**Online Supplemental Material**

In the following simulation study, we evaluate the performance of IPC regression for non-normally distributed data and more periods. Furthermore, we compare the performance of individual parameter contribution (IPC) regression with a multilevel model, a multigroup structural equation model (MGSEM), and a structural equation model (SEM) tree. Besides the multivariate normal distribution, we use Student’s *t*-distribution and the exponentially modified Gaussian distribution as data generating processes. Student’s *t*-distribution allows us to assess the performance of IPC regression for data sets with outliers, whereas the exponentially modified Gaussian distribution allows us to assess the performance of the method for skewed and non-symmetric data.

# **Simulation Setup**

We compare IPC regression with multilevel models, MGSEM, and SEM trees in their performance to identify and estimate a two-group difference in the intercept of a simple univariate autoregressive panel model in discrete time. We use a difference in the intercept, instead of differences in regression coefficients (as we did in the main article), because random effects for autoregressive or cross-lagged parameters are challenging to specify and estimate in standard structural equation modelling framework.

Figure 1 shows a path diagram for the first three measurement occasions of our simulation model. Here, $y\_{t,i}$ denotes the $t$-th measurement of individual $i$. The simulation model consists of the following parameters: $β$ is the autoregressive parameter which represents the stability of the process, $ψ$ denotes the unexplained variance after $y\_{t}$ has been regressed on its previous measurement $y\_{t-1}$, and $ϕ$ denotes the additional variance for the initial measurement $y\_{1}$. We used $β=0.5$, $ψ=0.75$, and $ϕ=0.25$ as parameter values. These parameter values imply that the variance of the process is $1$ for all measurement occasions. $μ\_{g}$ denotes the group-specific intercept of the observed variables and was set to $-0.1$ in the first group and to $0.1$ in the second group. The sample size per group was $125$ individuals, resulting in a total sample size of $250$ individuals.



Figure 1: Path diagram of the simulation model. Of interest is the group-difference in the mean $μ\_{g}$.

We varied the data generating processes and the length of the process (number of periods or measurement occasions) as experimental factors. As data generating processes, we used the multivariate normal distribution, Student’s *t*-distribution, and the exponentially modified Gaussian distribution. Normally distributed data were generated using the parameter values stated above. *t* distributed data were generated with 3 degrees of freedom and the exponentially modified Gaussian data were generated as the sum of a standard normal random variable and an exponentially distributed random variable with a rate parameter of $0.75$. The *t* distributed data and the exponentially modified Gaussian data were centered at the corresponding group-specific intercept $μ\_{g}$ and scaled to have a variance of $1$. We used either $5$ or $10$ measurement occasions. Each of the $3×2=6$ simulation conditions were replicated 10,000 times.

IPC regression was conducted in the following way. First, we fit the model shown in Figure 1 by estimating $β$, $ψ$, $ϕ$, and $μ$. Note that $μ$ was not allowed to vary between both groups. Then, we used vanilla IPC regression and iterated IPC regression to estimate group differences in $μ$ with a dummy variable indicating grouping. Iterated IPC regression was performed by re-estimating the IPC regression parameters until the change in all parameters was smaller than 0.0001. Multilevel models were estimated by adding a dummy variable with direct paths to all observed variables of the SEM used for IPC regression. This dummy variable can be seen as a predictor of a trait variable. MGSEMs were specified exactly as presented in Figure 1, where the intercepts $μ\_{1}$ and $μ\_{2}$ were allowed to differ between groups. For the SEM trees, two models were estimated and compared via the likelihood ratio test. A constrained model was estimated by setting all model parameters to be equal across both groups, whereas in the unconstrained model $β$, $ψ$, $ϕ$, and $μ$ were allowed to vary across groups. If the likelihood ratio test was significant (using the standard $5\%$ significance level), the SEM tree would give two sets of group-specific model parameters and a single set otherwise. All models were estimated using normal-theory maximum likelihood.

# **Simulation Results**

Table 1 presents the estimated differences in the intercept of the observed variables and the corresponding root mean square error (RMSE). Vanilla and iterated IPC regression, multilevel models, and MGSEMs performed equally well in terms of recovery of the difference and RMSE. As expected, SEM trees performed noticeably worse than the other methods. SEM trees will only attempt to estimate group-specific parameter values if the difference between the groups is found to be significant via a likelihood ratio test. Therefore, every non-significant simulation trial will bias the estimated difference towards zero and increase the RMSE. Outliers as produced by the *t*-distribution and skewed data as generated by the exponentially modified Gaussian distribution did not affect the estimate of the group difference. In case of SEM trees, non-normally data did even seem to improve the results slightly, which we will explain later. Finally, longer processes with 10 instead of 5 measurement occasions led to a decreased RMSE of all methods. One would expect such a finding as the amount of available data for estimating the group difference was doubled with 10 measurement occasions compared to only 5 measurement occasions.

Table 1

*Mean and RMSE of the estimated group difference*

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Dist. | *T* | Vanilla IPC | Iterated IPC | Multilevel | MGSEM | SEM Tree |
| M | R | M | R | M | R | M | R | M | R |
| $$N$$ | 5 | 0.199 | 0.082 | 0.200 | 0.082 | 0.200 | 0.082 | 0.200 | 0.082 | 0.119 | 0.159 |
| $$N$$ | 10 | 0.200 | 0.063 | 0.200 | 0.064 | 0.200 | 0.064 | 0.200 | 0.064 | 0.163 | 0.117 |
| *t* | 5 | 0.200 | 0.080 | 0.200 | 0.079 | 0.200 | 0.080 | 0.200 | 0.080 | 0.183 | 0.102 |
| *t* | 10 | 0.199 | 0.062 | 0.200 | 0.062 | 0.200 | 0.062 | 0.200 | 0.062 | 0.194 | 0.074 |
| EMG | 5 | 0.200 | 0.083 | 0.200 | 0.083 | 0.200 | 0.083 | 0.200 | 0.083 | 0.142 | 0.143 |
| EMG | 10 | 0.200 | 0.063 | 0.200 | 0.063 | 0.200 | 0.063 | 0.200 | 0.063 | 0.175 | 0.103 |

*Notes.* Dist. = data generating process. *T* = number of measurement occasions. M = mean difference. R = RMSE. $N$ = normal distribution. *t* = Student’s t-distribution. EMG = exponentially modified Gaussian distribution.

Table 2 summarizes the averaged RMSE of all model parameters. Taken all parameters into account, MGSEM performed best followed by the multilevel model approach, then both IPC regression methods, and, at last, SEM trees. This comparison, however, is slightly distorted by the fact that the IPC regression methods and SEM trees investigated differences in all model parameters, whereas the multilevel models and MGSEMs only considered group differences in the intercept of the observed variables. All methods showed an increased RMSE when the distribution was not normal, whereas *t*-distributed data had a more severe effect than exponentially modified Gaussian data. As expected, the RMSE was smaller in conditions with 10 instead of 5 measurement occasions.

Table 2

*Mean RMSE of all parameter estimates*

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Dist. | *T* | Vanilla IPC | Iterated IPC | Multilevel | MGSEM | SEM Tree |
| $$N$$ | 5 | 0.081 | 0.081 | 0.072 | 0.052 | 0.296 |
| $$N$$ | 10 | 0.071 | 0.071 | 0.065 | 0.043 | 0.080 |
| *t* | 5 | 0.183 | 0.184 | 0.122 | 0.109 | 0.191 |
| *t* | 10 | 0.170 | 0.170 | 0.112 | 0.100 | 0.164 |
| EMG | 5 | 0.108 | 0.108 | 0.083 | 0.083 | 0.158 |
| EMG | 10 | 0.095 | 0.095 | 0.074 | 0.074 | 0.103 |

*Notes.* Dist. = data generating process. *T* = number of measurement occasions. $N$ = normal distribution. *t* = Student’s t-distribution. EMG = exponentially modified Gaussian distribution.

Table 3 shows the power of the different methods to detect a group difference in the intercept of the observed variables and Table 4 presents the percentages of type I errors if this difference was set to zero. Power and proportions of type I errors of the IPC regression methods, the multilevel approach, and MGSEMs were very close to each other, whereas the power of SEM trees for normally distributed was slightly smaller. The high power of SEM trees for non-normally distributed data might be surprising at first but can be explained by the large number of type I errors committed for *t*-distributed and exponentially modified Gaussian data. The other methods appeared to be robust against deviations from normality with power and proportions of type I errors being almost identical for normal, t-distribution, and exponentially modified Gaussian data. Finally, the power to detect a difference increased with the number of measurement occasions.

Table 3

*Power to detect a group difference in the intercept*

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Dist. | *T* | Vanilla IPC | Iterated IPC | Multilevel | MGSEM | SEM Tree |
| $$N$$ | 5 | 66.65 | 66.90 | 67.35 | 67.16 | 45.41 |
| $$N$$ | 10 | 87.92 | 88.00 | 88.14 | 88.05 | 71.45 |
| *t* | 5 | 70.66 | 71.86 | 71.03 | 71.03 | 86.95 |
| *t* | 10 | 89.12 | 89.77 | 89.36 | 89.36 | 94.99 |
| EMG | 5 | 67.58 | 67.87 | 68.17 | 68.17 | 59.45 |
| EMG | 10 | 88.22 | 88.36 | 88.46 | 88.46 | 80.60 |

*Notes.* Dist. = data generating process. *T* = number of measurement occasions. $N$ = normal distribution. *t* = Student’s t-distribution. EMG = exponentially modified Gaussian distribution.

Table 4

*Proportions of type I errors*

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Dist. | *T* | Vanilla IPC | Iterated IPC | Multilevel | MGSEM | SEM Tree |
| $$N$$ | 5 | 4.96 | 5.14 | 5.10 | 5.02 | 5.08 |
| $$N$$ | 10 | 4.93 | 5.05 | 4.97 | 4.95 | 5.14 |
| *t* | 5 | 5.14 | 5.20 | 5.29 | 5.24 | 64.79 |
| *t* | 10 | 5.22 | 5.37 | 5.37 | 5.33 | 68.05 |
| EMG | 5 | 5.10 | 5.28 | 5.28 | 5.15 | 20.47 |
| EMG | 10 | 4.84 | 5.01 | 4.86 | 4.79 | 20.47 |

*Notes.* Dist. = data generating process. *T* = number of measurement occasions. $N$ = normal distribution. *t* = Student’s t-distribution. EMG = exponentially modified Gaussian distribution.

# **Summary**

# Overall, vanilla and iterated IPC regression performed almost as well as multilevel models and MGSEMs in detecting and estimating a group difference in the intercept of a univariate autoregressive panel model. Also, IPC regression exhibited a close to optimal type I error rate when the group difference was set to zero. The only noticeable difference between IPC regression and multilevel models and MGSEMs was the larger averaged RMSE of all model parameters. However, in contrast to multilevel models and MGSEMs, IPC regression considers differences in all model parameters and could have picked up random group-specific fluctuations which increased the averaged RMSE.

# Testing IPC regression under the condition of non-normality using the *t*-distribution and the exponentially modified Gaussian distribution revealed robust estimates that did not differ visibly from results obtained under normality. One could argue that the distributions used in this simple simulation could have been not extreme enough, however, the *t*-distributed and the exponentially modified Gaussian data were able to distort the type I errors of SEM model trees. Besides non-normality, using more measurement occasions improved the results for all methods under investigation.