Estimating Gravity Models of International Trade with Correlated Time-Fixed Regressors: To IV or not IV?

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Abstract

Gravity type models are widely used in international economics. In these models the inclusion of time-fixed regressors like geographical or cultural distance, language and institutional (dummy) variables is often of vital importance e.g. to analyse the impact of trade costs on internationalization activity. This paper analyses the problem of parameter inconsistency due to a correlation of the time-fixed regressors with the combined error term in panel data settings. A common solution is to use Instrumental-Variable (IV) estimation in the spirit of Hausman-Taylor (1981) since a standard Fixed Effect Model (FEM) estimation is not applicable. However, some potential shortcomings of the latter approach recently gave rise to the use of non-IV two-step estimators. Given their growing number of empirical applications, we aim to compare the performance of IV and non-IV approaches in the presence of time-fixed variables and right hand side endogeneity using Monte Carlo simulations, where we explicitly control for the problem of IV selection in the Hausman-Taylor case. The simulation results show that the Hausman-Taylor model with perfect-knowledge about the underlying data structure (instrument orthogonality) has on average the smallest bias. However, compared to the empirically relevant specification with imperfect-knowledge and instruments chosen by statistical criteria, simple non-IV rival estimators performs equally well or even better. We illustrate these findings by estimating gravity type models for German regional export activity within the EU. The results show that the HT specification tends to overestimate the role of trade costs proxied by geographical distance.

JEL-Classification: C15, C23, C52

Keywords: Gravity model, Exports, Instrumental variables, two-step estimators, Monte Carlo simulations.

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1   Motivation

In contemporary panel data analysis researchers are often confronted with the problem of parameter inconsistency due to the correlation of some of the exogenous variables with the model's error term. Assuming that this correlation is typically due to unobservable individual effects (see e.g. Mundlak, 1978), a consistent approach to deal with such type of right hand side endogeneity is to apply the standard Fixed Effects Model (FEM), which uses a within-type data transformation to erase the unobserved individual effects from the model. However, one drawback of this estimator is that the within transformation also wipes out all explanatory variables that to not change in the time dimension of the model. In this case no statistical inference can be made for these variables, if they have been included in the original untransformed model based on theoretical grounds.

The researcher's problem is then to find an alternative estimator, which is still capable of including time-fixed regressors in the estimation setup. A well-known example for the above sketched etimation setup in empirical work is the gravity model (of trade, capital or migration flows among other interaction effects), which assigns a prominent role given to time-fixed variables in the regression model. Taking the gravity model of trade as an example, the model is a highly used body of analysis for applied econometric work: With the recent switch from cross-section to panel data specifications, important shortcomings of earlier gravity model applications have been tackled (see e.g. Matyas, 1997, Breuss & Egger, 1999, as well as Egger, 2000), however, other methodological aspects such as the proper functional form of the Gravity equation are still subject to open debate in the recent literature (see e.g. Baldwin & Taglioni, 2006, and Henderson & Millimet, 2008, for an overview). Recently, also the time series properties of Gravity models have been more intensively studied by academic research (see e.g. Fidrmuc, 2008, Zwinkels & Beugelsdijk, 2010).

In this paper we focus on proper estimation strategies for Gravity type and related models, when some time-varying and -fixed right hand side regressors are correlated with the unobservable individual effects. Baltagi et al. (2003) have shown, that when there is endogeneity among the right hand side regressors the OLS and Random Effects estimators are substantially biased and both yield misleading inference. As an alternative solution the Hausman-Taylor (1981, thereafter HT) approach is typically applied. The HT estimator allows for a proper handling of data settings, when some of the the regressors are correlated with the individual effects. The estimation strategy is basically based on Instrumental-Variable (IV) methods, where instruments are derived from internal data transformations of the variables in the model. One of the advantages of the HT model is that it avoids the 'all or nothing' assumption with respect to the correlation between

right hand side regressors and error components, which is made in the standard FEM and REM approaches respectively. However, for the HT model to be operable, the researcher needs to classify variables as being correlated and uncorrelated with the individual effects, which is often not a trivial task.

As a response of this drawback in empirical application of the HT approach different estimation strategies have been suggested, which strongly rely on statistical testing to reveal the underlying correlation of the variables with the model's residuals: Given the fact that the HT estimator employs variable information that in between the range of the FEM and REM, Baltagi et al. (2003) for instance suggest to use a pre-testing strategy that either converts to a FEM, REM or Hausman-Taylor type model depending on the underlying characteristics of the variable correlation in focus. The estimation strategy centers around the standard Hausman (1978) test, which has been evolved as a standard tool to judge among the use of the REM vs. FEM in panel data settings. Ahn & Low (1996) additionally propose a reformulation of the Hausman test based on the Sargan (1958) / Hansen (1982) statistic for overidentifying restrictions. Together with the closely related C-Statistic derived by Eichenbaum et al. (1998), which allows for testing single instrument validity rather than full IV-sets, the Hansen-Sargen overidentification test may thus be seen as a more powerful tool to guide IV selection in the HT approach compared to the standard Hausman test.

As an alternative to IV estimation different 'two-step'-type estimators have been proposed recently: Plümper & Tröger (2007) for instance set up an augmented FEM model that also allows for the estimation of time-fixed parameters. Their model - labeled Fixed Effects Vector Decomposition (FEVD) - may be seen as a rival specification for the HT approach in estimating the full parameter space in the model including both time-varying and time-fixed regressors. The idea of the two step estimator is to first run a consistent FEM model to obtain parameter estimates of the time-varying variables. Using the regression residuals as a proxy for the unobserved individual effects in a second step this proxy is regressed against the set of time-fixed variables to obtain parameter values for the latter. Since this second step includes a 'generated regressand' (Pagan, 1984) the degrees of freedom have to be adjusted to avoid an underestimation of standard errors (see e.g. Atkinson & Cornwell, 2006, for a comparison of different bootstrapping techniques to correct standard errors in these settings).[1] Though it is typically argued that one main advantage of these non-IV estimators is their freedom of any arbitrary classification of

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[1]In a recent comment Greene (2010) criticises the original approach by Plümper & Troeger (2007) arguing that they use a wrong variance-covariance matrix resulting in systematically too small standard errors. Thus, bootstrapping these may be seen as a more appropriate choice.

hand side regressors as being endogenous or exogenous, as we will show latter on two-step estimators such as the FEVD also rests upon an implicit choice that may impact upon estimator consistency and efficiency.

Giving the growing number of empirical applications of the latter non-IV FEVD approach (see e.g. Akther & Daly, 2009, Belke & Spies, 2008, Caporale et al., 2008, Davies et al., 2008, Etzo, 2007, and Krogstrup & Wälti, 2008, Mitze et al., 2009 among others),[2] a systematic comparison of the HT instrumental variable approach with the non-IV FEVD is of great empirical interest regarding their small sample performance. However, there are relatively few existing studies comparing the two-step estimators with the Hausman-Taylor IV approach in a Monte-Carlo simulation experiment (in particular Plümper & Tröger, 2007, as well as Alfaro, 2006). Moreover, in these studies as well as the broader Monte Carlo based evidence on the Hausman-Taylor estimator (see e.g. Ahn & Low, 1996, Baltagi et al., 2003), the empirically unsatisfactory assumption is made that the true underlying correlation between right hand side variables and error term is known. Our approach therefore explicitly offsets from earlier simulation studies and allows for the existence of imperfect knowledge in the HT model estimation with IV selection based on different model/moment selection criteria (see e.g. Andrews, 1999, Andrews & Lu, 2001). The latter combines information from the Hansen-Sargan overidentification test and time-series information-criteria such as AIC/BIC. This allows for an empirical comparison of the HT and FEVD (two-step) estimators' performance, which comes much closer to the true estimation problem researchers face in applied modelling work in terms of 'To IV or not IV?'.

The remainder of the paper is organized as follows: Section 2 briefly sketches the Hausman-Taylor and non-IV FEVD alternative. In section 3 we present the results of our Monte Carlo simulation experiment. Section 4 illustrates the empirical relevance by adding an empirical application to trade estimates in a gravity model context for German regions (NUTS1-level) within the EU27. Section 5 concludes.

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[2]Searching for the term "Fixed Effects Vector Decomposition"(in quotation marks) by now gives almost 2100 entries in Google.

2 Panel Data Models with Time-Fixed Regressors

We consider a general static (one-way) panel data model of the form

$$y_{it} = \beta X_{it} + \gamma Z_i + u_{it} \text{ with: } u_{it} = \mu_i + \nu_{it} \tag{1}$$

where $i = 1, 2, \ldots, N$ is the cross-section dimension and $t = 1, 2, \ldots, T$ the time dimension of the panel data. X_{it} is a vector of time-varying variables, Z_i is a vector of time invariant right hand side variables, β and γ are coefficient vectors. The error term u_{it} is composed of two error components, where μ_i is the unobservable individual effect and ν_{it} is the remainder error term. μ_i and ν_{it} are assumed to be $iid(0, \sigma_\mu)$ and $iid(0, \sigma_\nu)$ respectively.

Standard estimators for the panel data model in eq.(1), which control for the existence for individual effects, are the FEM and REM approach. However, choosing among the FEM and REM estimator rests on an 'all or nothing' decision with respect to the assumed correlation of right hand side variables with the error term. In empirical applications, the truth may often lie in between these two extremes. This ideas motivates the specification of the Hausman–Taylor (1981) model as a hybrid version of the FEM/REM using IV techniques. The HT approach therefore simply splits the set of time varying variables into two subsets $X_{i,t} = [X1_{i,t}, X2_{i,t}]$, where $X1$ are supposed to be exogenous w.r.t μ_i and $\nu_{i,t}$. $X2$ variables are correlated with μ_i and thus endogenous w.r.t. the unobserved individual effects.[3] An analogous classification is done for the set of time–fixed variables $Z_i = [Z1_i, Z2_i]$. Note that the presence of $X2$ and $Z2$ is the cause of bias in the REM approach. The resulting augmented HT model can be written as:

$$y_{i,t} = \alpha + \beta_1' X1_{i,t} + \beta_2' X2_{i,t} + \gamma_1' Z1_i + \gamma_2' Z2_i + u_{i,t}.$$

The idea of HT model is to find appropriate internal instruments to estimate all model parameters. Thereby, deviations from group means of $X1$, $X2$ serve as instruments for $X1$ and $X2$ (in the logic of the FEM), $Z1$ serve as their own instruments and group means of $X1$ are used to instrument the time-fixed $Z2$. The FEM and the REM can be derived as special versions of the HT model, namely when all regressors are correlated with the individual effects the model reduces to the FEM. For the case that all variables are exogenous (in the sense of no correlation with the individual effects) the model takes

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[3] Here we use the terminology of 'endogenous' and 'exogenous' to refer to variables that are either correlated with the unobserved individual effects μ_i or not. An alternative classification scheme used in the panel data literature classifies variables as either 'doubly exogenous' with respect to both error components μ_i and $\nu_{i,t}$ or 'singly exogenous' to only ν. We use these two definitions interchangeably here.

the REM form. In empirical terms the HT model is typically estimated by GLS and throughout the paper we use a generalized instrumental variable (GIV) approach proposed by White (1984), which applies 2SLS to the GLS filtered model (including the instruments) as:[4]

$$\tilde{y}_{i,t} = \tilde{\alpha} + \beta_1' \widetilde{X1}_{i,t} + \beta_2' \widetilde{X2}_{i,t} + \gamma_1' \widetilde{Z1}_i + \gamma_2' \widetilde{Z2}_i + \tilde{u}_{i,t}, \qquad (3)$$

where $\tilde{y}_{i,t}$ denotes GLS transformed variables (for details see e.g. Baltagi, 2008). Finally, the order condition for the HT estimator to exist is $k_1 \geq g_2$. That is, the total number of time-varying exogenous variables k_1 that serve as instruments has to be at least as large as the number of time invariant endogenous variables (g_2).[5] For the case that $(k_1 > g_2)$ the equation is said to be overidentified and the HT estimator obtained from a 2SLS regression is generally more efficient than the within estimator (see Baltagi, 2008).

In empirical application of the HT approach the main points of critique focus on the arbitrary IV selection in terms of $X1/X2$ and $Z1/Z2$ variable classification as well as the poor small sample properties of IV–methods when instruments are 'weak' as well as similar small sample problems of the GLS estimator. Therefore, recent two-step non-IV alternatives such as the Fixed Effects Vector Decomposition (FEVD) by Plümper & Tröger (2007) have been proposed.[6] The goal of the model is to run a consistent FEM model and still get estimates for the time-invariant variables. The intuition behind the FEVD specification is as follows: Since the unobservable individual effects capture omitted variables including time-invariant variables, it should therefore be possible to regress a proxy of the individual effects obtained from a first stage FEM regression on the time-invariant variables to obtain estimates for these variables in a second step. Finally, the number of degrees of freedom for the use of a 'generated regressand' in this second step has to be corrected (e.g. by bootstrapping methods, see Atkinson & Cornwell, 2006). We can thus sum up the FEVD estimator as:

- **FEVD:** 1.) Run a standard FEM to get parameter estimates $(\hat{\beta}_{FEVD})$ of the time-varying variables.

- **FEVD:** 2.) Use the estimated group residuals as a proxy for the time-fixed individual effects $\hat{\pi}_i$ obtained from the first step as $\hat{\pi}_i = (\bar{y}_i - \hat{\beta}_{FEM} \bar{X}_i)$ to run a OLS regression of the explanatory time-invariant variables against this vector to obtain parameter

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[4]One also has to note that the HT model can also be estimated based on a slightly different transformation, namely the filtered instrumental variable (FIV) estimator. The latter transforms the estimation equation by GLS but uses unfiltered instruments. However, both approaches typically yield similar parameter estimates, see Ahn & Schmidt (1999).

[5]The total number of IVs in the HT model is $2k_1 + k_2 + g_1$ ($k_1 + k_2$ from $QX1$ and $QX2$, k_1 from $PX1$ and g_1 from $Z1$)

[6]The FEVD may be seen as an extension to an earlier model in Hsiao (2003). For details see Plümper & Tröger (2007).

estimates of the time-fixed variables ($\hat{\gamma}_{FEVD}$).

The residual term from the 2.step $\hat{\eta}_i$ is composed of $\hat{\eta}_i = \zeta_i + \bar{X}_i(\hat{\beta}_{FEM} - \beta)$, where $\zeta_i = \mu_i + \bar{\nu}_i$ and the over-bar indicates the sample period mean for cross-section i e.g. $\bar{X}_i = 1/T \sum_{t=1}^{T} X_{i,t}$ (for details see Atkinson & Cornwell, 2006). One has to note that standard errors have to be corrected for $\hat{\gamma}_{FEVD}$ either asymptotically or by bootstrapping techniques (see Murphy & Topel, 1985, as well as Atkinson & Cornwell, 2006) to avoid an overestimation of t-values. To sum up, the FEVD 'decomposes' the vector of unobservable individual effects into a part explained by the time invariant variables and an error term. Since the FEVD is built on the FEM it yields unbiased and consistent estimates of the time-varying variables. According to Plümper & Tröger one major advantage of the FEVD compared to the Hausman-Taylor model is that the estimator does not require prior knowledge of correlation between the explanatory variables and the individual effects.

However, estimates of the time invariant variables are only consistent if either the time invariant variables fully account for the individual effects or the unexplained part of η_i is uncorrelated with the time-invariant variables. As Caporale et al. (2008) note, otherwise the FEVD also suffer from omitted variable bias.[7]

Thus, though we are not directly confronted with the choice of classifying variables as endogenous or exogenous, the estimator itself does rely on an implicit choice: In specifying the time-varying variables the model follows the generality of the FEM approach, which assumes that these variables are possibly correlated with the unobservable individual effects (for estimation purposes deviations from group means are taken which wipe out the individual effects so that no explicit assumption about the underlying correlation needs to be stated). With respect to the time invariant variables the estimator assumes in its simple form that no time-fixed variable (Z) is correlated with the the second step error term, which is composed of the unobservable individual effects. However, if this implicit (and fixed) choice does not reflect the true correlation between the variables and the individual effects the estimator may in fact have lower power than the HT approach.

3 Monte Carlo Simulation Results

We run Monte Carlo Simulations in the spirit of Im et al. (1999) and Baltagi et al. (2003) for the FEVD and Hausman-Taylor estimator using different combinations of the cross-

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[7]A modification of the standard FEVD approach also allows for the possibility to estimate the second step as IV regression and thus account for endogeneity among time invariant variables and η_i. Following Atkinson & Cornwell, 2006, we can define a standard IV estimator as: $\hat{\gamma}_{FEVD} = \left(S'Z\right)^{-1}S'\hat{\pi}$, where S is the instrument set that satisfies the orthogonality condition $E(S\eta) = 0$. However, this brings back the classification problem of the HT approach, which we aim to avoid here.

section (N) and time-series (T) dimension. Details about the simulation design are given in the appendix. We use a static one-way model as in eq.(1) including 4 time-varying (X) and 3 time-fixed (Z) regressors of the form:

$$y_{i,t} = \beta_{11}x_{1_1,i,t} + \beta_{12}x_{1_2,i,t}$$
$$+\beta_{21}x_{2_1,i,t} + \beta_{22}x_{2_2,i,t}$$
$$+\gamma_{11}z_{1_1,i} + \gamma_{12}z_{1_2,i}$$
$$+\gamma_{21}z_{2_1,i} + u_{i,t},$$
$$\text{with: } u_{i,t} = \mu_i + \nu_{i,t}$$

(4)

where x_{1_1} and x_{1_2} are assumed to be uncorrelated with the error term, while x_{2_1} and x_{2_2} are correlated with μ_i. Analogously, z_{2_1} is correlated with the error term. The latter is composed of the unobserved individual effects (μ_i) and remainder disturbance ($\nu_{i,t}$). Since we are interested in consistency and efficiency of the respective estimators, we compute the empirical bias, its standard deviation and the root mean square error (rmse). The bias is defined as

$$bias(\hat{\delta}) = \sum_{m=1}^{M}(\hat{\delta} - \delta_{true})/M,$$

(5)

where $m = (1, 2, \ldots, M)$ is the number of simulation runs, $\hat{\delta}$ is the estimated coefficient evaluated w.r.t. to its true value. Next to the standard deviation of the estimated bias we also calculate the root mean square error, which puts a special weight on outliers, as:

$$rmse(\hat{\delta}) = \sqrt{\left(\sum_{m=1}^{M}(\hat{\delta} - \delta_{true})/M\right)^2}.$$

(6)

We first take a closer look at the individual parameter estimates for the parameter settings $N = 1000, T = 5$ and $\xi = 1$, which are typically assumed in the standard Panel data literature building on the large N, small T data assumption.[8]. In figure 1 we plot Kernel density distributions for all regression coefficients for the following three estimators: i.) the FEVD, ii.) the HT model with perfect knowledge about the underlying variable correlation with the error term and iii.) the HT model based on the MSC-BIC algorithm (in its restricted form). The latter estimator is based on model selection criteria (MSC) that center around the J-Statistic augmented by a 'bonus' term rewarding models with

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[8]ξ defines the ratio of the variance terms of the error components as $\xi = \sigma_\mu/\sigma_\nu$

more moment conditions. Since the resulting MSC specifications are closely related to the standard information criteria AIC, BIC and HQIC we label them MSC-AIC, MSC-BIC and MSC-HQIC respectively. Additionally we define a $C-$Statistic based model selection criteria. All criteria are applied to IV selection in the HT case. We apply both conservative IV selection rules, where instruments are not allowed to pass certain critical values of the $J-$ and or $C-$Statistic respectively in order to be selected, as well as less restrictive counterparts. Detail are given in the appendix. In the figure we focus on the MSC-BIC based HT model since it shows on average the best performance among all HT estimators with imperfect knowledge about the underlying data correlation - closely followed by the $C-$Statistic based model selection algorithm.

For the coefficients of the two exogenous time-varying variables β_{1_1} and β_{1_2} all three estimators give unbiased results centering around the true parameter value of one. The standard deviation and rmse are the smallest for the HT model with perfect knowledge about the underlying data correlation, followed by the MSC algorithm based HT estimators. The FEVD has a slightly higher standard deviation and rmse. For the estimated coefficients of the endogenous time-varying variables β_{2_1} and β_{2_2} the HT and FEVD give virtually identical results, while the HT based MSC-BIC in figure 1 is slightly biased for β_{2_1} but comes closer to the true parameter value for the parameter β_{2_2}. To sum up, though there are some minor differences among the three reported estimators for the time-varying variables in figure 1, the overall empirical discrepancy is rather marginal.

This picture however radically changes for the Monte Carlo simulation results of the time-fixed variable coefficients γ_{1_2} and γ_{2_1}: Here only the HT model with the ex-ante correctly specified variable correlation gives unbiased results for both the exogenous (γ_{1_2}) and endogenous variable (γ_{2_1}). Both the FEVD and HT model based on the MSC-BIC have difficulties in calculating these variable coefficients correctly, while the bias of the FEVD is lower than for the MSC-BIC Hausman-Taylor model in both cases. Especially for γ_{2_1} exclusively all HT based model selection algorithms have a large bias/standard deviation as well as a high rsme relative to the HT with perfect knowledge about the variable correlation with the error term. The FEVD has a significant bias (approximately 50 percent higher than the standard HT) but compared to the MSC-BIC based specification a lower bias/standard deviation.

<<< insert Figure 1 about here >>>

Turning to the small sample properties for the above mentioned estimators we additionally plot Kernel density plots for the parameter settings $N = 100, T = 5, \xi = 2$. Here the results in figure 4 show that the MSC-BIC based HT model is already more biased

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compared to the standard HT and FEVD for the parameter estimates of the time-varying variables β_{1_1}, β_{1_2}, β_{2_1} and β_{2_2}, where in all cases the bias is the smallest for the FEVD. With respect to the rmse the smallest value for β_{1_1} and β_{1_2} is given by the C-Statistic based HT model, while FEVD and the standard HT model perform best for β_{2_1} and β_{2_2}. For the time-fixed variables again the FEVD and the MSC-BIC based HT model have a significant bias, while the HT model with perfect knowledge about the underlying variable correlation comes on average much closer to the true parameter value (in particular for γ_{1_2}). However, as already observed in Plümper & Tröger (2007) the standard deviation of the latter estimator is much higher compared to the other two estimators. This leads to the result that in terms of the rmse the FEVD performs better than the standard HT in these settings (for both γ_{1_2} and γ_{2_1}), although it shows a larger bias compared to the latter. The results in figure 2 indicate that the HT instrumental variable approach is rather inefficient in small sample settings, though the average bias is small.

<<< insert Figure 2 about here >>>

A specific problem of the MSC-BIC based HT model in small sample settings is shown in figure 5. The Kernel density plot for the coefficient γ_{2_1} of the endogenous time-fixed variables reveals a 'duality' problem for the search algorithm based estimator, which significantly increases with smaller values for ξ. Different from the standard HT and FEVD estimators the MSC-BIC based HT model shows a clear double peak for parameter estimates of $\hat{\gamma}_{2_1}$, with one peakaround the true coefficient value of one and a second significantly biased one. This kind of duality problem with a possibly poor MSC based estimator performance has already been addressed in Andrews (1999) for those cases where there are typically two or more selection vectors that yield MSC values close to the minimum and parameter estimates that differ noticeably from each other. As the histogram in figure 6 shows, this is indeed the problem for the MSC-BIC based HT model: Based on the Monte Carlo simulation runs with 500 reps. the algorithm tends to pick two dominant IV-sets from which one has the (inconsistent) REM form with a full instrument list, while only the second one consistently excludes $Z21$ from the instrument list. This results may be seen as a first indication that in small samples and a small proportion of the total variance of the error term due to the random individual effects (through low values of ξ), $J-$statistic based IV selection may have a low power and yield inconsistent results.

<<< insert Figure 3 and Figure 4 about here >>>

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Turning from a comparison of single variable coefficients to an analysis of overall measures of bias and efficiency for an aggregated parameter space, we compute NOMAD and NORMSQD values, where 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 mean square error (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 & Chang, 2000). Both overall measures are thus extensions to the single parameter bias and rmse statistics defined above. We compare the FEVD model with the standard HT model and the algorithm based HT models using the C-Statistic approach, as well as the MSC-BIC1, MSC-HGIC1, MSC-AIC1 (where the index 1 denotes that all are based on the restricted specification). The overall results are shown in table 1.[9] The table shows that the HT model with perfect knowledge about the underlying variable correlation has the lowest NOMAD value, with the FEVD having two times and algorithm based HT specification even three times higher values for the average bias over all model coefficients. For the latter the C-Statistic based model selection criteria performs slightly better than the MSC based estimators. Contrary, with respect to the NORMSQD by far the best model is the non-IV FEVD. The difference between the standard HT model and the algorithm based specification is rather low. This broad picture indicates that the HT instrumental variable model is a consistent estimator given perfect knowledge about the true underlying correlation between the r.h.s. variables and the error term. However, when one has to rely on statistical criteria to guide moment condition selection the empirical performance for the specific setup in the Monte Carlo simulation design is considerably lower. This in turn speaks in favor of using non-IV two step estimators such as the FEVD, which has the lowest rmse due to its robust OLS estimation approach compared to the HT estimators.

<<< insert Table 1 >>>

4   Empirical Illustration: Trade Estimates for German Regions

Given the above findings from our Monte-Carlo simulation experiment in this section we aim to consider the empirical performance of the FEVD and HT model in an empirical

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[9]Disaggregated results for the vector of time-varying and time fixed regressors for different combinations of our MC simulation can be obtained from the authors upon request.

application estimating gravity type models. We take up the research question in Alecke et al. (2003) and specify trade equations for regional unit. In particular, we aim to estimate gravity models for export flows among German states (NUTS1-level) and its EU27 trading partners using data for the period 1993-2005. We are particularly interested in quantifying the effects of time-fixed variables including geographical distance as a general proxy for trading costs as well as a set time-fixed 0/1-dummies for border regions, the East German states as well as the specific trade pattern with the CEEC countries.[10] Earlier evidence in Belke & Spies (2008) for European data has shown that there is a considerable degree of heterogeneity for these time-fixed variables among different estimators. The empirical export model has the following form:[11]

$$
\begin{aligned}
log(EX_{ijt}) \; = \; & \alpha_0 + \alpha_1 log(GDP_{it}) + \alpha_2 log(POP_{it}) + \alpha_3 log(GPD_{jt}) + \alpha_4 log(POP_{jt}) \\
& + \alpha_5 log(PROD_{it}) + \alpha_6 log(DIST_{ij}) + \alpha_7 SIM + \alpha_8 RLF \qquad (7) \\
& + \alpha_9 EMU + \alpha_{10} EAST + \alpha_{11} BORDER + \alpha_{12} CEEC,
\end{aligned}
$$

where the index indicates German regional exports from region i to country j for time period t and imports to German state i from country j respectively. The variables in the model are defined as follows[12]:

- EX = Export flows from region i to country j
- GDP = Gross domestic product in i and j respectively
- POP = Population in i and j
- $PROD$ = Labour productivity in i and j
- $DIST$ = Geographical distance between state/national capitals
- SIM = Similarity index defined as: $log(1 - \left(\frac{GDP_{i,t}}{GDP_{i,t}+GDP_{j,t}}\right)^2 - \left(\frac{GDP_{j,t}}{GDP_{i,t}+GDP_{j,t}}\right)^2)$
- RLF = Relative factor endowments in i and j defined as: $log \left| \left(\frac{GDP_{i,t}}{POP_{i,t}}\right) - \left(\frac{GDP_{j,t}}{POP_{j,t}}\right) \right|$
- EMU = EMU membership dummy for i and j
- $EAST$ = East German state dummy for i
- $BORDER$ = Border region dummy between i and j
- $CEEC$ = CEE country dummy for j

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[10]The CEEC aggregate includes Hungary, Poland, the Czech Republic, Slovakia, Slovenia, Estonia, Latvia, Lithuania, Romania and Bulgaria.

[11]Results for an import equation with qualitatively similar results can be obtained from the author upon request.

[12]Further details can be found in the data appendix in table A.1.

The estimation results are shown in table 2. We particularly focus in the FEVD and HT estimates for the variable $log(DIST_{ij})$ as well as the time-fixed dummies $EAST$, $BORDER$ and $CEEC$. The HT approach rests on the C-Statistic based downward testing approach to find a consistent set of moment conditions.

Turning to the results, in line with our Monte Carlo simulations both the FEVD and HT estimators are very close in quantifying the time-varying variables in the gravity model for German regional export activity. As expected from its theoretical foundation (see e.g. Egger, 2000, Feenstra, 2004) both home and foreign country GDP have a positive and significant influence on German export activity, indicating that trade increases with absolute higher income levels. Moreover, also home region productivity (defined as GDP per total employment) is found to be statistically significant and highly positive, which in turn can be interpreted in line with recent findings based on firm-level data (see e.g. Helpman et al., 2003, or Arnold & Hussinger, 2006, for the German case) that the degree of internationalization of home firms (both trade and FDI) increases with higher productivity levels. The interpretation of the population variable in the gravity model is less clear cut: Both the FEVD and HT estimator find a positive coefficient sign for foreign population, which can be interpreted in favour of the market potential approach indicating that German export flows are higher for population intense economies. Also for the GDP based interaction variable SIM (definition see above) the two estimators show similar results.

However, as already observed throughout the Monte Carlo simulation experiment for the time-fixed variables the estimators show a considerable degree of heterogeneity. In our export model the C-Statistic based HT approach finds a coefficient for the distance variable (-1,73) that is almost twice as large as the respective coefficient in the in POLS, REM and FEVD (-0.97) case. A similar difference between FEVD and HT model results were also found in Belke & Spies (2008) for EU wide data (the authors report coefficients for the distance variable in the HT case as -1,83 compared to -1,39 in the FEVD case). Without the additional knowledge from the above Monte Carlo simulation experiment, we could hardly answer the question whether this discrepancy among estimators either indicates an upward bias of the HT model given the fact that (for national data) the parameter estimate for the distance variable typically ranges between -0.9 to -1.3 (see e.g. Disdier & Head, 2008 as well as Linders, 2005) or whether the use of smaller regional entities serves as a better proxy for geographical distance thus gives a more accurate estimate for trade costs (which may be possibly higher).

However, in the light of the Monte Carlo simulation results together the typical range of national estimates it seems plausible to rely on the FEVD estimation results, although

the HT model passes the Hansen/Sargan overidentification test (treating geographical distance as correlated with the unobserved individual effeckts). Also for the further time-fixed dummy variables in the model the FEVD estimates show more reliable coefficient signs than the HT model: That is, we would expect the border dummy to be positive as e.g. found in Lafourcade & Paluzie (2005) for European border regions. Also, German-CEEC trade was persistently found to be above its 'potential' in a couple of earlier studies (such as Schumacher & Trübswetter, 2000, Buch & Piazolo, 2000, Jakab et al., 2001, Caetano et al., 2002 as well as Caetano & Galego, 2003). In both cases the FEVD estimates are thus more in line with recent empirical findings than the HT IV-estimation.

<<< insert Table 2 about here >>>

5 Conclusion

In this paper we have performed a Monte Carlo simulation experiment supported by an empirical illustration to compare the empirical performance of IV and non-IV estimators for a regression setup, which includes time-fixed variables as right hand side regressors and where endogeneity matters. We define the latter as any correlation between the r.h.s. variables with the model's error term. In specifying empirical estimators we focus on the Hausman-Taylor (1981) IV model both with perfect and imperfect knowledge about the underlying variable correlation with the model's residuals and non-IV two-step estimators such as the Fixed Effects Vector Decomposition (FEVD) model recently proposed by Plümper & Tröger (2007). Our results show that the HT (with perfect knowledge) works better for time-varying, while the FEVD for time-fixed variables. Averaging over all parameters we find the the HT model (with perfect knowledge) generally has the smallest bias, while the FEVD show to have a by far lower root mean square error (rmse) as a general efficiency measure. Especially in small sample settings our Monte Carlo simulations show that the IV-based HT model has a large standard deviation and consequently high rmse values.

Additionally, relaxing the assumption of perfect knowledge for the HT model, the empirical performance of the latter significantly worsens. We compute different algorithms to select consistent IV-sets centering around the Hansen/Sargan overidentification test (J-Statistic), however all estimates based on these algorithms generally show a much weaker empirical performance than the non-IV alternative (FEVD). One major drawback of the HT models with imperfect knowledge is a 'duality' problem in small sample settings, where the estimator has difficulties to discriminate between consistent and inconsistent moment

condition vectors. We may thus conclude that IV selection solely based on statistical criteria has to be treated with some caution. An alternative choice for applied researcher are non-IV two-step estimators such as the FEVD proposed by Plümper & Tröger (2007), which show an on average good performance in our Monte Carlo simulations and yield very plausible results for the empirical estimation of German regional trade flows using gravity type models. The choice of an appropriate estimator is highly important for applied researchers aiming to quantify the effect of policy relevant variables such as trade costs.

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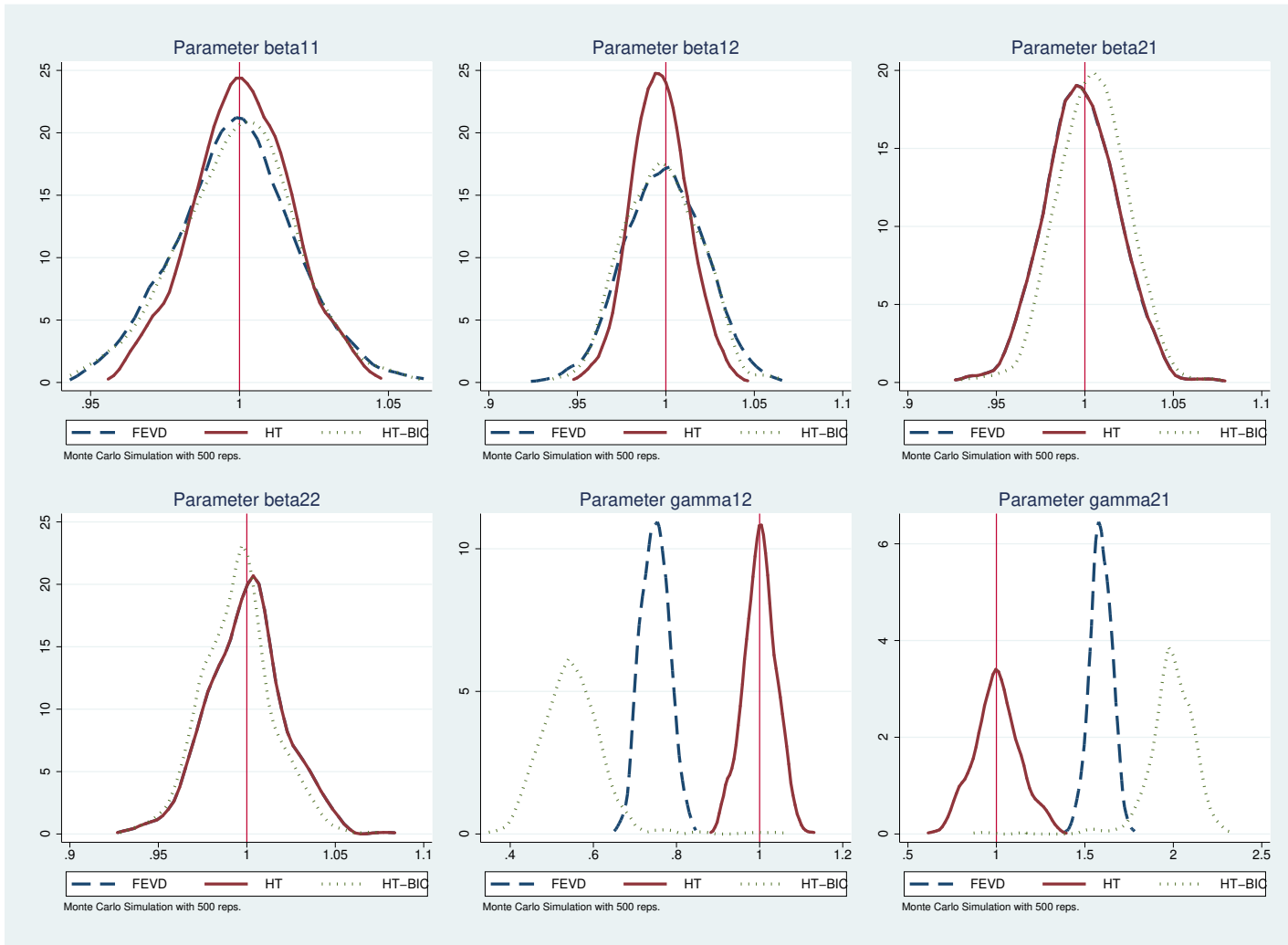Figure 1: Kernel density plots for Monte Carlo simulation results with $N = 1000, T = 5, \xi = 1$

Figure 2: Kernel density plots for Monte Carlo simulation results with $N = 100, T = 5, \xi = 2$
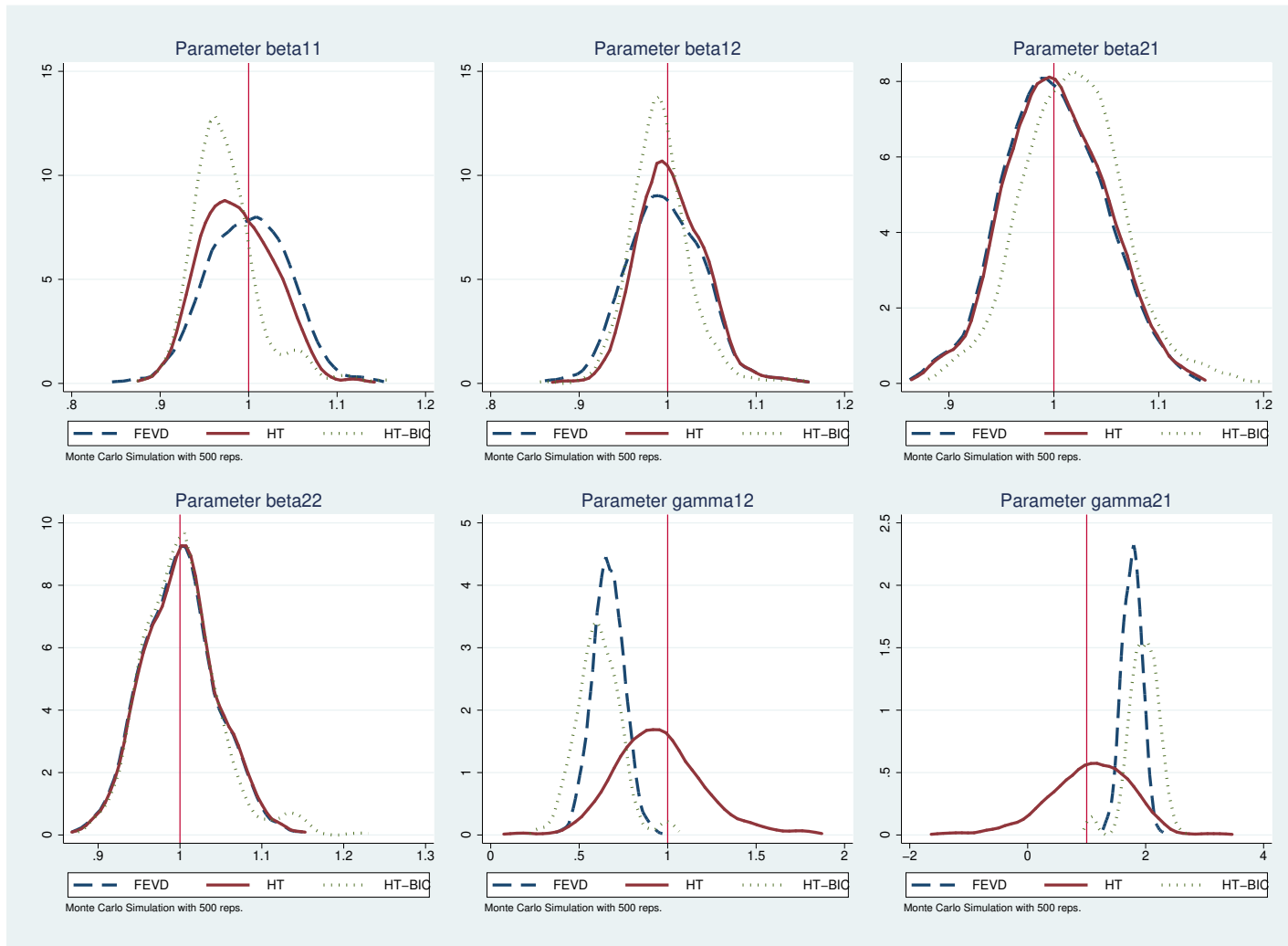
Figure 3: Kernel density plots for Monte Carlo simulation results of γ_{21} with
$$N = 100, T = 5, \xi = 1$$

Parameter gamma21
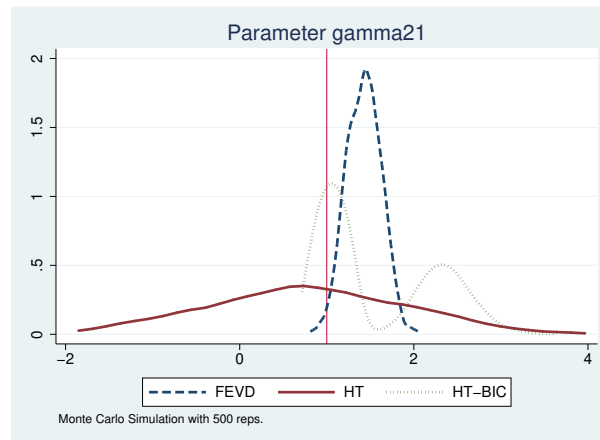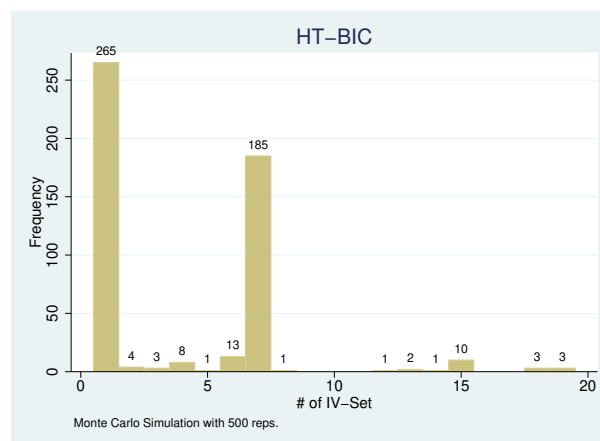
Monte Carlo Simulation with 500 reps.

FEVD — HT ⋯⋯ HT–BIC

Figure 4: Histogram of selected IV-sets for Monte Carlo simulation results of γ_{21} with
$$N = 100, T = 5, \xi = 1$$

HT–BIC

Monte Carlo Simulation with 500 reps.

Table 1: NOMAD and NORMSQD averaged over all MC simulations

	Crit.	NOMAD	NORMSQD
Time-varying	FEVD	0.0009	0.0321
	HT	0.0029	0.0292
	HT-Cstat	0.0030	0.0321
	HT-BIC1	0.0086	0.0337
	HT-HQIC1	0.0099	0.0346
	HT-AIC1	0.0058	0.0329
Time-fixed	FEVD	0.4105	0.0672
	HT	0.1911	0.1888
	HT-Cstat	0.6009	0.2615
	HT-BIC1	0.6171	0.1990
	HT-HQIC1	0.6238	0.1952
	HT-AIC1	0.6231	0.2132
All variables	FEVD	0.2057	0.0497
	HT	0.0970	0.1090
	HT-Cstat	0.3019	0.1468
	HT-BIC1	0.3129	0.1164
	HT-HQIC1	0.3168	0.1149
	HT-AIC1	0.3144	0.1230

Note: For details about the Monte Carlo simulation setup and the definition of the HT estimators based on model selection criteria see appendix.

Table 2: Gravity model for EU wide Export flows for German states (NUTS1 level)

Log(EX)	POLS	REM	FEM	FEVD	HT$
Log(GDP_i)	1,04***	0,35*	0,83**	0,83***	0,87***
	(0,135)	(0,034)	(0,273)	(0,273)#	(0,271)
Log(GDP_j)	0,64***	0,31***	0,34***	0,34**	0,35***
	(0,026)	(0,034)	(0,044)	(0,044)#	(0,043)
Log(POP_i)	0,03	0.69***	-1,38***	-1,38**	0,18
	(0,132)	(0,197)	(0,398)	(0,398)#	(0,263)
Log(POP_j)	0,19***	0,48***	1,79***	1,79***	0,38***
	(0,025)	(0,041)	(0,302)	(0,302)#	(0,084)
Log($PROD_i$)	-0,15	2,11***	1,48***	1,48***	1,76***
	(0,241)	(0,228)	(0,275)	(0,275)#	(0,268)
Log($DIST_{ij}$)	-0,87***	-1,04***	(dropped)	-0,97***	-1,73***
	(0,021)	(0,052)		(0,021)#	(0,403)
SIM	-0,03***	-0,17***	-0,18***	-0,18***	-0,29***
	(0,011)	(0,052)	(0,062)	(0,048)#	(0,039)
RLF	0,01	0,03***	0,03***	0,03	0,03***
	(0,011)	(0,008)	(0,008)	(0,044)#	(0,007)
EMU	0,45***	0,36***	0,31***	0,31***	0,34***
	(0,029)	(0,019)	(0,021)	(0,054)#	(0,019)
EAST	-0,80***	-0,38***	(dropped)	-1,03***	-0,26**
	(0,039)	(0,075)		(0,043)#	(0,110)
BORDER	0,28***	0,26*	(dropped)	0,07***	-0,38
	(0,050)	(0,150)		(0,008)#	(0,438)
CEEC	0,47***	-0,20**	(dropped)	0,93***	-0,22*
	(0,055)	(0,086)		(0,063)#	(0,131)
No. of obs.	4784	4784	4784	4784	4784
No. of Groups		368	368	368	368
Time effects		yes	yes	yes	yes
Wald test (P-val.)		(0.00)	(0.00)	(0.00)	(0.00)
P-value of BP LM (POLS/REM)		0.00			
P-value of F-Test (POLS/FEM)			0.00		
Hausman m-stat. (REM/FEM)			147.2 (0.00)		
DWH endogeneity test (P-value)					25.14 (0.00)
Sargan overid. test (P-value)					6.25 (0.05)
C-Statistic for $Dist_{ij}$ (P-value)					14.12 (0.00)
Pagan-Hall IV het.test (P-value)					35.9 (0.10)

Note: ***, **, * = denote significance levels at the 1%, 5% and 10% level respectively. Standard errors are robust to heteroskedasticity, # = corrected SEs for the FEVD estimator based on the *xtfevd* Stata routine provided by Plümper & Tröger (2007). $ = Using the C-Statistic based downward testing algorithm with group means of $X1 = [GDP_{j,t}, POP_{i,t}, RLF_{ij,t}]$ as IVs for $Z2 = [DIST_{ij}]$.

A   Monte Carlo Simulation Design

Starting point for the Monte Carlo simulation experiment is eq.(4). The time-varying regressors $x_{1_1}, x_{1_2}, x_{2_1}, x_{2_2}$ are generated by the following autoregressive process:

$$x_{n_m,i,t=1} \; = \; 0 \text{ with } n, m = 1, 2 \tag{8}$$

$$x_{1_1,i,t} \; = \; \rho_1 x1_{i,t-1} + \delta_i + \xi_{i,t} \text{ for } t = 2, \dots, T \tag{9}$$

$$x_{1_2,i,t} \; = \; \rho_2 x2_{i,t-1} + \psi_i + \omega_{i,t} \text{ for } t = 2, \dots, T \tag{10}$$

$$x_{2_1,i,t} \; = \; \rho_3 x3_{i,t-1} + \mu_i + \tau_{i,t} \text{ for } t = 2, \dots, T \tag{11}$$

$$x_{2_2,i,t} \; = \; \rho_4 x4_{i,t-1} + \mu_i + \lambda_{i,t} \text{ for } t = 2, \dots, T \tag{12}$$

For the time-fixed regressors $z_{1_1}, z_{1_2}, z_{2_1}$ we analogously define:

$$z_{1_1,i} \; = \; 1 \tag{13}$$

$$z_{1_2,i} \; = \; g_1 \psi_i + g_2 \delta_i + \kappa_i \tag{14}$$

$$z_{2_1,i} \; = \; \mu_i + \delta_i + \psi_i + \epsilon_i \tag{15}$$

The variable $z_{1_1,i}$ simplifies to a constant term, $z_{2_1,i}$ is the endogenous time-fixed regressor since it contains μ_i as r.h.s. variable, the weights g_1 and g_1 in the specification of $z_{1_2,i}$ control for the degree of correlation with the time-varying variables $x_{1_1,i,t}$ and $x_{1_2,i,t}$.[13] The remainder innovations in the data generating process are defined as follows:

$$\nu_{i,t} \; \sim \; N(0, \sigma_\nu^2) \tag{16}$$

$$\mu_i \; \sim \; N(0, \sigma_\mu^2) \tag{17}$$

$$\delta_i \; \sim \; U(-2, 2) \tag{18}$$

$$\xi_{i,t} \; \sim \; U(-2, 2) \tag{19}$$

$$\psi_i \; \sim \; U(-2, 2) \tag{20}$$

$$\omega_{i,t} \; \sim \; U(-2, 2) \tag{21}$$

$$\tau_{i,t} \; \sim \; U(-2, 2) \tag{22}$$

$$\lambda_{i,t} \; \sim \; U(-2, 2) \tag{23}$$

$$\epsilon_i \; \sim \; U(-2, 2) \tag{24}$$

$$\kappa_i \; \sim \; U(-2, 2) \tag{25}$$

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[13]We vary g_1 and g_2 on the interval [-2,2]. The default is $g_1 = g_2 = 2$.

Except μ_i and $\nu_{i,t}$, which are drawn from a normal distribution with zero mean and variance σ_μ^2 and σ_ν^2 respectively, all innovations are uniform on [-2,2]. For $\mu_i, \delta_i, \psi_i, \epsilon_i, \kappa_i$ the first observation is fixed over T. With respect to the main parameter settings in the Monte Carlo simulation experiment we set:

- $\beta_{1_1} = \beta_{1_2} = \beta_{2_1} = \beta_{2_2} = 1$

- $\gamma_{1_2} = \gamma_{2_1} = 1$

- $\rho_1 = \rho_2 = \rho_3 = \rho_4 = 0.7$

All variable coefficients are normalized to one, the specification of $\rho < 1$ assures that the time-varying variables are stationary. We also normalize σ_ν equal to one and define a load factor ξ determining the ratio of the variance terms of the error components as $\xi = \sigma_\mu / \sigma_\nu$. ξ takes values of 2;1 and 0.5. We run simulations with different combinations in the time and cross-section dimension of the panel as $N = (100, 500, 1000)$ and $T = (5, 10)$. All Monte Carlo simulations are conducted with 500 replications for each permutation in y and u. As in Arellano & Bond (1991) we set $T = T + 10$ and cut off first 10 cross-sections, which gives a total sample size of NT observations.

We apply the FEVD and Hausman-Taylor estimators.[14] As outlined above, one drawback in earlier Monte Carlo based comparisons between the HT model and rival non-IV candidates was the strong assumption made for IV selection in the HT case, namely that true correlation between r.h.s. variables and the error term is known. However, this may not reflect the identification and estimation problem in applied econometric work and Alfaro (2006) identifies it as one of the open questions for future investigation in Monte Carlo simulations. We therefore account for the HT variable classification problem by implementing algorithms from 'model selection criteria'-literature, which combine information from Hansen-Sargan overidentification test for moment condition selection as outlined above and time-series information-criteria. Following Andrews (1999) we define a general model selection criteria (MSC) based on IV estimation as

$$MSC_n(m) = J(m) - h(c)k_n \tag{26}$$

where n is the sample size, c as number of moment conditions selected by model m based on the Hansen-Sargan J-Statistic $J(m)$, $h(.)$ is a general function, k_n is a constant

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[14]For the FEVD estimator we employ the Stata routine *xtfevd* written by Plümper & Tröger (2007), the HT model is implemented using the user written Stata routine *ivreg2* by Baum et al. (2003).

term. As eq.(37) shows, the model selection criteria centers around the J-Statistic.[15]. The second part in eq.(37) defines a 'bonus' term rewarding models with more moment conditions, where the form of function $h(.)$ and the constants $(k_n :\geq 1)$ are specified by the researcher. For empirical application Andrews (1999) proposes three operationalizations in analogy to model selection criteria from time series analysis:

- MSC-BIC: $J(m) - (k - g)ln\ n$

- MSC-AIC: $J(m) - 2(k - g)$

- MSC-HQIC: $J(m) - Q(k - g)ln\ ln\ n$ with $Q = 2.01$

where $(k - g)$ is the number of overidentifying restrictions, and depending on the form of the 'bonus' term, the MSC may take the BIC (Bayesian), AIC (Akaike) and HQIC (Hannan Quinn) form. We apply all three information criteria in the Monte Carlo simulations motivated by the results in Andrews & Lu (2001) and Hong et al. (2003) that the superiority of one of the criteria over the others in terms of finding consistent moment conditions may vary with the sample size.[16] For each of these MSC criteria we specify the following algorithms:

1. Unrestricted form: For all possible IV combinations out of the full IV-set *S=(QX1, QX2, PX1, PX2, Z1, Z2)*, where Q denote deviations from group means and P are group means. The IV set satisfies the order condition $k_1 > g_2$ (giving a total number of 42 combinations). We calculate the value of the MSC criterion (for the BIC, AIC and HQIC separately) and choose that model as final HT specification, which has minimum MSC value over all candidates.

2. Restricted form: This algorithm follows the basic logic from above, but additionally puts the further restriction that only those models serves as MSC candidates for which the p-value of the J-Statistic is a above a critical value $C_{crit.}$, which we set to $C_{crit.} = 0.05$ to be sure that the selected moment conditions are true in terms of statistical pre-testing. The restricted version thus follows the advice of Andrews (1999) to ensure that the parameter space incorporates only information, which assumes that certain moment conditions are correct.

We present flow charts of the restricted and unrestricted MSC based search algorithm in figure A. 1. As Andrews (1999) argues, the above specified model selection criteria is

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[15]A detailed description of different moment selection criteria is given in a longer working paper version of this paper, see Mitze, 2009

[16]Generally, the MSC-BIC criterion is found to have the best empirical performance in large samples, while the MSC-AIC outranks the other criteria in small sample settings, but performs poor otherwise.

closely related to the C-Statistic approach by Eichenbaum et al. (1988) to test whether a given subset of moment conditions is correct or not.[17]

Thus alternatively to the above described algorithms, we specify a downward testing approach based on the C-Statistic: Here we start from the HT model with with full IV set in terms of the REM moment conditions as $S_1 = (QX1, QX2, PX1, PX2, Z1, Z2)$. We calculate the value of the J-Statistic for the model with IV-set S_1 and compare its p-value with a predefined critical value $C_{crit.}$, which we set in line with the above algorithm as $C_{crit.} = 0.05$. If $P_{S_1} > C_{crit.}$ we take this model as a valid representation in terms of the underlying moment conditions. If not, we calculate the value of the C-Statistic for each single instrument in S_1 and exclude that instrument from the IV-set that has the maximum value of the C-statistic.

We then re-estimate the model based on the IV-subset S_2 net of the selected instrument with the highest C-Statistic and again calculate the J-Statistic and its respective p-value. If $P_{S_2} > C_{crit.}$ is true, we take the HT-model with S_2 as final specification and otherwise again calculate the C-Statistic for each instrument to exclude that one with the highest value. We run this downward testing algorithm for moment conditions until we find a model that satisfies $P_{S.} > C_{crit.}$ or at the most until we reach the IV-sets S_n to S_m, where the number of overidentifying restrictions $(k - g) = 1$, since the J-Statistic is not defined for just identified models. Out of S_n to S_m we then pick the model with the lowest J-Statistic value. The C-Statistic based model selection algorithms is graphically summarized in figure A.2.

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[17]The C-Statistic can be derived as the difference of two Hansen-Sargan overidentification tests with $C = J - J_1 \sim \chi^2(M - M_1)$, where M_1 is the number of instruments in S_1 and M is the total number of IVs

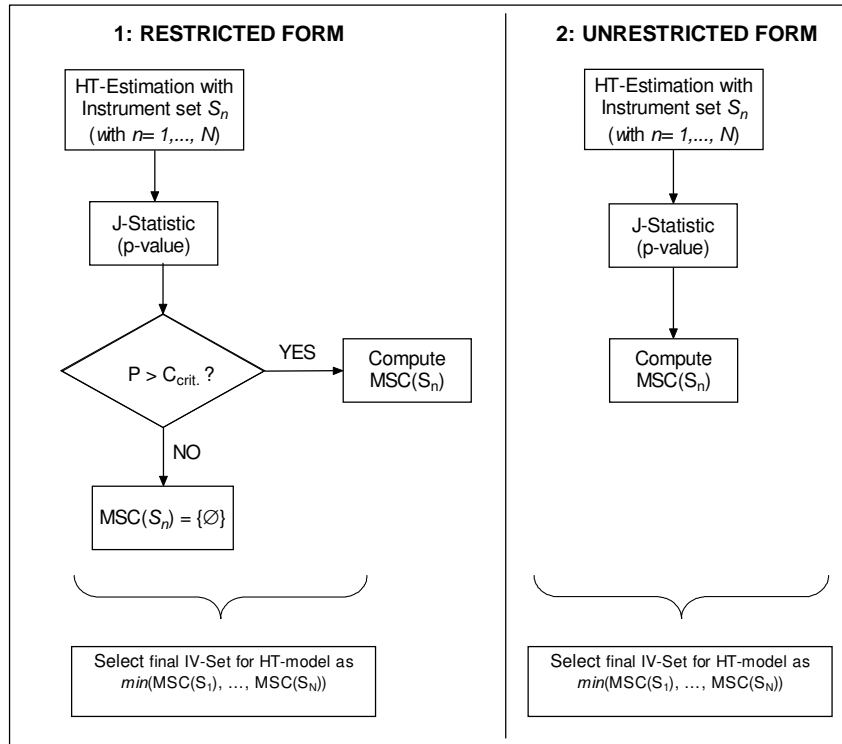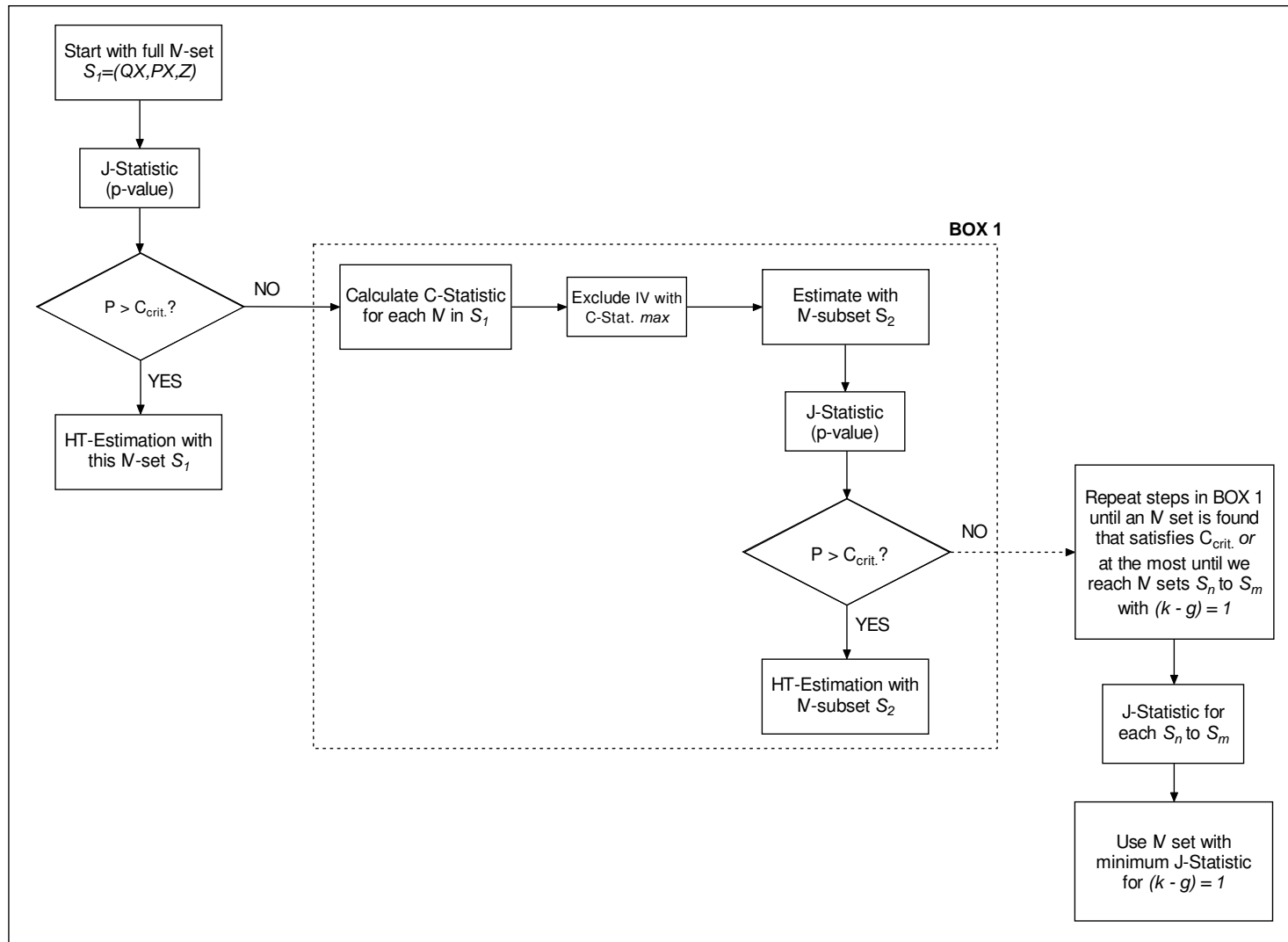**Figure A.1: MSC based model selection algorithm for HT-approach**

Figure A.2: C-Statistic based model selection algorithm for HT-approach

Table A.1: Data description and source for Export model

Variable	Description	Source
EX_{ijt}	Export volume, nominal values, in Mio.	Statistisches Bundesamt (German statistical office)
GDP_{it}	Gross Domestic Product, nominal values, in Mio.	VGR der Länder (Statistical office of the German states)
GDP_{jt}	Gross Domestic Product, nominal values, in Mio.	EUROSTAT
POP_{it}	Population, in 1000	VGR der Länder (Statistical office of the German states)
POP_{jt}	Population, in 1000	Groningen Growth & Development center (GGDC)
SIM_{ijt}	$SIM = log\left(1 - \left(\frac{GDP_{it}}{GDP_{it}+GDP_{jt}}\right)^2 - \left(\frac{GDP_{jt}}{GDP_{it}+GDP_{jt}}\right)^2\right)$	see above
RLF_{ijt}	$RLF = log\left|\left(\frac{GDP_{it}}{POP_{it}}\right) - \left(\frac{GDP_{jt}}{POP_{jt}}\right)\right|$	see above
EMP_{it}	Employment, in 1000	VGR der Länder (Statistical office of the German states)
EMP_{jt}	Employment, in 1000	AMECO database of the European Commission
$PROD_{it}$	$Prod_{it} = \left(\frac{GDP_{it}}{EMP_{it}}\right)$	see above
$PROD_{jt}$	$Prod_{jt} = \left(\frac{GDP_{jt}}{EMP_{jt}}\right)$	see above
$DIST_{ij}$	Distance between state capital for Germany and national capital for the EU27 countries, in km	Calculation based on coordinates, obtained from *www.koordinaten.de*
EMU	(0,1)-Dummy variable for EMU members since 1999	
EAST	(0,1)-Dummy variable for the East German states	
CEEC	(0,1)-Dummy variable for the Central and Eastern European countries	
BORDER	(0,1)-Dummy variable for country pairs with a common border	