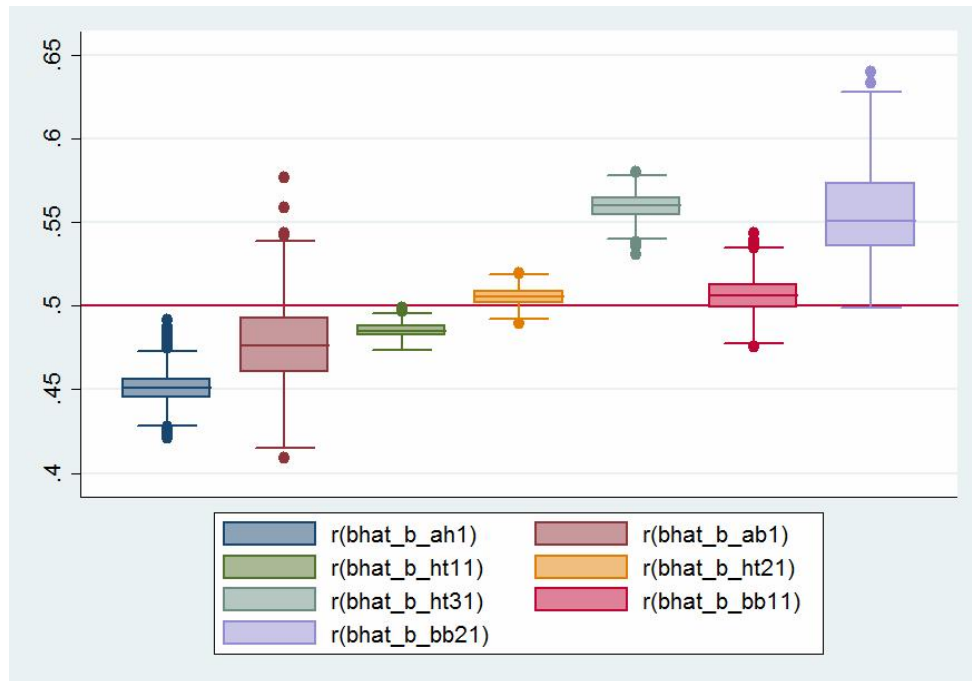


Figure 8: Monte Carlo simulation results for true $\alpha_2 = 0,5$ with $N = 25, T = 10, \xi = 4$

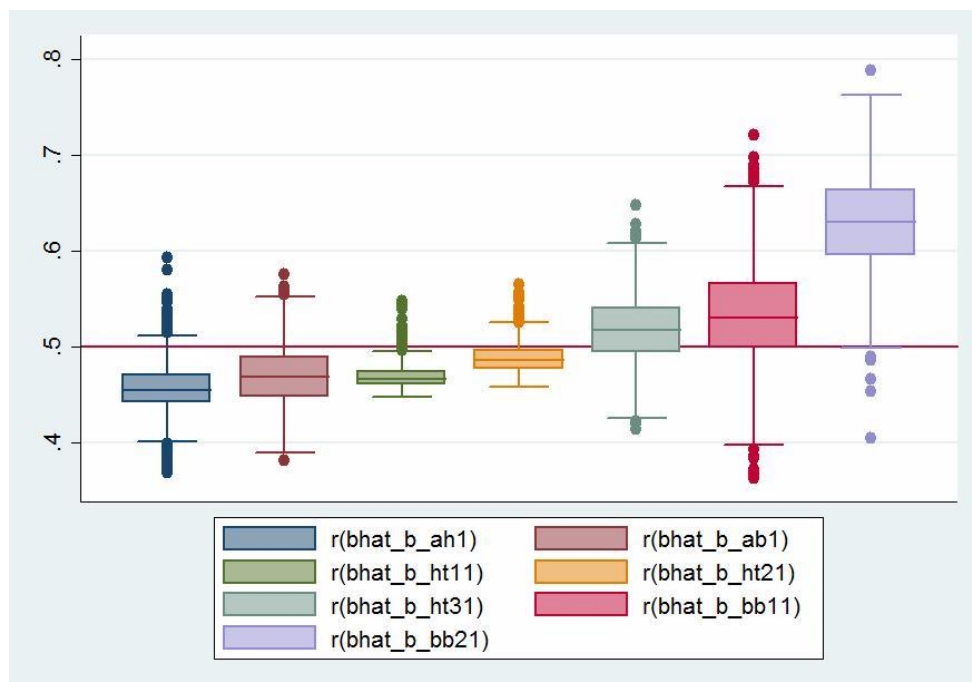


Figure 9: Monte Carlo simulation results for NORMSQD with $N = 100, T = 5, \xi = 1, \alpha_2 = 0,8$

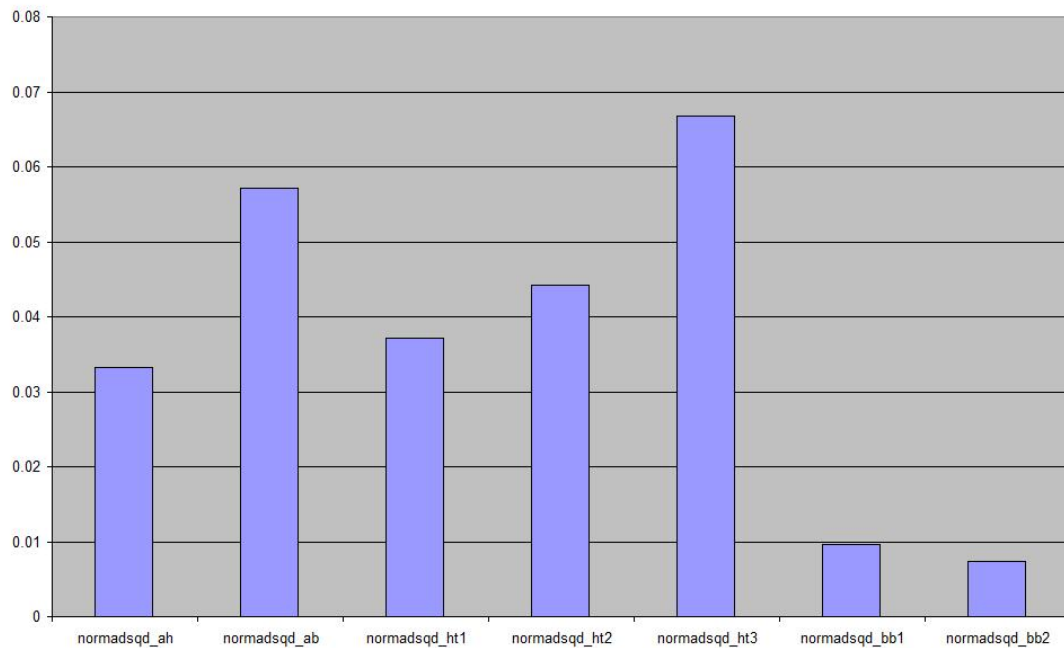


Figure 10: Monte Carlo simulation results for NORMSQD with $N = 100, T = 10, \xi = 1, \alpha_2 = 0,8$

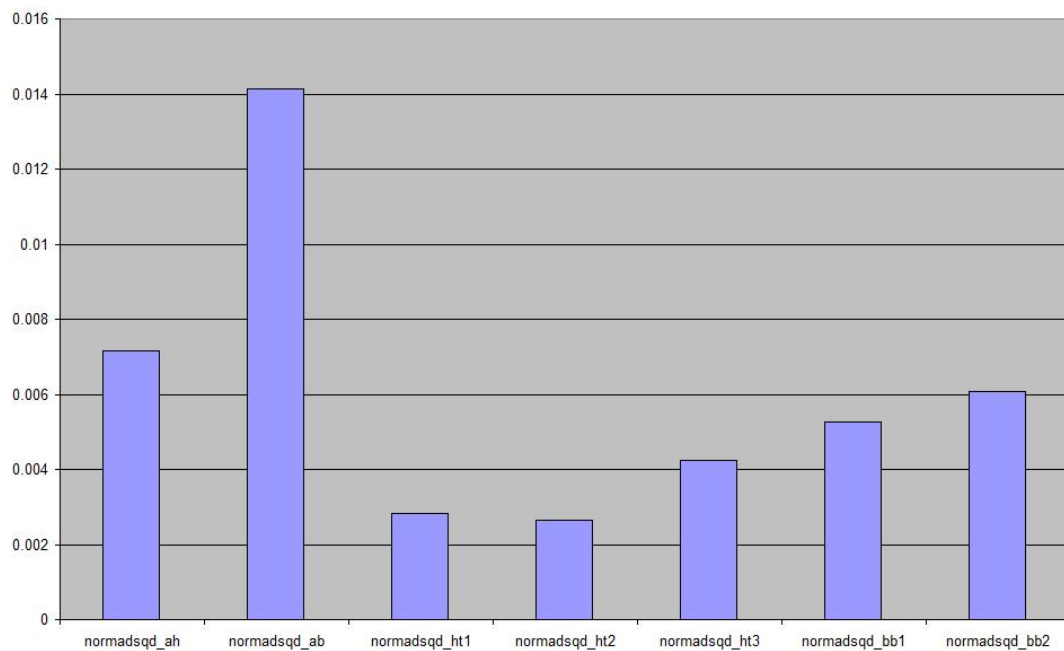


Figure 11: Monte Carlo simulation results for NORMSQD with
 $N = 25, T = 10, \xi = 1, \alpha_2 = 0, 8$

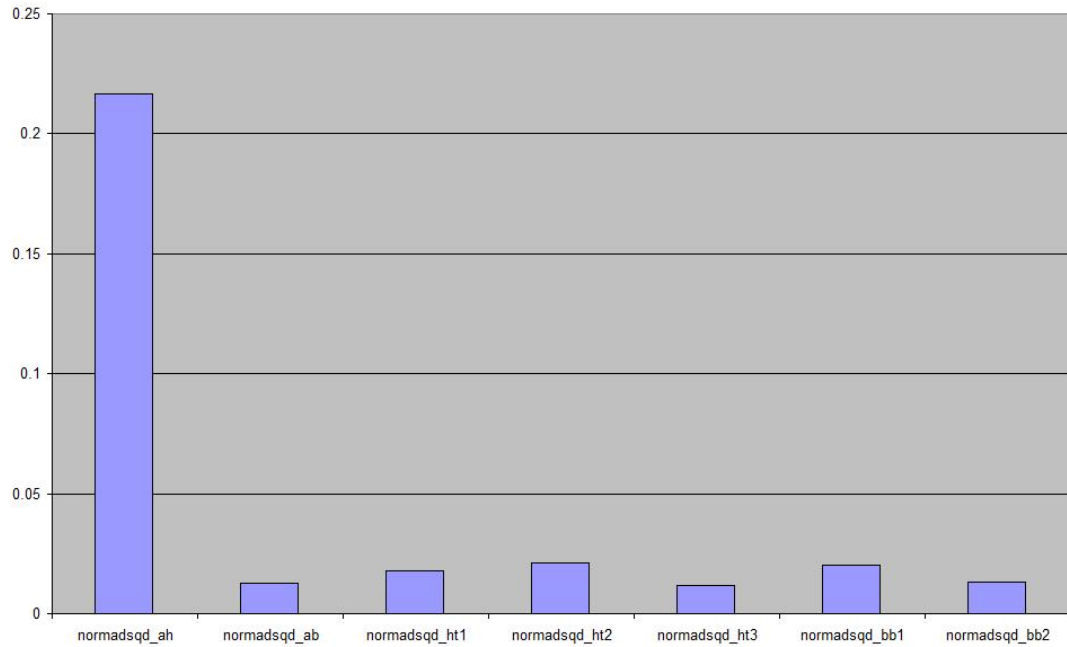


Figure 12: Monte Carlo simulation results for NORMSQD with
 $N = 25, T = 10, \xi = 4, \alpha_2 = 0, 8$

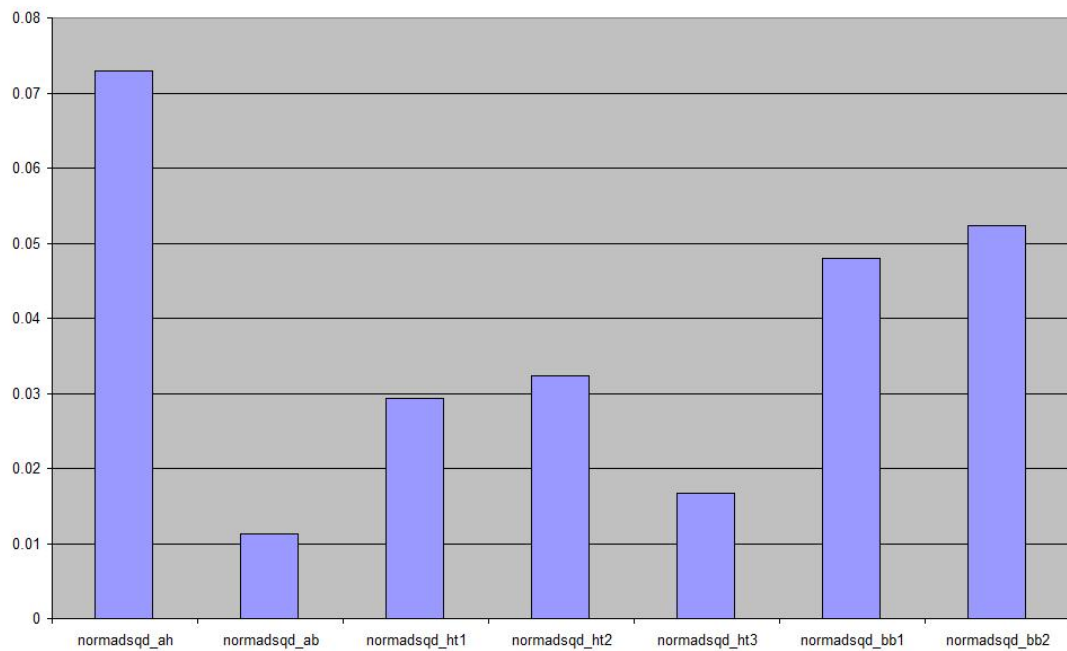


Figure 13: Monte Carlo simulation results for NORMSQD with
 $N = 25, T = 10, \xi = 1, \alpha_2 = 0, 5$

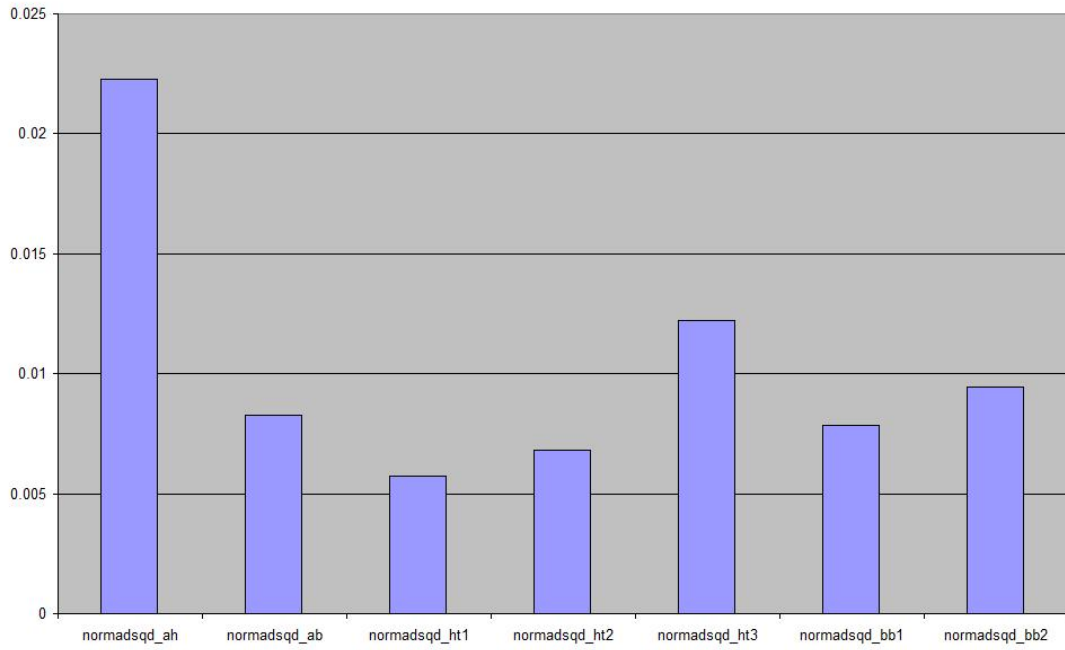


Figure 14: Monte Carlo simulation results for NORMSQD with
 $N = 25, T = 10, \xi = 0, 5, \alpha_2 = 0, 5$

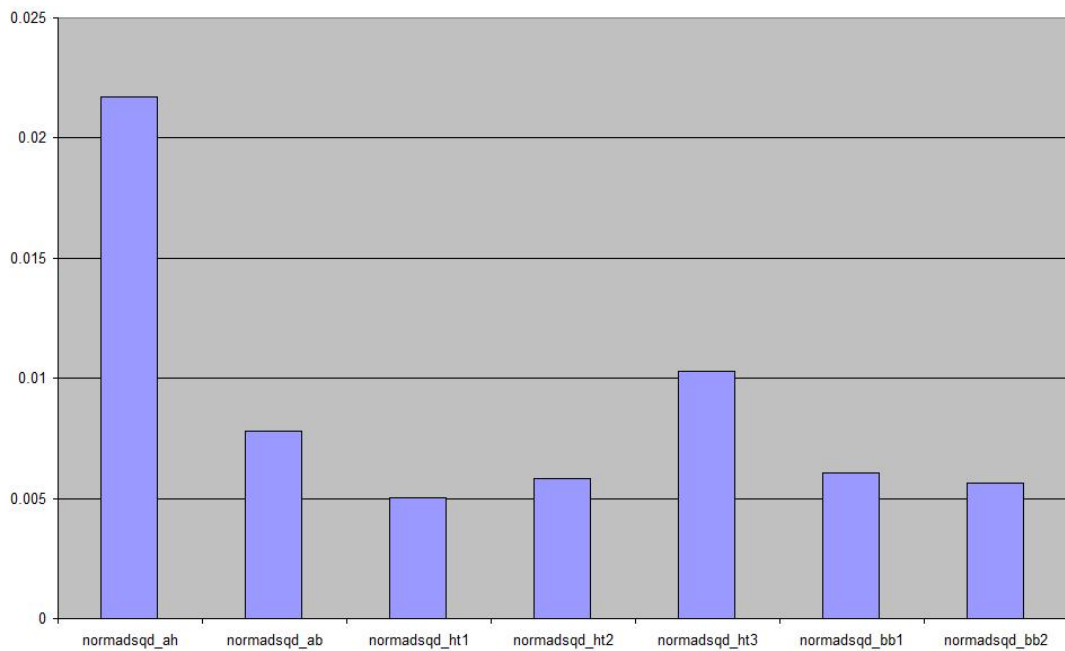


Figure 15: Monte Carlo simulation results for NORMSQD with $N = 25, T = 10, \xi = 4, \alpha_2 = 0, 5$

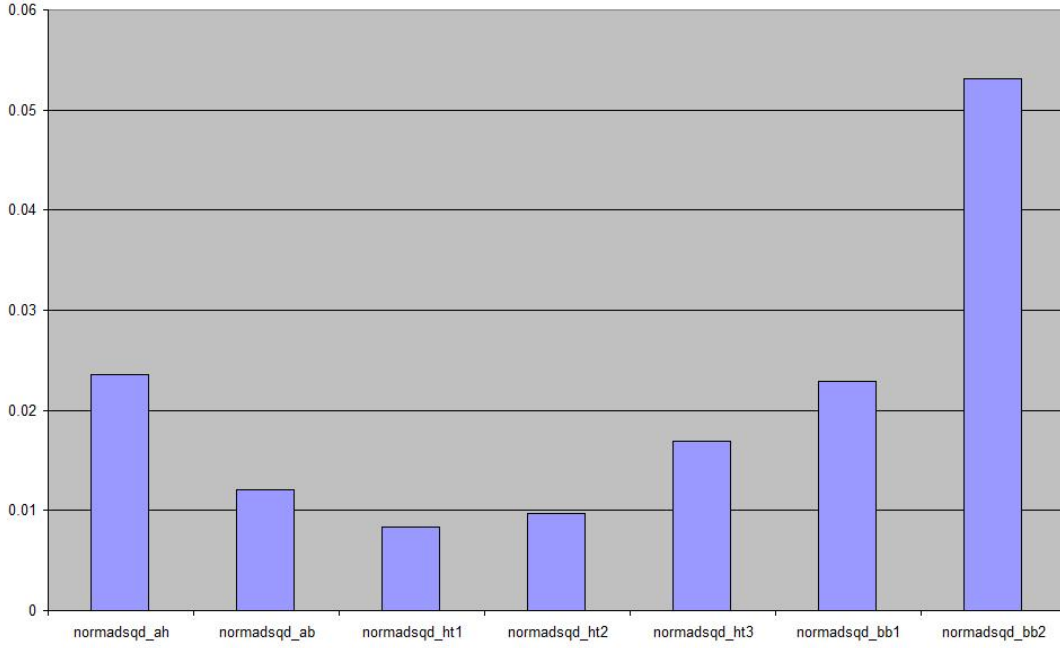


Figure 16: Results of (absolute) bias for $\alpha_2 = 0, 8$ with different N using $T = 10, \xi = 4$

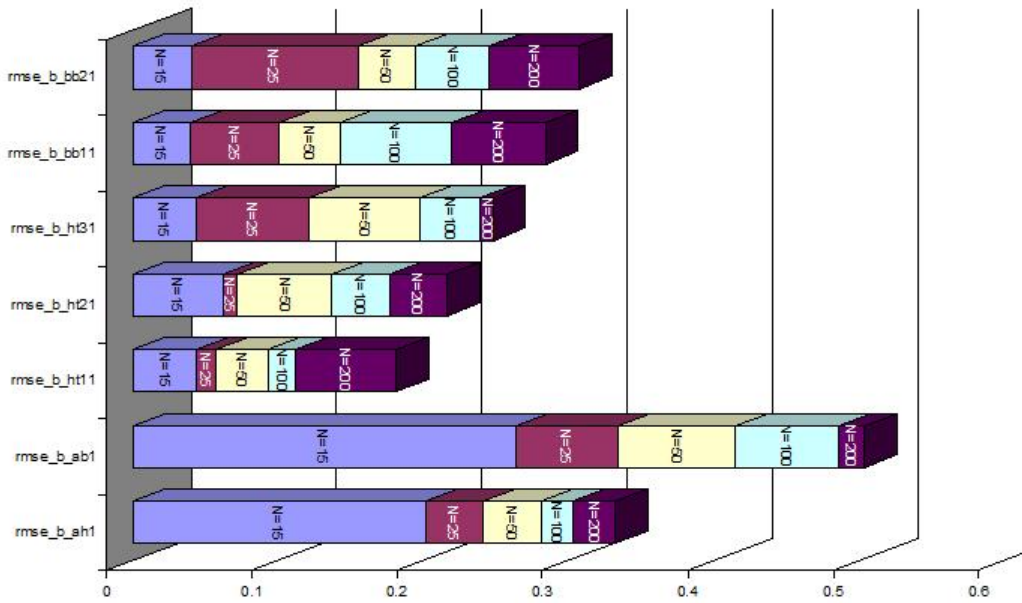


Figure 17: Results of RMSE for $\alpha_2 = 0,8$ with different N using $T = 10, \xi = 4$

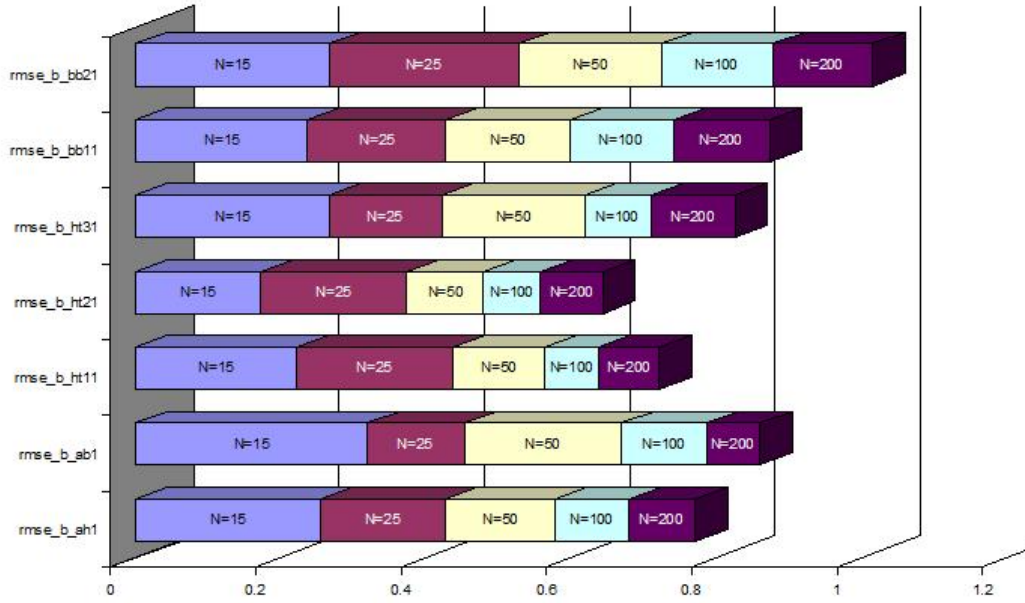


Figure 18: Results of NOMAD for different N using $T = 10, \xi = 4, \alpha_2 = 0,8$

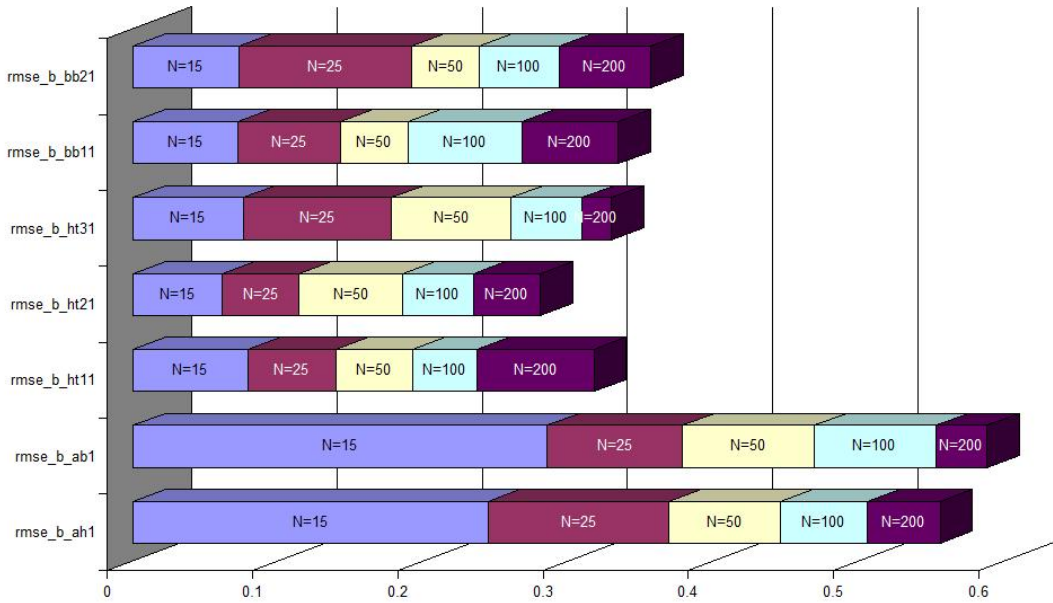


Figure 19: Results of NORMSQD for different N using $T = 10, \xi = 4, \alpha_2 = 0, 8$

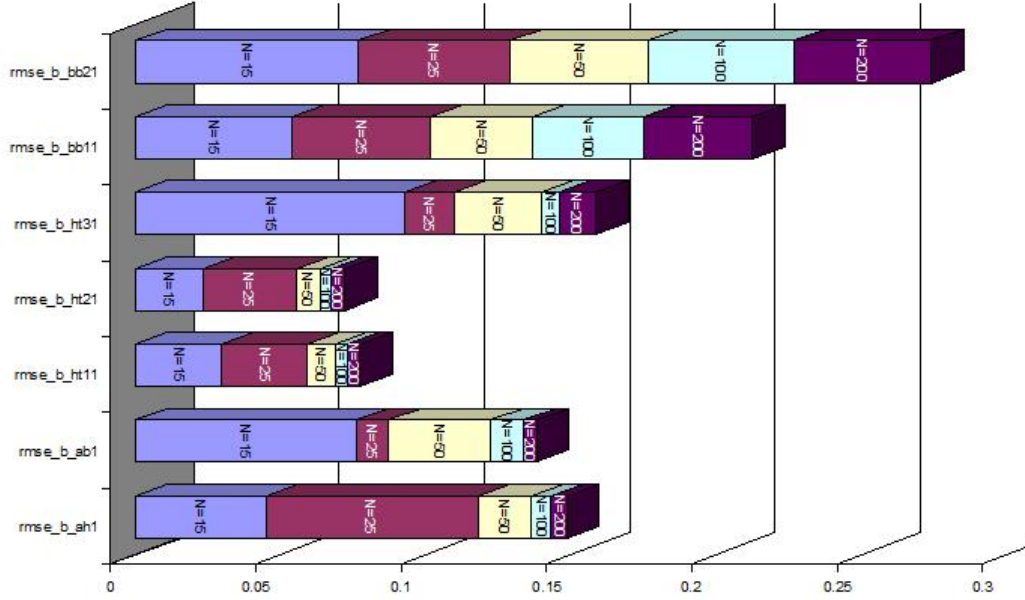


Figure 20: NOMAD comparison for limited and full information estimation with $N = 25, T = 10, \alpha_2 = 0, 8, \xi = 1$

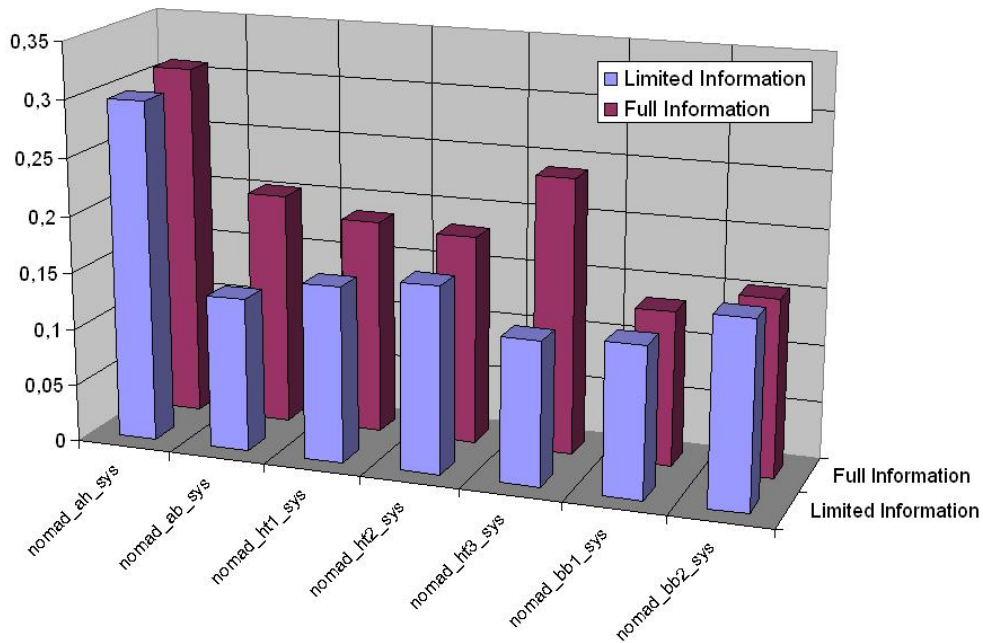


Table 1: Data description and source

Variable name	Description	Source
y_{it}	Output per employee, 1000 EUR, in real terms	VGRdL
inv_{it}	Private sector investment rate as ratio of GFCG relative to the regional capital stock (default) or GDP, in real terms	VGRdL
pub_{it}	Public sector investment rate as ratio of public investment relative to total regional government spendings, in real terms	SVR
$pubav_{it}$	Average of the public sector investment rate for all regions net of region i	Own calculation
hc_{it}	Human capital measure computed as a weighted composite indicator built up on the following ratios: 1.) high school graduates with university qualification per total population between 18-20 years ($hcschool$), 2.) number of university degrees per total population between 25-30 years ($hcuni$), 3.) share of employed persons with a university degree relative to total employment ($hcsvh$), 4.) number of patents per populations ($hcpat$); the following composite indicators have been tested: $hc1 = 0,50 \cdot hcsvh + 0,30 \cdot hcschool + 0,15 \cdot hcuni + 0,05 \cdot hcpat$ $hc2 = 0,33 \cdot hcsvh + 0,33 \cdot hcschool + 0,33 \cdot hcuni + 0,01 \cdot hcpat$ $hc3 = 0,35 \cdot hcsvh + 0,25 \cdot hcschool + 0,35 \cdot hcuni + 0,05 \cdot hcpat$ $hc4 = 0,35 \cdot hcsvh + 0,15 \cdot hcschool + 0,45 \cdot hcuni + 0,05 \cdot hcpat$ $hc5 = 0,30 \cdot hcsvh + 0,30 \cdot hcschool + 0,30 \cdot hcuni + 0,10 \cdot hcpat$ $hc6 = 0,20 \cdot hcsvh + 0,40 \cdot hcschool + 0,35 \cdot hcuni + 0,05 \cdot hcpat$ $hc7 = 0,25 \cdot hcsvh + 0,25 \cdot hcschool + 0,25 \cdot hcuni + 0,25 \cdot hcpat$	Statistisches Bundesamt (hc4 = default)
$(n + g + \delta)_{it}$	Employment growth plus constant (0,05)	VGRdL; own calculation
$unemp_{it}$	Unemployed persons	Statistisches Bundesamt
$Industryshare_{i,t}$	Share of industry sector GVA relative to total GVA	VGRdL
τ_{it}	Total regional tax volume (ex ante)	Statistisches Bundesamt
nmr_{it}	Net migration (in- minus outmigration) per population	Statistisches Bundesamt
pop_{it}	Population	VGRdL
$LFA[horizontal]_{it}$	Interstate redistribution transfer element per head, in real terms	Federal ministry of finance
$LFA[vertical]_{it}$	Federal redistribution transfer element per head, in real terms	Federal ministry of finance
$GRW[priv.Inv]_{it}$	Federal transfers to the private sector within GRW, in real terms	BAWA
$GRW[infra]_{it}$	Private sector related federal infrastructure spendings within GRW, in real terms	BAWA
$ALMP_{it}$	Active labour market spendings (ALMP) [#] per head of population, in real terms	Amtl. Nachrichten der BfA, various issues
East	(0,1)-Dummy for East Germany	Own calculation

Note: [#] = ALMP include no.5-14 (1993), no.5-15 (1994), no.5-17 (1995,1996,1997) all based on table III/1. no.1-32 (1998), no.1-34 (1999/2000), no.1-39 (2001,2002), no.1-46 (2003, 2004) all based on table VI/1.

Table 3: Estimation Results - Output equation

Dep. Var.: $\log(y_{i,t})$	First Differences			Levels			First Diff. & Levels	
	AH-2SLS	AB-GMM	HT-2SLS	HT2-2SLS	HT3-2SLS	BB1-GMM	BB2-GMM	
$\log(y_{i,t-1})$	0,65*** (0,119)	0,78*** (0,038)	0,93*** (0,039)	0,92*** (0,038)	0,93*** (0,034)	0,83*** (0,021)	0,87*** (0,019)	
$\log(inv_{i,t})$	-0,11* (0,058)	-0,03 (0,025)	-0,01 (0,016)	-0,01 (0,016)	0,01 (0,016)	0,01 (0,022)	0,01 (0,016)	
$\log(pub_{i,t})$	0,08 (0,077)	-0,002 (0,024)	0,02 (0,016)	0,02 (0,016)	0,02* (0,013)	0,01 (0,018)	0,02* (0,011)	
$hc_{i,t}$	2,41** (1,165)	0,76*** (0,036)	0,29* (0,168)	0,29* (0,168)	0,15 (0,100)	0,21 (0,155)	0,14 (0,114)	
$\log([n + g + \delta]_{i,t})$	0,07*** (0,024)	0,03** (0,011)	0,03* (0,014)	0,02* (0,013)	0,01 (0,014)	0,04*** (0,013)	0,03** (0,011)	
<i>East</i>			0,01 (0,023)	0,02 (0,023)	-0,04* (0,024)	-0,07*** (0,021)	-0,07*** (0,017)	
$LF A(horizontal)_{i,t}$	0,05 (0,049)	-0,06* (0,027)	-0,06*** (0,022)	-0,07*** (0,022)	-0,08*** (0,020)	-0,09*** (0,021)	-0,09*** (0,015)	
$LF A(vertical)_{i,t}$	-0,05 (0,057)	-0,02* (0,012)	0,01 (0,012)	0,01 (0,012)	0,03*** (0,009)	0,02 (0,013)	0,02 (0,012)	
$\log(GRW[priv.inv]_{i,t})$	-0,004* (0,002)	-0,003** (0,001)	-0,003* (0,001)	-0,003** (0,001)	-0,002 (0,001)	-0,003** (0,001)	-0,003** (0,001)	
$\log(GRW[in.fra]_{i,t})$	0,003* (0,001)	0,002* (0,001)	0,001 (0,001)	0,001 (0,001)	0,001 (0,001)	0,001 (0,001)	0,001 (0,001)	
$\log(ALMP_{i,t})$	-0,03 (0,026)	0,02 (0,016)	0,04* (0,021)	0,04* (0,021)	0,03* (0,019)	0,06** (0,021)	0,05*** (0,017)	
No. of obs.	160	160	160	160	160	160	160	
No. of groups	16	16	16	16	16	16	16	
No. of instruments	26	160	37	42	42	42	248	
$\sigma_{\mu}/\sigma_{\nu}$			0,58	0,62	0,06			
$\hat{\theta}$ (GLS correction)			0,62	0,63	0,21			
Pagan-Hall heteroskedast. test	$\chi^2(26) = 13,04$ (p=0,98)		$\chi^2(47) = 34,48$ (p=0,91)	$\chi^2(52) = 39,85$ (p=0,89)	$\chi^2(52) = 39,05$ (p=0,91)			
Arellano-Bond autocorrel. test	1,11 (p=0,26)	-0,03 (p=0,97)	0,00 (p=0,99)	0,05 (p=0,95)	0,47 (p=0,63)	-0,75 (p=0,45)	-0,53 (p=0,60)	
Anderson canon. corr. statistic	$\chi^2(16) = 12,01$ (p=0,74)		$\chi^2(27) = 88,70$ (p=0,00)	$\chi^2(32) = 100,19$ (p=0,00)	$\chi^2(32) = 68,48$ (p=0,00)			
C-Statistic ('diff-in-Sargan')			$\chi^2(5) = 1,85$ (p=0,87)	$\chi^2(5) = 4,77$ (p=0,44)	$\chi^2(5) = 33,07$ (p=0,00)	$\chi^2(94) = 73,91$ (p=0,93)		
RMSE	0,0319	0,0343	0,0189	0,0189	0,0193	0,0212	0,0202	

Note: ***, **, * = denote significance levels at the 1%, 5% and 10% level respectively.

Table 4: Estimation Results - Investment equation

Dep. Var.: $\log(inv_{i,t})$	First Differences			Levels			First Diff. & Levels	
	AH-2SLS	AB-GMM	HT-2SLS	HT2-2SLS	HT3-2SLS	BB1-GMM	BB2-GMM	
$\log(inv_{i,t-1})$	0,69*** (0,174)	0,69*** (0,075)	0,89*** (0,057)	0,86*** (0,053)	0,85*** (0,059)	0,87*** (0,058)	0,84*** (0,046)	
$\log(pub_{i,t})$	0,10 (0,199)	0,28*** (0,073)	0,12** (0,059)	0,12** (0,059)	0,14** (0,064)	0,15** (0,056)	0,13** (0,048)	
$\log(hc_{i,t})$	-1,08 (2,270)	1,26 (0,911)	0,82 (0,057)	1,25** (0,607)	0,37 (0,636)	-0,23 (0,618)	0,19 (0,430)	
$\log(unemp_{i,t})$	-0,09 (0,129)	-0,18 (0,126)	-0,03 (0,025)	-0,05* (0,025)	0,03 (0,026)	-0,01 (0,023)	-0,02 (0,019)	
$Industryshare_{i,t}$	-0,40 (1,203)	-2,24** (0,916)	-0,35 (0,341)	-0,36 (0,352)	-0,26 (0,374)	-0,08 (0,224)	0,03 (0,242)	
$\log(\tau_{i,t})$	0,31* (0,166)	0,32*** (0,093)	0,19** (0,095)	0,18* (0,096)	0,22** (0,102)	0,20*** (0,054)	0,18*** (0,052)	
$LFA(horizontal)_{i,t}$	0,14 (0,137)	-0,11 (0,104)	-0,09 (0,057)	-0,10* (0,059)	-0,06 (0,062)	-0,07* (0,037)	-0,08*** (0,028)	
$LFA(vertical)_{i,t}$	-0,09 (0,153)	0,02 (0,056)	0,08 (0,054)	0,05 (0,053)	0,03 (0,057)	0,03 (0,053)	-0,01 (0,057)	
$\log(GRW[priv.inv]_{i,t})$	-0,008 (0,007)	0,007 (0,007)	-0,001 (0,005)	0,001 (0,005)	-0,003 (0,005)	-0,001 (0,004)	0,002 (0,003)	
$\log(GRW[in.fra]_{i,t})$	-0,001 (0,004)	0,004 (0,003)	0,003 (0,004)	0,004 (0,004)	0,004 (0,005)	0,001 (0,004)	0,001 (0,003)	
$\log(ALMP_{i,t})$	0,04 (0,067)	0,002 (0,070)	-0,06 (0,066)	-0,04 (0,064)	-0,03 (0,070)	0,03 (0,056)	0,07 (0,061)	
No. of obs.	160	160	160	160	160	160	160	
No. of groups	16	16	16	16	16	16	16	
No. of instruments	26	160	37	42	42	42	205	
$\sigma_{\mu}/\sigma_{\nu}$			0,34	0,41	0,30			
$\hat{\theta}$ (GLS correction)			0,52	0,56	0,50			
Pagan-Hall heteroskedast. test	$\chi^2(26) = 28,26$ (p=0,35)		$\chi^2(47) = 52,59$ (p=0,27)	$\chi^2(52) = 57,03$ (p=0,29)	$\chi^2(52) = 59,05$ (p=0,23)			
Arellano-Bond autocorrel. test	0,45 (p=0,65)	0,37 (p=0,71)	-1,72 (p=0,09)	-1,70 (p=0,09)	-1,30 (p=0,19)	0,22 (p=0,82)	0,21 (p=0,83)	
Anderson canon. corr. statistic	$\chi^2(16) = 19,15$ (p=0,26)		$\chi^2(27) = 95,97$ (p=0,00)	$\chi^2(32) = 109,36$ (p=0,00)	$\chi^2(32) = 90,72$ (p=0,00)			
C-Statistic ('diff-in-Sargan')				$\chi^2(5) = 8,821$ (p=0,12)	$\chi^2(5) = 6,877$ (p=0,23)	$\chi^2(5) = 47,49$ (p=0,00)	$\chi^2(45) = 53,23$ (p=0,18)	
RMSE	0,0939	0,1675	0,0670	0,0664	0,0674	0,0697	0,0694	

Note: ***, **, * = denote significance levels at the 1%, 5% and 10% level respectively.

Table 5: Estimation Results - Public investment equation

Dep. Var.: $\log(pub_{i,t})$	First Differences			Levels			First Diff. & Levels	
	AH-2SLS	AB-GMM	HT-2SLS	HT-2SLS	HT2-2SLS	HT3-2SLS	BB1-GMM	BB2-GMM
$\log(pub_{i,t-1})$	0,30 (0,197)	0,56*** (0,140)	0,88*** (0,054)	0,86*** (0,055)	0,75*** (0,063)	0,81*** (0,098)	0,90*** (0,066)	
$\log([n + g + \delta]_{i,t})$	-0,03 (0,058)	0,09** (0,039)	0,15*** (0,053)	0,15*** (0,050)	0,12** (0,053)	0,08 (0,055)	0,09** (0,037)	
$\log(hc_{i,t})$	-0,24 (3,738)	-1,83* (0,914)	-0,55 (0,572)	-0,72 (0,599)	-0,41 (0,664)	0,87 (0,842)	0,18 (0,249)	
$\log(y_{i,t-1})$	0,20 (0,242)	-0,03 (0,109)	0,31** (0,142)	0,35** (0,146)	0,23 (0,191)	-0,15 (0,094)	-0,01 (0,060)	
$\log(invi_{i,t-1})$	0,39** (0,165)	0,26*** (0,077)	0,11** (0,054)	0,12** (0,052)	0,16*** (0,058)	0,07 (0,063)	0,06 (0,041)	
$Industryshare_{i,t}$	1,77 (1,287)	2,17** (0,891)	0,26 (0,311)	0,32 (0,323)	0,30 (0,39)	0,06 (0,264)	0,07 (0,162)	
$LFA[horizontal]_{i,t}$	-0,20 (0,153)	0,008 (0,066)	0,01 (0,067)	0,03 (0,070)	0,007 (0,083)	-0,03 (0,045)	-0,03 (0,025)	
$LFA[vertical]_{i,t}$	-0,09 (0,191)	0,05 (0,032)	0,09** (0,039)	0,09** (0,039)	0,09** (0,045)	0,08*** (0,018)	0,07** (0,027)	
$\log(GRW[in,frac]_{i,t})$	-0,002 (0,005)	0,001 (0,004)	0,001 (0,004)	0,001 (0,004)	0,002 (0,005)	-0,0004 (0,003)	0,001 (0,002)	
No. of obs.	160	160	160	160	160	160	160	
No. of groups	16	16	16	16	16	16	16	
No. of instruments	25	156	37	42	42	42	201	
$\sigma_{\mu}/\sigma_{\nu}$			0,22	0,29	0,41			
$\hat{\theta}$ (GLS correction)			0,44	0,49	0,56			
Pagan-Hall heteroskedast. test	$\chi^2(25) = 22,53$ (p=0,60)		$\chi^2(47) = 55,72$ (p=0,18)	$\chi^2(51) = 56,20$ (p=0,29)	$\chi^2(52) = 53,628$ (p=0,41)			
Arellano-Bond autocorrel. test	0,43 (p=0,67)	1,30 (p=0,19)	-4,20 (p=0,00)	-4,10 (p=0,00)	-3,65 (p=0,00)	0,29 (p=0,78)	0,35 (p=0,73)	
Anderson canon. corr. statistic	$\chi^2(17) = 22,53$ (p=0,26)		$\chi^2(29) = 95,25$ (p=0,00)	$\chi^2(33) = 102,08$ (p=0,00)	$\chi^2(34) = 60,16$ (p=0,00)			
C-Statistic ('diff-in-Sargan')				$\chi^2(5) = 0,68$ (p=0,98)	$\chi^2(5) = 10,09$ (p=0,07)	$\chi^2(5) = 32,19$ (p=0,00)	$\chi^2(41) = 31,67$ (p=0,85)	
RMSE	0,1112	0,1423	0,0824	0,0819	0,08074	0,0863	0,0845	

Note: ***, **, * = denote significance levels at the 1%, 5% and 10% level respectively.

Table 6: Estimation Results - Employment growth equation

Dep. Var.: $\log([n + g + \delta]_{i,t})$	First Differences			Levels			First Diff. & Levels	
	AH-2SLS	AB-GMM	HT-2SLS	HT2-2SLS	HT3-2SLS	BB1-GMM	BB2-GMM	
$\log([n + g + \delta]_{i,t-1})$	0,09 (0,113)	-0,03 (0,045)	0,56*** (0,139)	0,50*** (0,096)	0,34*** (0,112)	0,23** (0,095)	0,10* (0,053)	
$\log(inv_{i,t})$	2,05*** (0,535)	0,83*** (0,169)	0,64** (0,273)	0,50** (0,246)	0,43 (0,272)	1,25*** (0,374)	0,59*** (0,179)	
$\log(hc_{i,t})$	1,16 (6,974)	0,17 (1,265)	0,31 (0,624)	0,31 (0,655)	-0,07 (0,816)	-0,58 (0,694)	-0,30 (0,348)	
$\log(inv_{i,t-1})$	-1,70*** (0,521)	-0,58*** (0,174)	-0,77*** (0,283)	-0,55** (0,231)	-0,20 (0,231)	-1,01*** (0,339)	-0,36* (0,193)	
$\log(pub_{i,t-1})$	-0,31 (0,446)	-0,11 (0,124)	-0,07 (0,082)	-0,10 (0,084)	-0,14 (0,094)	-0,05 (0,116)	-0,03 (0,067)	
$\log(\Delta unemp_{i,t})$	-1,37*** (0,340)	-2,27*** (0,244)	-1,96*** (0,366)	-2,83*** (0,322)	-2,72*** (0,473)	-2,10*** (0,396)	-2,56*** (0,397)	
$nmr_{i,t}$	0,66 (9,804)	10,36 (8,346)	6,47 (4,679)	5,06 (4,346)	4,82 (4,495)	7,08 (6,056)	13,14 (6,057)	
$Industryshare_{i,t}$	0,09 (2,911)	-1,65** (0,737)	-0,08 (0,421)	-0,20 (0,438)	-0,40 (0,606)	0,68** (0,256)	0,40 (0,259)	
East			0,22* (0,135)	0,26** (0,132)	0,25 (0,169)	-0,05 (0,197)	-0,06 (0,097)	
$LFA[horizontal]_{i,t}$	-0,35 (0,333)	0,25* (0,121)	0,10 (0,119)	0,14 (0,118)	0,21 (0,170)	0,05 (0,143)	0,06 (0,085)	
$LFA[vertical]_{i,t}$	0,22 (0,383)	-0,13 (0,09)	-0,06 (0,064)	-0,03 (0,063)	0,03 (0,073)	-0,09 (0,057)	-0,06 (0,052)	
$\log(GRW[priv.inv.]_{i,t})$	0,02 (0,017)	0,02** (0,009)	0,004 (0,007)	0,004 (0,007)	0,003 (0,008)	0,007 (0,007)	0,007 (0,005)	
$\log(GRW[in.fra.]_{i,t})$	0,02 (0,011)	0,009 (0,013)	0,002 (0,006)	0,003 (0,006)	0,014** (0,007)	0,003 (0,009)	-0,0004 (0,007)	
$\log(ALMP_{i,t})$	-0,02 (0,171)	-0,19* (0,095)	0,39 (0,262)	0,35* (0,213)	0,05 (0,214)	0,07 (0,282)	-0,07 (0,238)	
$\log(ALMP_{i,t-1})$	0,12 (0,154)	0,08 (0,087)	-0,46** (0,233)	-0,49** (0,202)	-0,41* (0,211)	-0,12 (0,281)	-0,03 (0,245)	
No. obs. (groups) [instruments]	160 (16) [28]	160 (16) [160]	160 (16) [37]	160 (16) [42]	160 (16) [42]	160 (16) [42]	160 (16) [205]	
σ_μ/σ_ν ($GLScorr., \hat{\theta}$)			0,08 (0,25)	0,13 (0,34)	0,33 (0,52)			
Pagan-Hall heteroskedast. test	$\chi^2(28) = 9,28$ (p=0,99)		$\chi^2(47) = 38,97$ (p=0,79)	$\chi^2(51) = 45,51$ (p=0,69)	$\chi^2(51) = 44,16$ (p=0,74)			
Arellano-Bond autocorrel. test	0,36 (p=0,72)	-1,72 (p=0,09)	-1,60 (p=0,11)	-2,50 (p=0,01)	0,07 (p=0,94)	-1,51 (p=0,13)	-2,54 (p=0,01)	
Anderson canon. corr. statistic	$\chi^2(15) = 19,44$ (p=0,19)		$\chi^2(23) = 35,79$ (p=0,04)	$\chi^2(27) = 50,77$ (p=0,00)	$\chi^2(27) = 29,94$ (p=0,32)			
C-Statistics ('diff-in-Sargan')				$\chi^2(5) = 8,76$ (p=0,11)	$\chi^2(5) = 4,62$ (p=0,46)	$\chi^2(5) = 28,64$ (p=0,00)	$\chi^2(45) = 107,65$ (p=0,00)	
RMSE	0,2255	0,2313	0,1126	0,1091	0,1046	0,1237	0,1111	

Note: ***, **, * = denote significance levels at the 1%, 5% and 10% level respectively.

Table 7: Estimation Results - Human capital equation

Dep. Var.: $hc_{i,t}$	First Differences			Levels			First Diff. & Levels	
	AH-2SLS	AB-GMM	HT-2SLS	HT2-2SLS	HT3-2SLS	BB1-GMM	BB2-GMM	
$\log(hc_{i,t-1})$	0,24* (0,141)	0,58*** (0,083)	0,98*** (0,365)	0,95*** (0,037)	0,99*** (0,040)	0,98*** (0,028)	0,96*** (0,026)	
$\log(y_{i,t})$	0,02*** (0,023)	0,04** (0,006)	-0,0004 (0,005)	0,001 (0,009)	-0,02 (0,114)	-0,006 (0,007)	-0,0003 (0,004)	
$\log(\Delta inv_{i,t})$	0,005 (0,011)	0,007 (0,007)	0,02* (0,123)	0,02* (0,011)	0,016 (0,011)	-0,01 (0,014)	0,005 (0,009)	
$\log(\Delta nmv_{i,t})$	-0,50 (0,333)	0,22 (0,355)	0,32 (0,375)	0,32 (0,372)	0,25 (0,406)	-0,34 (0,324)	-0,39 (0,366)	
$\log(\Delta pop_{i,t})$	1,40*** (0,404)	0,37 (0,248)	-0,22 (0,410)	-0,20 (0,407)	-0,12 (0,450)	0,58* (0,325)	0,48 (0,365)	
$LFA(horizontal)_{i,t}$	-0,002 (0,003)	-0,01** (0,005)	-0,0005 (0,006)	-0,002 (0,006)	-0,01 (0,007)	-0,01* (0,003)	-0,007** (0,003)	
$LFA(vertical)_{i,t}$	-0,0002 (0,002)	0,002 (0,003)	0,002 (0,003)	0,002 (0,003)	0,003 (0,003)	0,004** (0,002)	0,002* (0,001)	
$\log(ALMP_{i,t})$	0,01*** (0,004)	0,01*** (0,004)	-0,01 (0,009)	-0,01 (0,008)	-0,01 (0,009)	-0,01* (0,006)	-0,01** (0,006)	
$\log(ALMP_{i,t-1})$	-0,004 (0,004)	-0,006** (0,003)	0,005 (0,008)	0,006 (0,008)	0,009 (0,008)	0,01* (0,006)	0,02** (0,006)	
No. of obs.	160	160	160	160	160	160	160	
No. of groups	16	16	16	16	16	16	16	
No. of instruments	30	160	37	42	42	42	209	
$\sigma_{\mu}/\sigma_{\nu}$			0,20	0,24	0,22			
$\hat{\theta}$ (GLS correction)			0,42	0,46	0,44			
Pagan-Hall heteroskedast. test	$\chi^2(30) = 18,56$ (p=0,95)		$\chi^2(47) = 49,72$ (p=0,37)	$\chi^2(51) = 55,06$ (p=0,32)	$\chi^2(51) = 51,58$ (p=0,45)			
Arellano-Bond autocorrel. test	0,47 (p=0,64)	0,59 (p=0,55)	-3,56 (p=0,00)	-3,88 (p=0,00)	-3,41 (p=0,00)	0,14 (p=0,88)	0,36 (p=0,72)	
Anderson canon. corr. statistic	$\chi^2(21) = 26,98$ (p=0,17)		$\chi^2(27) = 46,44$ (p=0,01)	$\chi^2(31) = 59,88$ (p=0,00)	$\chi^2(31) = 60,51$ (p=0,00)			
C-Statistic ('diff-in-Sargan')			$\chi^2(5) = 30,34$ (p=0,00)	$\chi^2(5) = 30,34$ (p=0,00)	$\chi^2(5) = 26,56$ (p=0,00)	$\chi^2(5) = 8,97$ (p=0,11)	$\chi^2(49) = 31,7$ (p=0,97)	
RMSE	0,0064	0,1119	0,0057	0,0056	0,0057	0,0059	0,0058	

Note: ***, **, * = denote significance levels at the 1%, 5% and 10% level respectively.

Table 8: Estimation Results for the dynamic HT2-3SLS model

Dep. Var.:	$\log(y_{i,t})$	$\log(inv_{i,t})$	$\log(pub_{i,t})$	$\log[n + g + \delta]_{i,t}$	$hc_{i,t}$
$\log(y_{i,t})$					-0,01 (0,009)
$\log(y_{i,t-1})$	0,95*** (0,029)		0,07 (0,119)		
$\log(inv_{i,t})$	-0,002 (0,014)			0,81*** (0,241)	
$\log(inv_{i,t-1})$		0,82*** (0,054)	0,09** (0,049)	-0,83*** (0,222)	
$\log(\Delta inv_{i,t})$					0,03*** (0,009)
$\log(pub_{i,t})$	0,03** (0,013)	0,21*** (0,062)			
$\log(pub_{i,t-1})$			0,86*** (0,053)	-0,14 (0,097)	0,004 (0,004)
$\log([n + g + \delta]_{i,t})$	0,02		0,13*** (0,047)		
$\log([n + g + \delta]_{i,t-1})$				0,59*** (0,099)	
$hc_{i,t}$	0,06 (0,098)	1,37** (0,645)	-0,16 (0,522)	-0,12 (0,845)	
$hc_{i,t-1}$					0,92*** (0,039)
$\log(unemp_{i,t})$		-0,02 (0,026)			
$\log(\Delta unemp_{i,t})$				-1,94*** (0,315)	
$\log(\Delta pop_{i,t})$					-0,19 (0,398)
$\log(nmr_{i,t})$				3,94 (4,587)	0,26 (0,363)
$\log(\tau_{i,t})$		0,06 (0,106)			
$Industryshare_{i,t}$		-0,58* (0,338)	0,29 (0,268)	0,06 (0,516)	
$East$	-0,03 (0,022)	-0,08 (0,097)		0,25* (0,141)	
$LFA(horizontal)_{i,t}$	-0,06*** (0,018)	-0,15** (0,073)	-0,01 (0,059)	0,14 (0,128)	-0,003 (0,005)
$LFA(vertical)_{i,t}$	0,01 (0,009)	0,07 (0,057)	0,07** (0,037)	-0,04 (0,077)	0,001 (0,003)
$\log(GRW[priv.inv.]_{i,t})$	-0,002* (0,001)	0,0008 (0,005)		0,003 (0,007)	
$\log(GRW[infra]_{i,t})$	0,001 (0,001)	0,002 (0,004)	0,002 (0,004)	0,004 (0,006)	
$\log(ALMP_{i,t})$	0,03* (0,017)	0,03 (0,071)		0,36* (0,212)	-0,008 (0,008)
$\log(ALMP_{i,t-1})$				-0,49** (0,202)	0,003 (0,008)
No. of obs.	160	160	160	160	160
Time effects	yes	yes	yes	yes	yes
Hausman $m - stat.$ (3sls vs. 2sls)	$\chi^2(21) = 6,8$ (p=0,99)	$\chi^2(21) = 30,1^\#$ (p=0,09)	$\chi^2(19) = 10,6$ (p=0,93)	$\chi^2(25) = 19,9$ (p=0,75)	$\chi^2(20) = 5,9$ (p=0,99)

Note: ***, **, * = denote significance levels at the 1%, 5% and 10% level respectively. # = Excluding time effects: $\chi^2(11) = 8,81$ (p = 0,64).

Figure 21: Net dynamic multiplier effect of lfa (both vertical and horizontal) on endogenous variables of the system

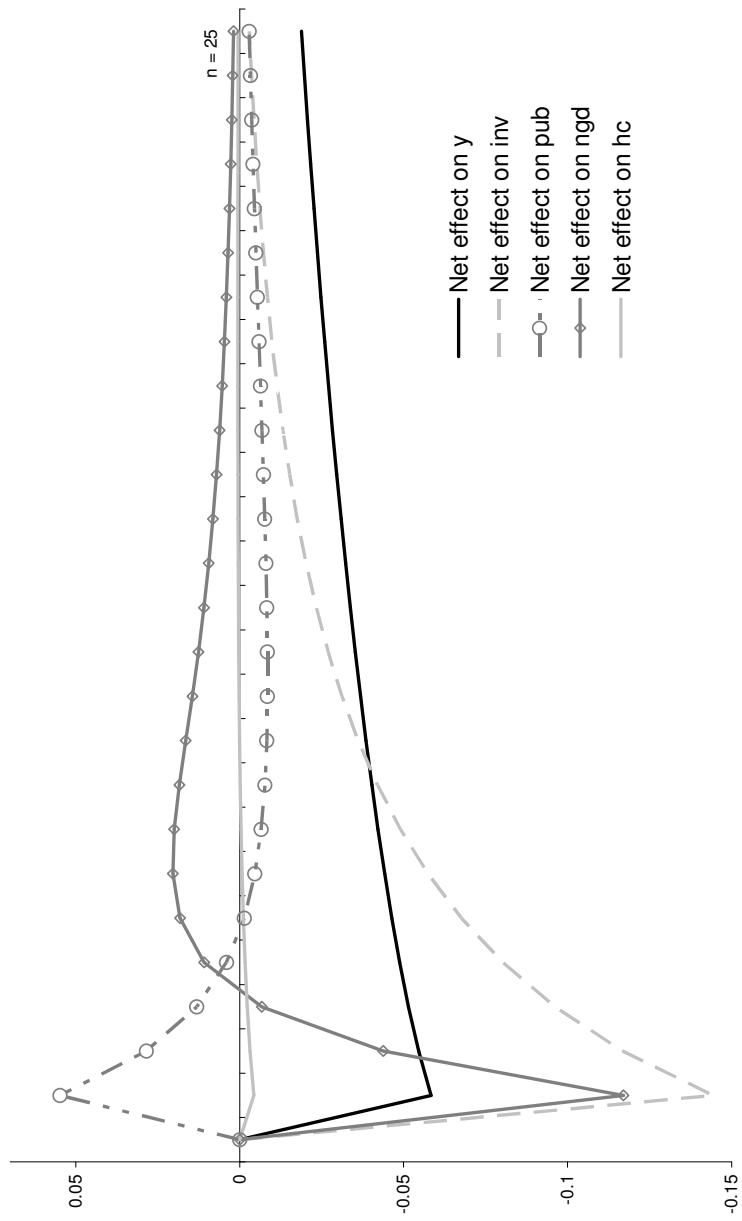


Figure 22: Time evolution of dynamic multipliers (top left: *lfav*, top right: *raampr*, bottom left: *unemp*)

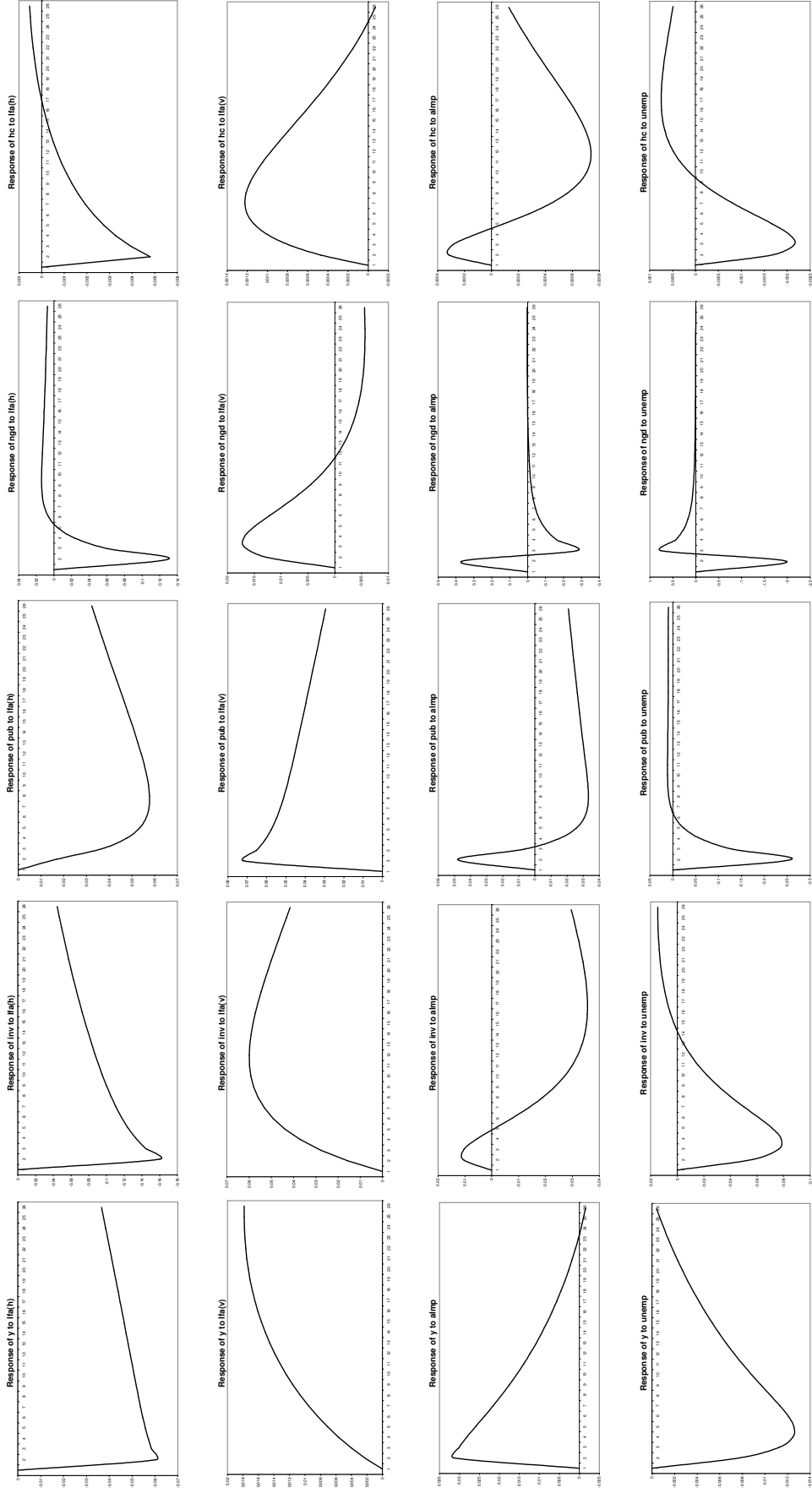


Table A.1: Standard Monte Carlo simulation results with $N = (25, 100)$ and $T = (5, 10)$ for $\alpha_2 = 0, 8$ and $\xi = 1$

Coef.	α_1			α_2			α_3			β_1			β_2			β_3			
	0,2			0,8			0,2			0,5			0,5			0,5			
	bias	s.d.	rmse	bias	s.d.	rmse	bias	s.d.	rmse	bias	s.d.	rmse	bias	s.d.	rmse	bias	s.d.	rmse	
$T = 5$																			
N=25	AH	0,10	0,03	0,11	-0,60	0,11	0,10	0,01	0,10	-0,08	0,10	0,13	-0,16	0,01	0,16	-0,09	0,02	0,09	
	AB	0,10	0,03	0,20	-0,80	0,15	0,13	0,02	0,13	-0,08	0,10	0,28	-0,09	0,03	0,10	-0,03	0,05	0,06	
	HT1	0,21	0,04	0,21	-0,04	0,12	0,13	0,06	0,06	0,05	0,06	0,08	-0,14	0,01	0,14	0,00	0,04	0,04	
	HT2	0,25	0,07	0,25	-0,06	0,06	0,09	0,01	0,01	-0,02	0,05	0,05	-0,17	0,02	0,17	0,09	0,04	0,10	
	HT3	0,32	0,10	0,33	-0,10	0,05	0,11	0,00	0,01	-0,02	0,05	0,05	-0,04	0,03	0,05	0,05	0,06	0,07	
	BB1	0,00	0,07	0,07	0,08	0,08	0,12	0,06	0,06	-0,05	0,13	0,14	-0,11	0,10	0,14	-0,01	0,12	0,12	
N=100	BB2	0,02	0,06	0,06	0,02	0,06	0,06	0,01	0,08	0,05	0,12	-0,10	0,09	0,14	-0,05	0,12	0,13		
	AH	0,02	0,01	0,02	-0,23	0,05	0,24	0,00	0,02	-0,06	0,04	0,07	0,07	0,00	0,14	0,14	0,14		
	AB	0,02	0,01	0,02	-0,33	0,04	0,33	0,01	0,03	-0,06	0,04	0,08	0,05	0,01	0,06	0,12	0,12		
	HT1	0,13	0,02	0,13	0,02	0,03	0,04	0,01	0,01	-0,01	0,03	0,03	0,03	0,01	0,03	0,11	0,01	0,11	
	HT2	0,14	0,03	0,14	-0,04	0,02	0,05	0,00	0,00	-0,02	0,03	0,04	-0,01	0,01	0,01	0,14	0,01	0,14	
	HT3	0,17	0,03	0,17	-0,06	0,02	0,07	0,04	0,00	-0,03	0,03	0,04	-0,02	0,01	0,03	0,17	0,01	0,17	
N=25	BB1	0,03	0,01	0,04	-0,02	0,02	0,03	0,00	0,02	0,00	0,04	0,04	0,03	0,04	0,05	0,10	0,04	0,11	
	BB2	0,05	0,01	0,05	-0,02	0,01	0,03	0,00	0,03	0,02	0,05	0,05	0,03	0,04	0,05	0,06	0,04	0,08	
	$T = 10$																		
	N=25	AH	-0,02	0,01	0,02	-0,13	0,08	0,15	0,00	0,05	0,51	0,08	0,51	-0,05	0,01	0,05	0,08	0,02	0,08
		AB	-0,02	0,01	0,05	-0,05	0,05	0,07	0,01	0,04	0,51	0,08	0,11	0,02	0,03	0,03	0,01	0,04	0,04
		HT1	0,01	0,05	0,05	0,00	0,03	0,03	0,03	0,04	0,14	0,01	0,14	0,07	0,00	0,07	-0,03	0,00	0,03
HT2		0,07	0,04	0,08	-0,03	0,03	0,04	0,01	0,03	0,14	0,01	0,14	0,09	0,00	0,09	0,00	0,00	0,01	
HT3		0,04	0,04	0,06	0,06	0,03	0,06	0,02	0,02	0,05	0,01	0,05	0,11	0,01	0,11	-0,02	0,01	0,02	
BB1		-0,02	0,02	0,03	0,03	0,03	0,04	0,01	0,02	0,15	0,04	0,16	-0,05	0,05	0,07	0,02	0,06	0,06	
N=100	BB2	-0,05	0,03	0,06	0,09	0,03	0,10	0,01	0,04	0,06	0,05	0,08	-0,03	0,07	0,08	0,03	0,08	0,08	
	AH	-0,05	0,00	0,05	0,02	0,03	0,04	0,00	0,00	0,05	0,02	0,06	0,07	0,00	0,07	-0,04	0,00	0,04	
	AB	-0,05	0,00	0,01	-0,12	0,03	0,12	0,01	0,01	0,05	0,02	0,08	0,11	0,01	0,11	-0,04	0,01	0,04	
	HT1	0,01	0,01	0,01	0,01	0,02	0,02	0,00	0,02	0,02	0,00	0,02	0,06	0,00	0,06	0,01	0,00	0,01	
	HT2	0,01	0,01	0,02	0,02	0,01	0,03	0,00	0,03	0,00	0,00	0,00	0,05	0,00	0,05	0,01	0,00	0,01	
	HT3	-0,01	0,02	0,02	0,03	0,01	0,03	0,04	0,00	-0,01	0,01	0,01	0,03	0,00	0,03	-0,01	0,00	0,01	
N=25	BB1	-0,04	0,01	0,04	0,06	0,01	0,06	0,00	0,00	0,02	0,03	0,04	0,06	0,03	0,06	-0,02	0,02	0,03	
	BB2	0,01	0,01	0,01	0,01	0,01	0,02	0,00	0,01	0,06	0,03	0,07	0,07	0,03	0,08	0,00	0,02	0,02	

Note: For details about the Monte Carlo simulation setup see text.

Table A.2: Standard Monte Carlo simulation results with $N = (25, 100)$ and $T = (5, 10)$ for $\alpha_2 = 0, 8$ and $\xi = 0, 5$

Coef.	α_1			α_2			α_3			β_1			β_2			β_3			
	0,2		rmse	0,8		rmse	0,2		rmse	0,5		rmse	0,5		rmse	0,5		rmse	
	bias	s.d.		bias	s.d.		bias	s.d.		bias	s.d.		bias	s.d.		bias	s.d.		
$T = 5$																			
N=25	AH	0,10	0,01	0,10	0,02	0,10	0,09	0,01	0,09	-0,08	0,07	0,11	-0,16	0,01	0,16	-0,09	0,01	0,09	
	AB	0,10	0,01	0,26	0,06	0,75	-0,12	0,01	0,12	-0,08	0,07	0,29	-0,09	0,02	0,09	-0,05	0,04	0,06	
	HT1	0,21	0,02	0,21	0,00	0,06	-0,05	0,00	0,05	-0,01	0,05	0,05	-0,13	0,01	0,13	-0,01	0,04	0,04	
	HT2	0,26	0,04	0,26	-0,04	0,05	0,00	0,00	0,00	-0,04	0,03	0,05	-0,17	0,02	0,17	0,06	0,04	0,07	
	HT3	0,35	0,06	0,35	-0,08	0,08	0,00	0,01	0,01	-0,05	0,03	0,06	-0,05	0,03	0,06	0,02	0,05	0,05	
	BB1	0,03	0,05	0,06	0,11	0,13	-0,06	0,01	0,06	-0,12	0,09	0,15	-0,13	0,06	0,14	0,01	0,08	0,08	
N=100	BB2	0,03	0,04	0,04	0,02	0,05	-0,08	0,01	0,08	-0,03	0,08	0,09	-0,08	0,07	0,10	-0,07	0,08	0,10	
	AH	0,02	0,01	0,02	-0,18	0,19	-0,01	0,00	0,01	-0,03	0,03	0,04	0,07	0,00	0,07	0,14	0,00	0,14	
	AB	0,02	0,01	0,02	-0,27	0,27	-0,02	0,01	0,02	-0,03	0,03	0,08	0,06	0,01	0,06	0,11	0,01	0,11	
	HT1	0,13	0,01	0,13	0,03	0,03	-0,01	0,00	0,01	-0,02	0,02	0,03	0,03	0,03	0,01	0,03	0,10	0,01	
	HT2	0,14	0,01	0,14	-0,04	0,04	0,00	0,00	0,00	-0,02	0,02	0,03	-0,01	0,01	0,01	0,14	0,01	0,14	
	HT3	0,17	0,01	0,18	-0,06	0,06	0,04	0,00	0,04	-0,03	0,02	0,03	-0,03	0,01	0,03	0,17	0,01	0,17	
N=100	BB1	0,02	0,01	0,02	-0,03	0,03	-0,01	0,00	0,01	-0,03	0,03	0,04	0,01	0,02	0,03	0,06	0,03	0,07	
	BB2	0,04	0,01	0,04	-0,03	0,03	-0,02	0,00	0,02	-0,01	0,03	0,03	0,02	0,02	0,03	0,04	0,03	0,05	
	$T = 10$																		
	N=25	AH	-0,02	0,00	0,02	-0,12	0,05	-0,05	0,00	0,05	0,50	0,06	0,50	-0,05	0,00	0,05	0,09	0,01	0,09
		AB	-0,02	0,00	0,04	-0,03	0,03	-0,04	0,01	0,04	0,50	0,06	0,11	0,02	0,02	0,03	0,03	0,04	0,05
		HT1	0,01	0,03	0,03	0,00	0,02	-0,04	0,01	0,04	0,13	0,01	0,13	0,06	0,00	0,06	-0,03	0,00	0,03
HT2		0,07	0,02	0,07	-0,03	0,01	-0,02	0,00	0,03	0,12	0,01	0,12	0,08	0,00	0,08	-0,01	0,00	0,01	
HT3		0,04	0,02	0,05	0,06	0,01	0,07	0,02	0,02	0,03	0,01	0,03	0,10	0,01	0,10	-0,01	0,01	0,01	
BB1		-0,02	0,01	0,03	0,02	0,02	-0,02	0,00	0,02	0,15	0,02	0,15	-0,06	0,03	0,07	0,00	0,03	0,03	
N=100	BB2	-0,07	0,03	0,08	0,11	0,03	-0,04	0,00	0,04	0,03	0,03	0,04	-0,02	0,04	0,05	0,03	0,05	0,06	
	AH	-0,05	0,00	0,05	0,02	0,02	0,00	0,00	0,00	0,05	0,01	0,06	0,07	0,00	0,07	-0,04	0,00	0,04	
	AB	-0,05	0,00	0,01	-0,09	0,02	-0,01	0,00	0,01	0,05	0,01	0,07	0,12	0,01	0,12	-0,04	0,01	0,04	
	HT1	0,01	0,01	0,01	0,01	0,01	0,02	0,00	0,02	0,02	0,00	0,02	0,06	0,00	0,06	0,01	0,00	0,01	
	HT2	0,01	0,00	0,01	0,02	0,01	0,02	0,03	0,00	0,01	0,00	0,01	0,05	0,00	0,05	0,01	0,00	0,01	
	HT3	-0,02	0,01	0,02	0,03	0,01	0,03	0,05	0,00	0,02	0,01	0,02	0,03	0,00	0,03	-0,01	0,00	0,01	
N=100	BB1	-0,04	0,00	0,04	0,06	0,00	0,00	0,00	0,00	0,00	0,02	0,02	0,06	0,02	0,07	-0,01	0,01	0,02	
	BB2	0,00	0,01	0,01	0,00	0,01	-0,01	0,00	0,01	0,03	0,02	0,03	0,08	0,02	0,08	0,01	0,01	0,02	

Note: For details about the Monte Carlo simulation setup see text.

Table A.3: Standard Monte Carlo simulation results with $N = (25, 100)$ and $T = (5, 10)$ for $\alpha_2 = 0, 8$ and $\xi = 4$

Coef.	α_1			α_2			α_3			β_1			β_2			β_3			
	0,2			0,8			0,2			0,5			0,5			0,5			
	bias	s.d.	rmse	bias	s.d.	rmse	bias	s.d.	rmse	bias	s.d.	rmse	bias	s.d.	rmse	bias	s.d.	rmse	
$T = 5$																			
N=25	AH	0,12	0,07	0,13	-0,27	0,20	0,34	-0,08	0,01	0,08	-0,04	0,19	-0,16	0,01	0,16	-0,10	0,03	0,10	
	AB	0,12	0,07	0,18	-0,44	0,23	0,50	-0,10	0,03	0,11	-0,04	0,19	-0,09	0,04	0,10	0,00	0,07	0,07	
	HT1	0,16	0,13	0,20	-0,01	0,17	0,17	-0,06	0,02	0,07	0,19	0,10	-0,15	0,02	0,15	-0,03	0,05	0,05	
	HT2	0,16	0,15	0,22	-0,04	0,13	0,13	0,00	0,02	0,02	0,10	0,08	-0,16	0,03	0,16	0,09	0,05	0,11	
	HT3	0,19	0,17	0,26	-0,07	0,13	0,15	0,00	0,02	0,02	0,11	0,08	-0,03	0,04	0,05	0,05	0,07	0,09	
	BB1	-0,04	0,09	0,10	0,08	0,08	0,11	-0,05	0,03	0,06	0,27	0,10	-0,06	0,15	0,17	-0,06	0,18	0,19	
N=100	BB2	-0,05	0,09	0,11	0,09	0,08	0,12	-0,07	0,02	0,08	0,29	-0,11	0,16	0,19	-0,09	0,20	0,22		
	AH	0,03	0,01	0,03	-0,07	0,09	0,12	-0,01	0,00	0,01	-0,05	0,09	0,07	0,00	0,07	0,14	0,01	0,14	
	AB	0,03	0,01	0,03	-0,14	0,09	0,17	-0,02	0,01	0,02	-0,05	0,09	0,04	0,01	0,04	0,14	0,02	0,14	
	HT1	0,13	0,05	0,14	0,00	0,10	0,10	-0,02	0,01	0,02	0,03	0,05	0,03	0,01	0,03	0,11	0,01	0,11	
	HT2	0,14	0,06	0,15	-0,05	0,04	0,06	0,00	0,01	0,01	0,01	0,05	0,00	0,02	0,02	0,15	0,02	0,15	
	HT3	0,16	0,07	0,18	-0,07	0,04	0,08	0,04	0,01	0,05	-0,01	0,06	-0,01	0,03	0,03	0,18	0,02	0,18	
N=25	BB1	0,07	0,03	0,08	0,01	0,03	0,03	-0,02	0,01	0,02	0,24	0,04	0,06	0,07	0,09	0,17	0,06	0,18	
	BB2	0,06	0,03	0,07	0,01	0,02	0,02	-0,03	0,01	0,03	0,25	0,04	0,08	0,07	0,11	0,12	0,06	0,14	
	$T = 10$																		
	N=25	AH	-0,02	0,01	0,02	-0,04	0,12	0,12	-0,05	0,00	0,05	0,25	0,16	-0,02	0,02	0,03	0,03	0,01	0,03
		AB	-0,02	0,01	0,04	-0,07	0,06	0,09	-0,05	0,01	0,06	0,25	0,16	0,02	0,03	0,03	0,00	0,03	0,03
		HT1	0,05	0,08	0,09	0,01	0,06	0,06	-0,06	0,02	0,06	0,16	0,02	0,08	0,01	0,08	-0,04	0,01	0,05
HT2		0,08	0,07	0,11	-0,01	0,05	0,05	-0,04	0,01	0,04	0,16	0,02	0,09	0,01	0,09	0,00	0,01	0,01	
HT3		0,02	0,07	0,07	0,08	0,07	0,10	0,02	0,03	0,03	0,08	0,04	0,11	0,01	0,11	0,00	0,01	0,01	
BB1		-0,01	0,04	0,04	0,06	0,04	0,07	-0,04	0,02	0,04	0,23	0,07	-0,04	0,09	0,10	0,02	0,05	0,06	
N=100	BB2	-0,07	0,04	0,08	0,11	0,03	0,12	-0,04	0,01	0,04	0,22	0,05	-0,07	0,15	0,17	-0,01	0,09	0,09	
	AH	-0,05	0,00	0,05	0,02	0,06	0,06	0,00	0,00	0,00	0,02	0,04	0,08	0,00	0,08	-0,04	0,00	0,04	
	AB	-0,05	0,00	0,03	-0,07	0,05	0,08	-0,02	0,00	0,02	0,02	0,04	0,11	0,01	0,11	-0,04	0,01	0,04	
	HT1	0,03	0,03	0,04	0,02	0,04	0,04	0,01	0,00	0,01	0,03	0,01	0,06	0,00	0,06	0,01	0,00	0,01	
	HT2	0,03	0,02	0,04	0,04	0,03	0,05	0,02	0,00	0,02	0,01	0,01	0,05	0,00	0,05	0,01	0,00	0,01	
	HT3	0,01	0,04	0,04	0,04	0,03	0,05	0,04	0,01	0,04	0,00	0,02	0,03	0,00	0,03	-0,01	0,00	0,01	
N=25	BB1	-0,02	0,02	0,03	0,08	0,02	0,08	-0,01	0,01	0,01	0,21	0,04	0,04	0,04	0,06	-0,03	0,04	0,05	
	BB2	0,00	0,03	0,03	0,05	0,02	0,06	-0,02	0,01	0,02	0,25	0,03	0,04	0,05	0,06	-0,01	0,04	0,05	

Note: For details about the Monte Carlo simulation setup see text.

Table A.4: Standard Monte Carlo simulation results with $N = (25, 100)$ and $T = (5, 10)$ for $\alpha_2 = 0, 5$ and $\xi = 1$

Coef.	α_1			α_2			α_3			β_1			β_2			β_3				
	0,5			0,5			0,5			0,5			0,5			0,5				
	bias	s.d.	rmse	bias	s.d.	rmse	bias	s.d.	rmse	bias	s.d.	rmse	bias	s.d.	rmse	bias	s.d.	rmse		
$T = 5$																				
N=25	AH	0,12	0,03	0,12	-0,21	0,03	0,21	-0,12	0,01	0,12	-0,10	0,02	0,10	-0,13	0,01	0,13	-0,06	0,01	0,06	
	AB	0,12	0,03	0,14	-0,18	0,05	0,19	-0,09	0,02	0,10	-0,10	0,02	0,10	-0,10	0,04	0,11	0,02	0,06	0,06	
	HT1	0,15	0,03	0,15	-0,02	0,03	0,04	-0,09	0,01	0,09	-0,04	0,04	0,06	-0,11	0,02	0,12	0,05	0,04	0,06	
	HT2	0,19	0,05	0,20	-0,02	0,03	0,04	-0,03	0,01	0,03	-0,06	0,03	0,07	-0,15	0,03	0,15	0,12	0,05	0,13	
	HT3	0,25	0,06	0,26	-0,06	0,03	0,07	-0,05	0,01	0,05	-0,04	0,04	0,06	-0,03	0,03	0,04	0,07	0,06	0,09	
	BB1	-0,03	0,08	0,08	0,07	0,04	0,08	-0,07	0,03	0,08	-0,08	0,07	0,10	-0,09	0,10	0,14	0,00	0,13	0,13	
N=100	BB2	-0,03	0,05	0,06	0,06	0,04	0,07	-0,09	0,03	0,10	-0,02	0,07	0,07	-0,10	0,10	0,14	-0,05	0,14	0,15	
	AH	0,02	0,00	0,03	-0,07	0,02	0,07	-0,01	0,00	0,01	-0,04	0,01	0,04	0,07	0,00	0,07	0,15	0,00	0,15	
	AB	0,02	0,00	0,02	-0,10	0,01	0,10	-0,03	0,01	0,04	-0,04	0,01	0,02	0,05	0,01	0,05	0,11	0,02	0,11	
	HT1	0,11	0,02	0,11	-0,05	0,01	0,05	-0,03	0,00	0,03	-0,01	0,01	0,01	0,03	0,01	0,03	0,11	0,01	0,11	
	HT2	0,12	0,01	0,12	-0,03	0,01	0,04	0,00	0,00	0,00	-0,01	0,01	0,02	0,00	0,01	0,01	0,15	0,01	0,15	
	HT3	0,15	0,02	0,15	-0,02	0,01	0,03	0,04	0,00	0,04	-0,05	0,02	0,06	-0,02	0,02	0,03	0,17	0,01	0,17	
N=25	BB1	0,04	0,02	0,04	-0,05	0,01	0,05	-0,01	0,01	0,01	-0,02	0,03	0,03	0,03	0,04	0,05	0,10	0,04	0,11	
	BB2	0,04	0,02	0,04	-0,04	0,01	0,04	-0,02	0,01	0,03	-0,01	0,03	0,03	0,03	0,04	0,05	0,07	0,04	0,08	
	$T = 10$																			
	N=25	AH	-0,01	0,01	0,01	-0,05	0,02	0,05	-0,05	0,01	0,05	0,16	0,01	0,16	-0,05	0,00	0,05	0,06	0,01	0,06
		AB	-0,01	0,01	0,07	-0,02	0,03	0,04	-0,07	0,02	0,07	0,16	0,01	0,08	0,00	0,03	0,03	-0,04	0,04	0,06
		HT1	0,01	0,04	0,04	-0,02	0,01	0,02	-0,05	0,02	0,05	0,08	0,00	0,08	0,04	0,00	0,04	-0,03	0,00	0,03
HT2		0,06	0,03	0,06	0,00	0,01	0,01	-0,05	0,01	0,05	0,08	0,00	0,08	0,06	0,00	0,06	-0,01	0,00	0,01	
HT3		0,05	0,03	0,06	0,05	0,02	0,05	0,01	0,01	0,01	0,08	0,01	0,09	0,11	0,01	0,11	-0,02	0,01	0,02	
BB1		-0,01	0,04	0,04	0,01	0,02	0,02	-0,02	0,02	0,03	0,08	0,03	0,09	-0,03	0,05	0,06	0,03	0,06	0,07	
N=100	BB2	-0,01	0,05	0,05	0,06	0,03	0,06	-0,05	0,02	0,06	0,07	0,03	0,07	-0,05	0,07	0,08	-0,01	0,07	0,07	
	AH	-0,04	0,01	0,04	0,01	0,01	0,02	0,01	0,00	0,01	0,02	0,02	0,02	0,07	0,00	0,07	-0,04	0,00	0,04	
	AB	-0,04	0,01	0,06	-0,04	0,01	0,04	-0,04	0,01	0,04	0,02	0,02	0,03	0,09	0,01	0,10	-0,05	0,01	0,05	
	HT1	0,01	0,01	0,02	-0,01	0,00	0,01	0,01	0,00	0,01	0,01	0,00	0,01	0,05	0,00	0,05	0,01	0,00	0,01	
	HT2	0,02	0,01	0,02	0,00	0,00	0,01	0,02	0,00	0,02	0,01	0,00	0,01	0,05	0,00	0,05	0,01	0,00	0,01	
	HT3	0,01	0,02	0,02	0,01	0,00	0,01	0,04	0,01	0,04	-0,01	0,01	0,01	0,03	0,00	0,03	-0,01	0,00	0,01	
N=25	BB1	0,00	0,03	0,04	0,03	0,02	0,04	0,00	0,02	0,02	0,04	0,04	0,06	0,04	0,04	0,06	-0,04	0,04	0,05	
	BB2	0,07	0,04	0,08	0,02	0,03	0,03	-0,04	0,02	0,04	0,08	0,04	0,09	0,03	0,07	0,07	-0,03	0,06	0,06	

Note: For details about the Monte Carlo simulation setup see text.

Table A.5: Standard Monte Carlo simulation results with $N = (25, 100)$ and $T = (5, 10)$ for $\alpha_2 = 0, 5$ and $\xi = 0, 5$

Coef.	α_1			α_2			α_3			β_1			β_2			β_3			
	0,5			0,5			0,5			0,5			0,5			0,5			
	bias	s.d.	rmse	bias	s.d.	rmse	bias	s.d.	rmse	bias	s.d.	rmse	bias	s.d.	rmse	bias	s.d.	rmse	
$T = 5$																			
N=25	AH	0,11	0,02	0,11	0,02	0,21	-0,12	0,00	0,12	-0,10	0,01	0,10	-0,13	0,01	0,13	-0,06	0,01	0,06	
	AB	0,11	0,02	0,15	0,04	0,20	-0,10	0,02	0,10	-0,10	0,01	0,08	-0,11	0,03	0,11	0,02	0,05	0,05	
	HT1	0,15	0,02	0,15	0,02	0,02	-0,09	0,01	0,09	0,09	0,03	0,05	-0,11	0,02	0,11	0,02	0,04	0,04	
	HT2	0,19	0,03	0,19	0,02	0,02	-0,03	0,01	0,03	0,03	0,02	0,06	-0,15	0,02	0,15	0,08	0,04	0,09	
	HT3	0,25	0,04	0,25	0,01	0,05	-0,04	0,01	0,05	0,05	0,02	0,05	-0,04	0,03	0,05	0,04	0,05	0,06	
	BB1	-0,04	0,05	0,06	0,07	0,02	0,07	-0,07	0,02	0,07	-0,09	0,04	0,10	-0,12	0,06	0,13	0,02	0,07	0,08
N=100	BB2	-0,06	0,03	0,07	0,06	0,06	-0,09	0,02	0,09	-0,04	0,04	0,06	-0,10	0,06	0,12	-0,08	0,08	0,11	
	AH	0,02	0,00	0,02	-0,07	0,01	-0,01	0,00	0,01	-0,04	0,01	0,04	0,07	0,00	0,07	0,15	0,00	0,15	
	AB	0,02	0,00	0,01	-0,09	0,01	-0,03	0,01	0,03	-0,04	0,01	0,01	0,06	0,01	0,06	0,11	0,01	0,11	
	HT1	0,10	0,01	0,10	-0,04	0,01	0,04	-0,03	0,00	0,03	0,01	0,02	0,03	0,01	0,03	0,10	0,01	0,10	
	HT2	0,12	0,01	0,12	-0,03	0,01	0,03	0,00	0,00	0,03	0,01	0,02	0,00	0,01	0,01	0,15	0,01	0,15	
	HT3	0,14	0,01	0,14	-0,02	0,00	0,02	0,04	0,00	0,04	0,01	0,04	-0,03	0,01	0,03	0,17	0,01	0,17	
N=25	BB1	0,03	0,01	0,04	-0,05	0,01	-0,01	0,00	0,01	-0,02	0,01	0,02	0,03	0,02	0,03	0,08	0,03	0,08	
	BB2	0,04	0,01	0,04	-0,04	0,01	-0,02	0,00	0,02	-0,01	0,01	0,02	0,02	0,02	0,03	0,04	0,03	0,05	
	$T = 10$																		
	N=25	AH	-0,02	0,00	0,02	-0,05	0,01	-0,05	0,00	0,05	0,16	0,01	0,16	-0,05	0,00	0,05	0,06	0,00	0,06
		AB	-0,02	0,00	0,07	-0,02	0,02	-0,07	0,02	0,07	0,16	0,01	0,06	0,01	0,03	0,03	-0,06	0,04	0,07
		HT1	0,00	0,02	0,02	-0,01	0,00	0,02	-0,04	0,01	0,04	0,07	0,07	0,04	0,00	0,04	-0,04	0,00	0,04
HT2		0,05	0,02	0,06	0,01	0,00	0,01	-0,04	0,01	0,05	0,07	0,07	0,05	0,00	0,05	-0,01	0,00	0,01	
HT3		0,04	0,02	0,05	0,06	0,01	0,06	0,02	0,01	0,02	0,07	0,07	0,10	0,01	0,10	-0,02	0,01	0,02	
BB1		-0,01	0,02	0,03	0,01	0,01	0,01	-0,01	0,01	0,02	0,08	0,08	-0,03	0,03	0,04	0,03	0,04	0,05	
N=100	BB2	-0,02	0,04	0,05	0,06	0,03	-0,04	0,02	0,05	0,05	0,02	0,05	-0,04	0,04	0,06	-0,02	0,04	0,05	
	AH	-0,04	0,00	0,04	0,02	0,00	0,01	0,00	0,01	0,02	0,00	0,02	0,07	0,00	0,07	-0,04	0,00	0,04	
	AB	-0,04	0,00	0,05	-0,03	0,01	0,04	-0,03	0,01	0,03	0,02	0,04	0,10	0,01	0,10	-0,05	0,01	0,05	
	HT1	0,00	0,00	0,00	0,00	0,00	0,00	0,01	0,00	0,01	0,01	0,01	0,06	0,00	0,06	0,01	0,00	0,01	
	HT2	0,01	0,00	0,01	0,01	0,00	0,01	0,02	0,00	0,02	0,00	0,00	0,05	0,00	0,05	0,01	0,00	0,01	
	HT3	-0,01	0,01	0,01	0,03	0,00	0,03	0,05	0,00	0,05	0,00	0,00	0,04	0,00	0,04	-0,01	0,00	0,01	
N=25	BB1	-0,02	0,01	0,03	0,01	0,00	0,00	0,00	0,01	-0,01	0,01	0,01	0,07	0,02	0,07	-0,01	0,01	0,02	
	BB2	0,02	0,01	0,03	-0,01	0,00	-0,02	0,00	0,02	0,01	0,01	0,01	0,07	0,02	0,08	0,00	0,02	0,02	

Note: For details about the Monte Carlo simulation setup see text.

Table A.6: Standard Monte Carlo simulation results with $N = (25, 100)$ and $T = (5, 10)$ for $\alpha_2 = 0, 5$ and $\xi = 4$

Coef.	α_1			α_2			α_3			β_1			β_2			β_3				
	0,5			0,5			0,5			0,5			0,5			0,5				
	bias	s.d.	rmse	bias	s.d.	rmse	bias	s.d.	rmse	bias	s.d.	rmse	bias	s.d.	rmse	bias	s.d.	rmse		
$T = 5$																				
N=25	AH	0,11	0,02	0,12	-0,21	0,02	0,21	-0,12	0,01	0,12	-0,10	0,01	0,10	-0,13	0,01	0,13	-0,06	0,01	0,06	
	AB	0,11	0,02	0,15	-0,20	0,04	0,20	-0,10	0,02	0,10	-0,10	0,01	0,08	-0,11	0,03	0,11	0,02	0,05	0,05	
	HT1	0,15	0,02	0,15	-0,01	0,02	0,03	-0,09	0,01	0,09	0,09	-0,05	0,05	-0,11	0,02	0,11	0,02	0,04	0,04	
	HT2	0,19	0,03	0,19	-0,02	0,02	0,03	-0,03	0,01	0,03	0,03	-0,05	0,06	-0,15	0,02	0,15	0,08	0,04	0,09	
	HT3	0,25	0,05	0,25	-0,05	0,02	0,06	-0,05	0,01	0,05	0,05	-0,04	0,05	-0,04	0,03	0,05	0,04	0,05	0,06	
	BB1	-0,04	0,05	0,06	0,07	0,03	0,07	-0,07	0,02	0,07	0,07	-0,08	0,10	-0,12	0,07	0,14	0,01	0,09	0,09	
N=100	BB2	-0,06	0,04	0,07	0,06	0,03	0,07	-0,09	0,02	0,09	-0,03	0,06	0,07	-0,10	0,07	0,13	-0,08	0,09	0,12	
	AH	0,02	0,00	0,02	-0,07	0,01	0,07	-0,01	0,00	0,01	-0,04	0,01	0,04	0,07	0,00	0,07	0,15	0,00	0,15	
	AB	0,02	0,00	0,02	-0,09	0,01	0,10	-0,03	0,01	0,03	-0,04	0,01	0,02	0,06	0,01	0,06	0,11	0,01	0,11	
	HT1	0,10	0,01	0,10	-0,04	0,01	0,04	-0,03	0,00	0,03	-0,02	0,01	0,02	0,03	0,01	0,03	0,10	0,01	0,10	
	HT2	0,12	0,01	0,12	-0,03	0,01	0,03	0,00	0,00	0,00	-0,02	0,01	0,02	0,00	0,01	0,01	0,15	0,01	0,15	
	HT3	0,14	0,01	0,15	-0,02	0,01	0,02	0,04	0,00	0,04	-0,04	0,01	0,05	-0,03	0,01	0,03	0,17	0,01	0,17	
N=100	BB1	0,04	0,01	0,04	-0,05	0,01	0,06	-0,01	0,01	0,01	-0,02	0,02	0,03	0,03	0,03	0,04	0,08	0,03	0,09	
	BB2	0,04	0,01	0,04	-0,04	0,01	0,04	-0,02	0,01	0,02	-0,01	0,02	0,03	0,02	0,03	0,04	0,04	0,03	0,05	
	$T = 10$																			
	N=25	AH	-0,01	0,01	0,02	-0,04	0,03	0,05	-0,05	0,01	0,05	0,17	0,01	0,17	-0,05	0,01	0,05	0,05	0,01	0,05
		AB	-0,01	0,01	0,06	-0,03	0,03	0,04	-0,08	0,02	0,08	0,17	0,01	0,11	-0,01	0,03	0,03	-0,03	0,04	0,05
		HT1	0,03	0,07	0,07	-0,03	0,01	0,03	-0,06	0,03	0,07	0,08	0,00	0,08	0,04	0,00	0,04	-0,03	0,00	0,03
HT2		0,07	0,05	0,09	-0,01	0,02	0,02	-0,06	0,02	0,07	0,08	0,01	0,08	0,06	0,01	0,06	0,00	0,01	0,01	
HT3		0,07	0,06	0,10	0,02	0,04	0,04	-0,02	0,03	0,04	0,11	0,02	0,11	0,12	0,01	0,12	-0,03	0,01	0,03	
BB1		0,03	0,07	0,08	0,03	0,05	0,06	-0,05	0,05	0,07	0,13	0,07	0,15	-0,03	0,09	0,10	0,00	0,11	0,11	
N=100	BB2	-0,04	0,08	0,09	0,13	0,05	0,14	-0,07	0,05	0,08	0,18	0,06	0,19	-0,09	0,16	0,19	-0,05	0,18	0,18	
	AH	-0,04	0,00	0,04	0,02	0,01	0,02	0,01	0,00	0,01	0,02	0,02	0,02	0,07	0,00	0,07	-0,04	0,00	0,04	
	AB	-0,04	0,00	0,06	-0,04	0,01	0,04	-0,03	0,01	0,04	0,02	0,00	0,04	0,09	0,01	0,10	-0,05	0,01	0,05	
	HT1	0,01	0,01	0,01	-0,01	0,01	0,01	0,01	0,00	0,01	0,01	0,00	0,01	0,05	0,00	0,06	0,01	0,00	0,01	
	HT2	0,02	0,01	0,02	0,00	0,01	0,01	0,02	0,00	0,02	0,01	0,00	0,01	0,05	0,00	0,05	0,01	0,00	0,01	
	HT3	0,00	0,02	0,02	0,01	0,01	0,02	0,04	0,01	0,04	-0,01	0,01	0,01	0,03	0,00	0,03	-0,01	0,00	0,01	
N=100	BB1	-0,01	0,03	0,03	0,03	0,02	0,03	0,00	0,02	0,02	0,03	0,04	0,05	0,05	0,04	0,06	-0,03	0,04	0,05	
	BB2	0,06	0,04	0,08	0,01	0,03	0,03	-0,04	0,02	0,04	0,07	0,04	0,08	0,03	0,07	0,07	-0,03	0,05	0,06	

Note: For details about the Monte Carlo simulation setup see text.