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Abstract

Panel local projections have become a standard tool for estimating impulse response functions in empirical macroeconomics, yet their theoretical properties remain only partially understood. Recent work has shown that conventional fixed-effects estimators suffer from incidental-parameter (Nickell-type) bias, motivating analytical and jackknife bias corrections. This paper proposes a cumulative-difference OLS estimator for panel local projections that eliminates individual effects without relying on the within transformation. We show that cumulative differencing asymptotically removes the individual effects, derive the appropriate lag-augmented local projection specification, and prove that the resulting pooled OLS estimator is unbiased under standard exogeneity and stationarity assumptions. Monte Carlo simulations covering alternative persistence structures, sample dimensions, and dynamic specifications demonstrate that the proposed estimator consistently exhibits the smallest finite-sample bias and coverage probabilities close to their nominal levels, while the performance of fixed-effects, random-effects, and split-panel jackknife estimators depends critically on the persistence of both shocks and outcomes. Empirical applications further illustrate that estimator choice can materially affect estimated impulse responses. The results suggest that many biases recently documented in panel local projections arise from the interaction between within transformations and dynamic persistence rather than from local projections themselves, providing a simple and robust alternative for empirical researchers.

Keywords: Local projection, panel data, cumulative-differences, Nickell bias, impulse-response, split-panel jackknife, lag-augmentation

JEL Classification: C1, C13, C180, C5, C510, C8, C870, C33, C53, E44, F37, F47

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1 Introduction

Estimating dynamic causal effects in panel data settings is central to empirical macroeconomics and applied econometrics. Over the past two decades, local projections (LPs), introduced by Jordà (2005), have become a standard framework for estimating impulse response functions (IRFs). Panel LP applications are now widespread in peer-reviewed research and policy institutions analysis; however, despite their extensive empirical use, theoretical understanding of LP estimators in panel environments remains comparatively underdeveloped.

Recent contributions by Mei, Sheng and Shi (2026) and Herbst and Johannsen (2024) document that conventional fixed-effects (FE) or least-squared dummy-variables (LSDV) estimators used in panel LP regressions suffer from a Nickell (1981)-type bias, even when lagged dependent variables are absent. Mei, Sheng and Shi (2026) demonstrates that FE estimator for the panel LP model is asymptotically biased leading to systematic attenuation of estimated impulse responses, and they propose a split-panel jackknife (SPJ) correction that effectively mitigates bias under the data-generating process they consider. Herbst and Johannsen (2024) derive an analytical bias correction based on their estimated theoretical bias.

However, none of them consider whether the incidental-parameter problem and the the need for bias correction can be avoided altogether by reformulating the estimation problem. This paper proposes that differencing the dependent variable and estimating LP in what is usually called cumulative o long-differences removes the need to use a fixed-effect (FE) estimator and the within transformation that is at the center of the Nickell-bias problem.

Although differencing has long been used to eliminate individual effects in dynamic panel models, beginning with Anderson and Hsiao (1981), in conventional dynamic panel models, first differencing removes the individual effects but creates an endogeneity problem because the autoregressive coefficient governing the dynamics must still be estimated, requiring instrumental-variable methods.

Local projections, however, estimate the object of interest, the impulse response, directly at each horizon, so recovering the autoregressive coefficient is not necessary for estimating the dynamic response of the shock. In local projections, the whole impulse response function is embedded in the regression coefficient of the shock at each horizon, which can be consistently estimated through pooled OLS after eliminating the individual effects.

To our knowledge, this paper is the first to formalize this insight in the context of panel local projections. It formally establishes that differencing eliminates the individual effects in a local projection setting, derives the corresponding cumulative-difference pooled OLS estimator with an appropriate lag specification, and proves that the resulting estimator is unbiased under standard exogeneity and stationarity assumptions. The inclusion of the first lag of the shock is essential to avoid an omitted variable problem when the shock exhibits persistence.

Through extensive Monte-Carlo simulations we examine the behavior of panel LP estimators under three dynamic environments: (i) persistent shocks with non-persistent outcomes, (ii) persistent outcomes with serially uncorrelated shocks, and (iii) joint persistence in both shocks and outcomes. Within each setting, we evaluate the finite-sample properties of the conventional FE estimator, the split-panel jackknife correction (SPJ), the Random Effects estimator (RE) and several versions of an estimator that uses cumulative-difference transformations of the dependent variable, all under different sample sizes and autocorrelation parameters, including high-persistence levels.

The paper makes several contributions to the emerging theoretical literature on panel local projections. First, it develops a broader characterization of panel impulse responses by explicitly showing that their dynamic behavior depends jointly on the persistence of both the outcome variable and the shock process. Second, it proves that cumulative-difference local projections estimated by pooled OLS are unbiased under the maintained assumptions, thereby providing an alternative to fixed-effects estimation that avoids the incidental-parameter problem rather than correcting it ex post.

Third, the Monte Carlo experiments confirm the unbiasedness of our proposed estimator and also reveal several important findings: the finite-sample performance of fixed-effects, random-effects and split-panel jackknife estimators depends critically on the persistence structure of the data and that split-panel jackknife corrections need not be uniformly robust. The simulations show that pooled OLS is the estimation method that exhibits the smallest bias at all horizons of the IRF, is the most robust under different DGPs and the most robust to specifications changes regarding the lags of the dependent and shock variables.

Through our simulations, we also find that even the RE estimator could be vulnerable to the Nickell bias, even in cases in which the data generating process include individual effects that are uncorrelated to the shock, confirming the insight that the source of the problem is the within transformation. This is so because RE also uses a pseudo within transformation that in some cases could be almost exactly to the within transformation of the FE estimator. Our simulations also contribute to remind that there are many cases where the Nickell-bias is close to irrelevant. For instance, if only the outcome variable exhibits a moderate persistence and the sample has a number of time periods T large relative to the number of cross-sectional units N, then the bias of the FE estimator is almost negligible.

Finally, we revisit several influential empirical panel local projection applications and compare the resulting impulse responses across fixed-effects, split-panel jackknife, and cumulative-difference OLS estimators. These empirical replications illustrate that estimator choice can materially affect estimated impulse responses and suggest that the larger responses often obtained with split-panel jackknife corrections are consistent with the over-correction patterns documented in our Monte Carlo experiments under joint persistence.

These findings contribute to a more complete theoretical understanding of incidental parameter bias in panel local projections. For instance, it clarifies that the Nickell bias documented in recent work is a property of estimating panel local projections with within transformations, not a property of local projections themselves. They also provide practical guidance for empirical researchers estimating impulse responses in macroeconomic panels, where persistence is pervasive and time dimensions are moderate.

The rest of this paper is organized as follows: Section 2 briefly reviews the literature related to local projections in time series, the literature on dynamic panel bias and the Nickell bias and the short intersection between them. Section 3 presents the theoretical framework, it shows mathematically that time differencing actually eliminates the individual effects and presents a propose an estimator that does not require the within-transformation. Section 4 describes the simulation design and the estimations performed under different parameterizations of the DGP, different specifications, sample sizes and estimators. Section 5 presents and discuss the simulation results. Section 6 studies some empirical applications and Section 7 concludes and discuss other possible complications that we can encounter in empirical applications and other possible extensions and future research.

2 Literature Review

2.1 Local Projections in Time Series

Local projections (LPs), introduced by Jordà (2005), have become one of the standard approaches for estimating impulse response functions. Unlike vector autoregressions (VARs), LPs estimate horizon-specific regressions directly, allowing for flexible specifications and greater robustness to dynamic misspecification.

A substantial theoretical literature has analyzed the statistical properties of LP estimators in time-series environments. Under correct specification, LP and VAR impulse responses are asymptotically equivalent, although finite-sample properties may differ substantially. Recent work has emphasized the robustness advantages of LPs under misspecification, as well as the role of lag augmentation, smoothing, and alternative transformations in improving inference and finite-sample performance. Jordà and Taylor (2025) provide a comprehensive survey of this literature.

Particularly relevant for this paper is the literature that studies cumulative or long-difference transformations in dynamic environments. Such transformations can improve finite-sample performance in persistent settings by reducing dynamic misspecification and mitigating persistence-related distortions. However, existing results are primarily developed in pure time-series contexts and do not directly address panel data environments with individual effects.

2.2 Dynamic Panel Bias

Separately, a large econometric literature studies incidental parameter bias in dynamic panel models. Since the seminal contribution of Nickell (1981), it has been well understood that fixed-effects estimators in panels with finite time dimension T exhibit biases of order $O(1/T)$ whenever regressors are correlated with transformed disturbances. Numerous bias-correction procedures have subsequently been proposed, including analytical corrections and jackknife estimators such as the split-panel jackknife (SPJ).

This literature, however, focuses primarily on autoregressive panel models rather than horizon-by-horizon local projection regressions. As a result, its implications for panel LP estimation remain only partially understood.

2.3 Panel Local Projections

Despite the widespread use of local projections in macroeconomic panels, the theoretical literature on panel LP estimators remains comparatively limited. The leading contribution in this area is Mei, Sheng and Shi (2026), who show that fixed-effects estimators in panel LP regressions suffer from a Nickell-type bias even in the absence of lagged dependent variables. Their analysis demonstrates that persistence in the shock variable induces correlation between regressors and transformed errors, generating attenuation bias in estimated impulse responses and invalidating standard inference based on conventional t-statistics.

In another recent paper, Herbst and Johannsen (2024) document that LP point estimates can be severely biased because LP are often used with very small samples in the time dimension. They extend the analysis to settings using panel data and show that, when using fixed effects, the bias persists. They derive formulas to approximate the bias, which could be used to bias-correct LP estimators. Their bias estimation is actually very close to the Nickell-bias since they include individual effects in their specification and they estimate a bias of order $1/T$.

The main difference between Herbst and Johannsen (2024) and Mei, Sheng and Shi (2026) is that the first one analyzes the properties of the least-square dummy-variable (LSDV) estimator and they focus on the bias when the dependent variable exhibits autocorrelation, whereas the latter analyzes the fixed-effect estimator that relies on the within-transformation, while focusing on the case when the regressor exhibits autocorrelation.

Mei, Sheng and Shi (2026) show that split-panel jackknife corrections can substantially reduce the bias under the persistence structure considered in their framework and they point out that their solution is free of analytical bias calculation.

Crucially, neither Herbst and Johannsen (2024) nor Mei, Sheng and Shi (2026) consider or evaluate the case in which differencing the dependent variable and estimating LP in what is usually called cumulative-differences can be done without the within transformation necessary to estimate the fixed-effect (FE) estimator, something that is at the root of the Nickell-bias problem.

Mei, Sheng and Shi (2026) do evaluate analytically and through simulations a specification with the dependent variable in long-differences. However, they assume in the data generating process that the individual effects remained included in such specification. Moreover, they proceed to estimate it using FE, which causes that they find that such estimator still suffers from the Nickel bias.

Moreover, many empirical macroeconomic applications involve high persistence of both the shock variable and the dependent variable. Output, inflation, credit aggregates, and financial variables typically exhibit substantial intrinsic high serial correlation. In such environments, the statistical properties of panel LP estimators remain a challenge. In particular, it is unclear whether the SPJ bias correction performs adequately under highly persistent dynamics.

For instance, Mei, Sheng and Shi (2026) documented a significant deviation in the coverage probability of the confidence interval of the SPJ estimator when the persistence of the shock was above 90%, while acknowledging the limitation of its proposed correction because "the theoretical foundations of SPJ do not cover highly persistent regressors". Moreover, they only analyzed the case of highly persistent shocks, but extending the framework to settings where both shocks and outcomes are highly persistent could still be more challenging.

Through extensive Monte Carlo simulations, we demonstrate that cumulative-difference local projections estimated using pooled OLS and including one lag of the shock variable consistently outperform conventional fixed-effects estimators and split-panel jackknife corrections across a wide range of persistence structures, sample sizes, and specifications, even under highly persistent dynamic environments.

Our results clarify that many of the distortions emphasized in recent panel LP research are not intrinsic to local projections themselves, but instead arise from the use of within transformations in persistent dynamic environments.

3 Theory and Data Generating Process

To understand the theoretical framework of the simulation, we present a prototype model where the dependent variable $y_{i,t}$ is generated from the following data generating process (DGP):

$$y_{i,t} = \rho_y y_{i,t-1} + \beta s_{i,t} + u_i + e_{i,t} \tag{1}$$

$$s_{i,t} = \rho_s s_{i,t-1} + v_{i,t} \qquad i = 1, ..., N; \qquad t = 1, ..., T, \tag{2}$$

where $|\rho_y| < 1$ and $|\rho_s| < 1$ to ensure stationarity.

Assumption 1: $s_{i,t}$ is orthogonal to $e_{i,t}$ and $v_{i,t}$

- $E[s_{i,t}|e_{i,t}] = 0$
- $E[s_{i,t}|v_{i,t}] = 0$
- $E[s_{i,t}|e_{i,s}] = 0, \forall s \neq t$
- $E[s_{i,t}|v_{i,s}] = 0, \forall s \neq t$

Assumption 2: $s_{i,t}$ is a stationary variable with autocorrelation of order 1:

- $E[s_{i,t}|s_{i,t-1}, ..., s_{i,t-k}] = \rho_s s_{i,t-1}, \forall k \geq 2$

We do not consider the case of time effects, although they could be added relatively easy.

Following Jordà and Taylor (2025), we are interested in characterizing how an intervention today affects the average outcome at some time in the future relative to a baseline of no-intervention. Let y_t denote an outcome variable of interest, s_t the policy intervention variable, and let x_t denote a vector of controls variables. Formally, we define an impulse response as:

$$\mathcal{R}_{s\to h} = E[y_{t+h}|s_t = s_0 + \delta; x_t] - E[y_{t+h}|s_t = s_0; x_t]; \qquad h = 0, 1, ..., H, \tag{3}$$

where s_0 denotes the value of the variable s_t without intervention and δ is the size of the intervention, which is commonly normalized so that $\delta = 1$. This allows to omit δ from the notation and write $\mathcal{R}_{s\to h}(h, 1) \equiv \mathcal{R}_{s\to h}(h) \equiv \mathcal{R}_{sh}(h)$.

We want to understand what the theoretical Impulse Response Function (IRF) is for different values and combinations of ρ_y and ρ_s. For simplicity, we first assume that u_i, $e_{i,t}$ and $v_{i,t}$ are all equal to zero and rewrite (1) and (2) as an expression for $y_{i,t}$ and $s_{i,t}$, h periods ahead:

$$y_{i,t+h} = \rho_y y_{i,t+h-1} + \beta s_{i,t+h} \tag{4}$$

$$s_{i,t+h} = \rho_s s_{i,t+h-1}; \qquad h = 0, ..., H, \tag{5}$$

3.1 Only the dependent variable is persistent

Since we assume that $\rho_y \neq 0$ but $\rho_s = 0$, then (5) becomes irrelevant.

When $h = 0$ The response $\mathcal{R}_{sh}(h = 0)$ is simply equal to β. For $h = 1$ we substitute (4) with $h = 0$ into itself one period ahead i.e. (4) with $h = 1$ and we obtain that $\mathcal{R}_{sh}(h = 1) = \rho_y \beta$. For $h \geq 2$ we repeat the substitution to obtain that $\mathcal{R}_{sh}(h) = \rho_y^h \beta$, which can also be denoted as $\beta_h = \rho_y^h \beta$.

3.2 Only the shock variable is persistent

Since we assume that $\rho_y = 0$ and $\rho_s \neq 0$, then (4) becomes simply:

$$y_{i,t+h} = \beta s_{i,t+h} \tag{6}$$

For $h = 0$, the response $\mathcal{R}_{sh}(h = 0)$ is again β. For $h = 1$ we substitute (6) with $h = 0$ into (4) with $h = 1$ and we obtain that $\mathcal{R}_{sh}(h = 1) = \rho_s \beta$. For $h \geq 2$ we repeat the substitution to obtain that $\mathcal{R}_{sh}(h) = \rho_s^h \beta$, which again, can also be denoted as $\beta_h = \rho_y^h \beta$.

3.3 Both the dependent variable and the shock are persistent

We assume that both $\rho_y \neq 0$ and $\rho_s \neq 0$. For $h = 0$, the response $\mathcal{R}_{sh}(h = 0)$ is again β. For $h = 1$ we substitute (5) and (4) with $h = 0$ into (4) with $h = 1$:

$$\begin{aligned} y_{i,t+1} &= \rho_y y_{i,t} + \beta s_{i,t+1} \\ ... &= \rho_y(\rho_y y_{i,t-1} + \beta s_{i,t}) + \beta(\rho_s s_{i,t}) \\ ... &= \rho_y^2 y_{i,t-1} + \beta s_{i,t}(\rho_y + \rho_s) \end{aligned} \tag{7}$$

For $h = 2$:

$$\begin{aligned} y_{i,t+2} &= \rho_y y_{i,t+1} + \beta s_{i,t+2} \\ ... &= \rho_y(\rho_y^2 y_{i,t-1} + \beta(\rho_y + \rho_s)s_{i,t}) + \beta(\rho_s^2 s_{i,t}) \\ ... &= \rho_y^3 y_{i,t-1} + \beta_s s_t(\rho_y^2 + \rho_y\rho_s + \rho_s^2) \end{aligned} \tag{8}$$

We can continue the iteration and we can see that for $h = 3$ we obtain

$$y_{i,t+3} = \rho_y^4 y_{i,t-1} + \beta_s s_t(\rho_y^3 + \rho_y^2\rho_s + \rho_y\rho_s^2 + \rho_s^3) \tag{9}$$

And for $h = 4$;

$$y_{i,t+4} = \rho_y^5 y_{i,t-1} + \beta_s s_t(\rho_y^4 + \rho_y^3\rho_s + \rho_y^2\rho_s^2 + \rho_y\rho_s^3 + \rho_s^4) \tag{10}$$

Thus, the impulse response function $\mathcal{R}_{sh}(h)$ or β^h can be generalized to:

$$\begin{aligned} &\mathcal{R}_{sh}(0) = \beta_0 = \beta \\ &\mathcal{R}_{sh}(1) = \beta 1 = \beta(\rho_y + \rho_s) \\ &\mathcal{R}_{sh}(h) = \beta_h = \beta(\rho_y^h + \rho_s^h + \sum_{i=1}^{h-1} \rho_y^{h-i}\rho_s^i); \qquad h = 2, ..., H \end{aligned} \tag{11}$$

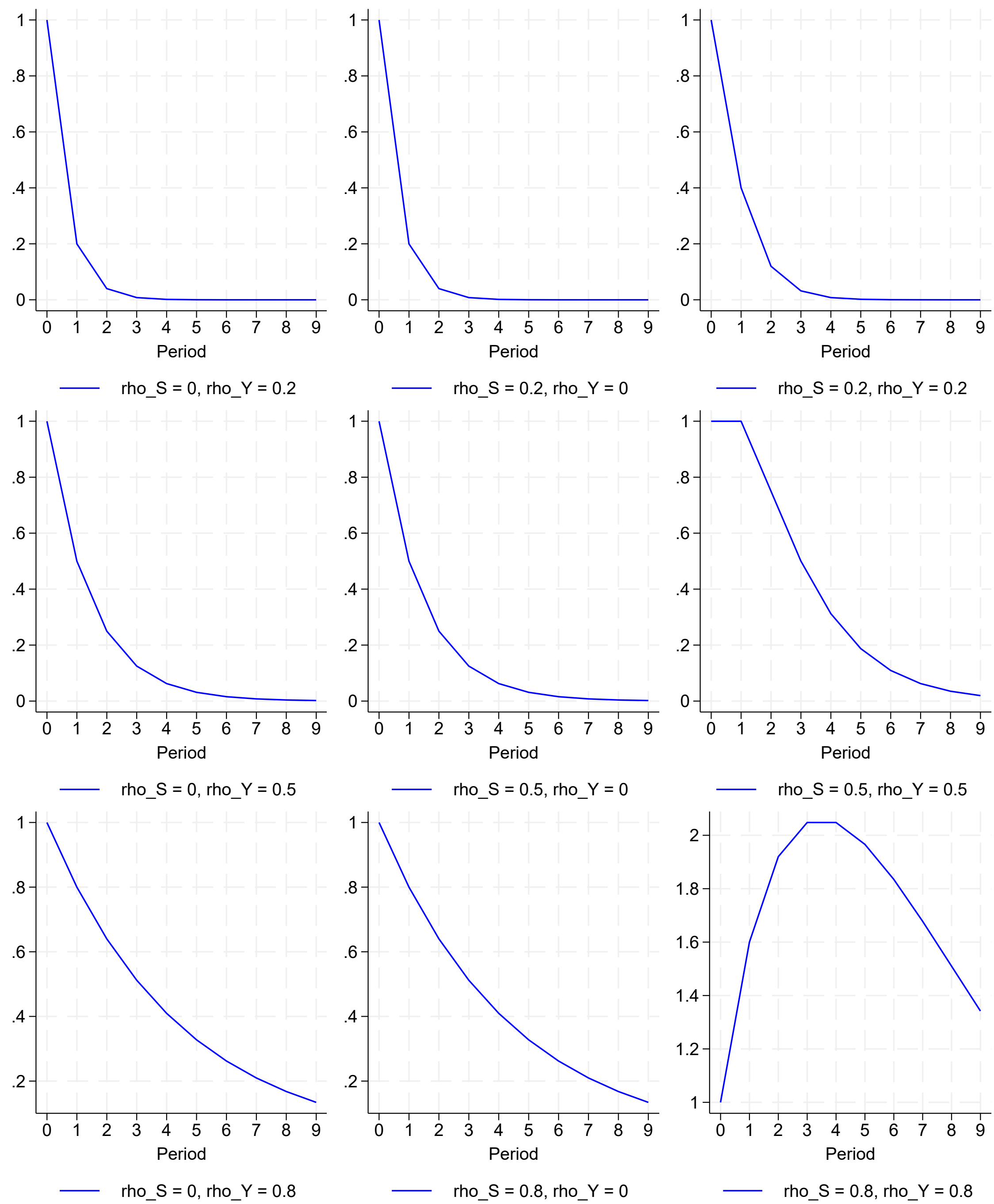
We can see the IRF for the three different cases in Figure 1 for $\beta = 1$

The panel version of Jordà (2005)'s local projection (LP) has become widely used in empirical analyses for its simplicity, robustness, and flexible specifications. One of the theoretical advantages of a panel data setting in local projections is that, in addition to having potentially more observations with which to increase the precision of the estimates, it also opens a large set of methodological possibilities like different types of nonlinearities. A typical panel data local projection could be specified as:

$$y_{i,t+h} = \mu_h + \beta_h s_{i,t} + \gamma_h' x_{i,t} + u_i + e_{i,t+h}; \qquad h = 0, ..., H \tag{12}$$

As long as $E[s_{i,t}|e_{i,t+h}] = 0$, i.e. s_t is exogenous, and $E[u_i|s_{i,t}] = 0$, i.e. individual effects are not correlated with the shock, then we might use a Random Effects (RE) local projection to estimate the IRFs and we would get that $\mathcal{R}_{sh}(h) = \beta_h$ in all of the theoretical cases

Figure 1: Impulse response according to different autocorrelations of Y and S, with Beta=1



considered in this section.

However, if $E[u_i|s_{i,t}] \neq 0$ we would have to use a Fixed-Effects (FE) estimator to get rid of the u_i. In that case, Mei, Sheng and Shi (2026) have shown that the FE estimator has an intrinsic attenuation bias which could be corrected by using the Split-Panel Jackknife SPJ estimator.

However, another possible solution to get rid of the individual effects could be to differentiate the dependent variable and estimate equation (12) using the RE estimator, or OLS which is not affected by the Nickell bias.

We want to derive an expression for the cumulative differences LP estimator of s_t on y_t in $h = 0$. For simplicity, we are going to ignore any control variable x_t. Notice that $y_{i,t}$ and $y_{i,t-1}$ are given by:

$$\begin{aligned} y_{i,t} &= \rho_y y_{i,t-1} + \beta s_{i,t} + u_i + e_{i,t} \\ y_{i,t-1} &= \rho_y y_{i,t-2} + \beta s_{i,t-1} + u_i + e_{i,t-1} \end{aligned} \tag{13}$$

If we replace $y_{i,t-1}$ into $y_{i,t}$, and then $y_{i,t-2}$ into the resulting equation, and keep on replacing recursively up until the initial period $y_{i,t-T_0} = \beta s_{i,t-T_0} + e_{i,T_0} + u_i$, then we can express $y_{i,t}$ as a weighted sum of all the current and previous values of $s_{i,t}$, u_i and $e_{i,t}$, or its MA representation:

$$y_{i,t} = \sum_{k=1}^{T_0} \rho_y^k (\beta s_{i,t-k} + u_i + e_{i,t-k}) + \beta s_{i,t} + u_i + e_{i,t} \tag{14}$$

or as

$$y_{i,t} = \sum_{k=1}^{T_0} \rho_y^k (\beta s_{i,t-k} + e_{i,t-k}) + \beta s_{i,t} + e_{i,t} + \sum_{k=0}^{T_0} \rho_y^k u_i \tag{15}$$

If we repeat the same recursive process for y_{t-1}, we would get a very similar expression:

$$y_{i,t-1} = \sum_{k=1}^{T_0} \rho_y^{k-1} (\beta s_{i,t-k} + e_{i,t-k}) + \sum_{k=1}^{T_0} \rho_y^{k-1} u_i \tag{16}$$

Which can be rearranged to get the following:

$$y_{i,t-1} = \sum_{k=1}^{T_0} \rho_y^{k-1} (\beta s_{i,t-k} + e_{i,t-k}) + \sum_{k=0}^{T_0-1} \rho_y^{k} u_i \tag{17}$$

Therefore if we differentiate y_t to get $y_{i,t} - y_{i,t-1}$, we can subtract equation (17) from equation (15). Notice that the difference between the last two terms in each of those equations $\sum_{k=0}^{T_0} \rho_y^k u_i - \sum_{k=0}^{T_0-1} \rho_y^k u_i$ is equal to $\rho_y^{T_0} u_i$.

Therefore $y_{i,t} - y_{i,t-1}$ would be equal to:

$$y_{i,t} - y_{i,t-1} = \sum_{k=1}^{T_0} (\rho_y^k - \rho_y^{k-1})(\beta s_{i,t-k} + e_{i,t-k}) + \beta s_{i,t} + e_{i,t} + \rho_y^{T_0} u_i \tag{18}$$

Since $|\rho_y| < 1$ then $\rho_y^{T_0} u_i \to 0$ when $T_0 \to \infty$, so it follows that differentiating y_t effectively eliminates asymptotically the individual effects u_i. Eliminating individual effects by differencing was used by Anderson and Hsiao (1981) for designing their dynamic panel estimator.

Rearranging equation (18), and using the fact that s_t is not correlated with s_{t-k} for $k > 2$, it follows that we can estimate $\mathcal{R}_{sh}(h = 0)$, or β_0, through the local projection given by the following specification:

$$y_{i,t} - y_{i,t-1} = \beta_0 s_{i,t} + \gamma_0 s_{i,t-1} + \epsilon_{i,t} \tag{19}$$

Where $\beta_0 = \beta$, $\gamma_0 = (\rho_y - 1)\beta$
and $\epsilon_{i,t} = \sum_{k=2}^{T_0} (\rho_y^k - \rho_y^{k-1}) \beta s_{i,t-k} + e_{i,t} + \sum_{k=1}^{T_0} (\rho_y^k - \rho_y^{k-1}) e_{i,t-k}$.

It is important to note that as long as $\rho_s > 0$, s_t is correlated with s_{t-1} and therefore, we must include the latter in the specification otherwise we would run into an omitted variable bias problem.

Since there are no individual effects in equation (19) we can efficiently estimate it through OLS or RE. In fact, estimating it by FE would bring back the Nickell Bias problem.

It is also important to notice that in this specification we cannot estimate ρ_y, but if we are only interested in the response of y_t to a shock in s_t we do not need an estimate of ρ_y.

In the Appendix we derive similar expressions for $h = 1, ..3$ showing that in those cases the individual effects are effectively wiped out when we apply long-differences. Using those results we can generalize equation (19) into the following local projection specification in cumulative differences:

$$y_{i,t+h} - y_{i,t-1} = \beta_h s_{i,t} + \gamma_h s_{i,t-1} + \epsilon_{i,t+h}; \qquad h = 0, ..., H \tag{20}$$

Where $\beta_h = \beta$ for $h = 0$;
$\beta_h = \beta(\rho_y + \rho_s)$ for $h = 1$;
$\beta_h = \beta(\rho_y^h + \rho_s^h + \sum_{i=1}^{h-1} \rho_y^{h-i} \rho_s^i)$ for $h = 2, ..., H$,
$\gamma_h = (\rho_y^h - 1)\beta$;
and $\epsilon_{i,t+h} = \sum_{k=0}^{h} \rho_y^k e_{i,t+h-k} + \beta \sum_{k=0}^{h-1} \rho_y^k v_{i,t+h-k} + \sum_{k=1}^{T_0} (\rho_y^{k+h} - \rho_y^{k-1}) e_{i,t-k}$
$+ \sum_{k=2}^{T_0} (\rho_y^{k+h} - \rho_y^{k-1}) \beta s_{i,t-k}$.

Proposition 1 Being $\widehat{\beta_h}$ the pooled OLS estimator given by equation 20 we can show that it is unbiased as long as Assumption 1 and Assumption 2 hold, i.e.:

$$E[\widehat{\beta_h}] = \beta_h; \qquad h = 0, ..., H \tag{21}$$

Proof:

In the case where $\rho_s = 0$, the proof is trivial since, following Assumption 1 and Assumption 2, $E[s_{i,t}|s_{i,t-k}] = 0$ for $\forall k \geq 1$, $E[s_{i,t}|e_{i,t}] = 0$, $E[s_{i,t}|v_{i,t}] = 0$, $E[s_{i,t}|e_{i,t+k}] = 0$ and $E[s_{i,t}|v_{i,t+k}] = 0$ $\forall k \neq 0$. Then it follows that $E[s_{i,t}|\epsilon_{i,t+h}] = 0$, and therefore we can consistently estimate β_h for each $h = 0, ..., T$

The proof where $\rho_s \neq 0$ requires the use of the Frisch–Waugh–Lovell (2008)[1] partial-regression theorem and it is shown in subsection A.2 in the Appendix.

Note that $\epsilon_{i,t+h}$ would display autocorrelation since it includes the lags of multiple variables and therefore we should use a robust estimator of variance or the Driscoll-Kraay estimator of variance.

We study all these possibilities in the simulations described in Section (4).

4 Simulations

4.1 Simulation Data

We create panel datasets for use in Monte Carlo experiments as pseudo-random realizations from dynamic linear panel data models. We rely on the Stata command **xtarsim** created by Bruno (2005) to generate datasets originated from the following data generating

[1] Greene (2003)

process:

$$y_{i,t} = \rho_y y_{i,t-1} + \beta s_{i,t} + u_i + u_t + e_{i,t} \tag{22}$$

$$s_{i,t} = \rho_s s_{i,t-1} + v_{i,t} \qquad i = 1, ..., N; \qquad t = 1, ..., T_0, \tag{23}$$

where

$e_{i,t}$ are iid $N(0, \sigma^2)$ $v_{i,t}$ are iid $N(0, \sigma_v^2)$, with σ_v determined by the signal to noise ratio which in our simulations is chosen to be equal to 20.

$e_{i,t}$ and $v_{i,t}$ are not correlated, so that $s_{i,t}$ is a strictly exogenous regressor in the first equation of the model. However, u_i are the individual effects that may or may not be correlated with $s_{i,t}$. Initially, we assume that they are correlated and therefore, they are determined by $u_i = \alpha(1 - \rho_y)(1 + \bar{s}_i - \bar{s})$, where $\bar{s}_i$ and $\bar{s}$, respectively, are the group mean and the overall mean of $s_{i,t}$, and α is a load factor we have assumed equal to 10.

If not correlated, individual effects are taken to be i.i.d. $N(0, \alpha^2(1 - \rho_y)^2)$.

We simulate three different types of samples according to the autocorrelation of the dependent and shock variables, following the three cases considered in section 3.

- A sample in which only the shock variable has autocorrelation, which is the case examined by Mei, Sheng and Shi (2026) in their main simulations.
- A sample in which only the dependent variable has autocorrelation.
- A sample in which both of them have autocorrelation.

We also consider two different sample sizes:

- Sample of size $N = 100$ and $T = 50$ since this could be considered a typical sample size when we work with macroeconomic data coming, for example, from the IMF World Economic Outlook (WE0).
- Sample of size $N = 30$ and $T = 60$ since this is the sample size considered by Mei, Sheng and Shi (2026) that has the largest bias in their simulations.

The parameters that we have used for the simulation are: $\beta = 1$, $\rho_s = 0.8$ and $\rho_y = 0.8$. We chose a higher autocorrelation since according to Mei, Sheng and Shi (2026) this is the case in which the size of the bias in local projections with Fixed-Effects is the largest.

We also considered two additional cases:

- A sample with lower autocorrelation parameters: $\rho_s = 0.5$ and $\rho_y = 0.5$
- A sample in which the individual effects are not correlated with $s_{i,t}$, in which case, Random Effects are unbiased and we do not need to use Fixed Effects.

4.2 Local Projection Monte Carlo Experiments

For each generated sample we perform multiple estimations of local projections with different specifications and different estimators, and we average the IRFs and their confidence bands for the 100 replications. For estimating each local projection we use the Stata command **locproj** created by Ugarte-Ruiz (2023).

We consider the following eight estimators:

- Random Effects with robust standard errors (RE)
- Fixed (Within) Effects with robust standard errors (FE)
- Split-Panel Jackknife Estimator (SPJ)
- Random Effects taking cumulative (long) differences of the dependent variable (robust standard errors) (CMRE)
- Fixed Effects taking cumulative (long) differences of the dependent variable (robust standard errors) (CMFE)
- Random Effects taking cumulative (long) differences of the dependent variable (robust standard errors) but including by default one lag of the shock (CMRE1)
- Fixed Effects taking cumulative (long) differences of the dependent variable (robust standard errors) but including by default one lag of the shock (CMFE1)
- OLS taking cumulative (long) differences of the dependent variable (robust standard errors) but including by default one lag of the shock (CMOLS)

When using estimators RE, FE and SPJ we start with the specification defined by (12) although in our case we do not include any control variables or time-fixed effects:

$$y_{i,t+h} = \mu_h + \beta_h s_{i,t} + u_i + e_{i,t+h}; \qquad h = 0, ..., H \tag{24}$$

When using estimators CMRE and CMFE we start with the following specification:

$$y_{i,t+h} - y_{i,t-1} = \beta_h s_{i,t} + e_{i,t+h}; \qquad h = 0, ..., H \tag{25}$$

Finally, when using estimators CMRE1, CMFE1 and CMOLS we start with the specification defined in (20).

For each case, we also consider three modifications to the initial specification. In each case, we add lags of the dependent variable, the shock, or both variables. Therefore, the four specifications considered for each estimator are the following:

- No added lags of either variable
- One added lag of the dependent variable
- One added lag of the shock variable
- One added lag of each variable.

Thus, in the cases where we add one lag of the shock, estimators CMRE1, CMFE1 and CMOLS would actually have two lags of s_t.

Moreover, it is important to clarify that the lags of the dependent variable are included in a different way depending on the estimator. For the RE, FE and SPJ cases, the lags of the dependent variable are in levels, whereas in the case of the cumulative differences (CMRE, CMFE, CMRE1, CMFE1) the lags of the dependent variable are in first-differences.

For estimating the local projections through the SPJ estimator, we combine the Stata command **locproj** selecting as estimation method the Stata command **xtspj** created by Sun and Dhaene (2019). A complete description of the way of including the lags of the shock and dependent variable can be found in Ugarte-Ruiz (Forthcoming).

5 Simulation Results

We present the results of the following simulation exercises:

- Sample with N=100, T=50 and high autocorrelation coefficients (p_s and/or p_y equal to 0.8
- Sample with N=100, T=50 and very high autocorrelation coefficients (p_s and/or p_y equal to 0.9
- Sample with N=100, T=50 and high autocorrelation coefficients (p_s and/or p_y equal to 0.8, but individual effects u_i are not correlated with s_t

In the Appendix, We present the results of two further exercises:

- Sample with N=30, T=60 and high autocorrelation coefficients (p_s and/or p_y equal to 0.8
- Sample with N=100, T=50 and low autocorrelation coefficients (p_s and/or p_y equal to 0.5

The results for each sample are all presented a similar structure. The first three figures displays the simulated IRFs of the Fixed Effects (FE), Split-Panel-Jackknife (SPJ) and Random Effects (RE) estimators with robust standard errors, and the different versions of the estimators in cumulative differences (CMRE, CMFE, CMRE1, CMFE1 and CMOLS) for the four basic specifications in each one of the three DGP cases considered.

The tables that follow the figures show the bias and the coverage probability of the confidence interval of the eight estimators, as an average of all the horizons and for the first and last estimated ones, i.e. $h = 0$ and $h = 9$.

For the case where ρ_y and ρ_s are equal to 0.8 (or zero), we show the results by DGP and for each specification. For all the other cases, we summarize the results and only show, for each DGP, the average of the four specifications and the results for the best specification.

All tables are ordered from the highest to the lowest average coverage probability. In some of them, we can also see which one out of the four specifications has the best average coverage probability.

In subsections A.4 and A.5 in the Appendix, we show the results of the simulations when there are more time periods than individuals, $T > N$, and when autocorrelation is much lower, ρ_s or ρ_y are either 0 or 0.5.

5.1 Sample with more individuals than time periods, i.e. N=100, T=50

Figure 2 reports the average of the estimated IRFs over the 100 replications and compares them with the true IRFs for the first DGP case, i.e. when only s_t has autocorrelation. Figure 3 reports the results for the cases where only the dependent variable has autocorrelation, something that was not considered by Mei, Sheng and Shi (2026) in their main simulations. Finally, 4 reports the results when both the outcome and the shock have correlation. Each row shows the results for each one of the different specifications.

Then Tables 1 to 4 report the bias and coverage probability of the confidence interval for all combinations of the three DGP processes and the four specifications considered.

We can see that the results of the top left panel clearly replicate the results obtained by Mei, Sheng and Shi (2026). FE estimator is downward biased (attenuation) while the SPJ seems to be unbiased at most horizon periods. However, we can see that the SPJ estimator displays a small bias in the longer periods.

We can also see that as we add lags of the dependent variable or the shock (lag augmentation), the bias of the FE estimator diminishes, although does not disappear, it goes from around -17.8% to -11.7% when $h = 9$.

One of the most important results that can be seen in Figure 2, is that the OLS and RE estimators in cumulative differences appear to be unbiased in all four specifications when specified as in equation (20), i.e. in the CMOLS and CMRE1 cases. A somewhat less surprising result is that the CMRE estimator appears clearly biased due to the omission of the first lag of s_t in the first two specifications, although it is noticeable that the size of the bias is pretty substantial.

The FE estimator in cumulative differences (CMFE and CMFE1) always displays an attenuation bias compared to the RE alternative, which is also a consequence of the Nickell bias.

The RE estimator is clearly biased in most cases, although the bias also seems to diminish once we add lags of the shock. In this case, we have to be cautious and highlight that this could be a result of the combination of parameters and not something that can be generalized without considering other parameter combination, such as the sign of the correlation between the individual effect and the shock.

In Figure 3 and Tables 5 to 8 we can see that the bias of the FE is smaller than when only the shock is persistent. The bias now is around -10% at $h = 9$ compared to -18% when only the shock was persistent. However, in this case the bias does not seem to decrease when we add lags of the dependent variable and/or the shock, is always around -10% on average.

In general, when only the dependent variable is persistent, it is clear that not only the bias of FE decreases, but it does for all the estimators considered, even the RE estimator also exhibits a much lower bias in most cases.

Importantly, replicating the case when only the shock was persistent, the CMOLS and CMRE1 estimators appear to be unbiased in all specifications. Moreover, CMOLS displays the highest coverage probability and it is always around 95%.

Also the CMRE estimator now look unbiased in all specifications while before it was severely bias when no lags of $y_{i,t}$ or $s_{i,t}$ were included. Even the FE estimator in cumulative differences appears to be unbiased, although its bias increases when we add lags of the shock and at longer horizons.

Although the SPJ estimator shows a relatively small bias, its coverage probability is clearly low and is only superior to the RE and all the estimators that use FE.

Finally, another important contribution of this paper could be seen in Figures 4 and Tables 9 to 12. Now, it is noticeable that both the FE estimator and the SPJ estimator have an upward bias (an intensification bias), which is actually more intense in the SPJ than in the FE one. In Table 9 the bias of the SPJ is 178% when $h = 0$.

The positive bias of both estimators seems to decrease once we add lags of the shock or the dependent variable in the specification, although in the FE case the bias turns negative and considerably large. In the SPJ case, the positive bias diminishes, but never disappears, when adding a lag of $y_{i,t}$ the SPJ estimator shows an average bias of 13%, and when adding a lag of both $y_{i,t}$ and $s_{i,t}$ the average bias is around 5%.

Considering that most variables studied in macroeconomic are usually highly persistent, this could suggest that the SPJ could be problematic in many applications if we do not include lags of either $s_{i,t}$ or $y_{i,t}$, and it could still remain positively biased after lag-augmentation.

We can see that the CMOLS and CMRE1 estimators remain fairly unbiased in all four specifications. However, it seems that at the longer horizons a negative bias starts to appear in the CMRE1 case. This could be due to the pseudo-differentiation in RE which could make it somewhat vulnerable to the Nickell bias.

Importantly, this does not occur in the CMOLS case, which looks clearly unbiased in all specifications and horizons. Moreover, the coverage probability of the CMOLS estimator is clearly very close to 95% in all cases. Interestingly, the CMRE1 estimator although sometimes shows a higher coverage probability than the CMOLS one, in general displays a much larger bias at horizon $h = 9$.

Figure 2: IRF, $N = 100, T = 50$ when $\rho_s = 0.8$ and $\rho_y = 0$

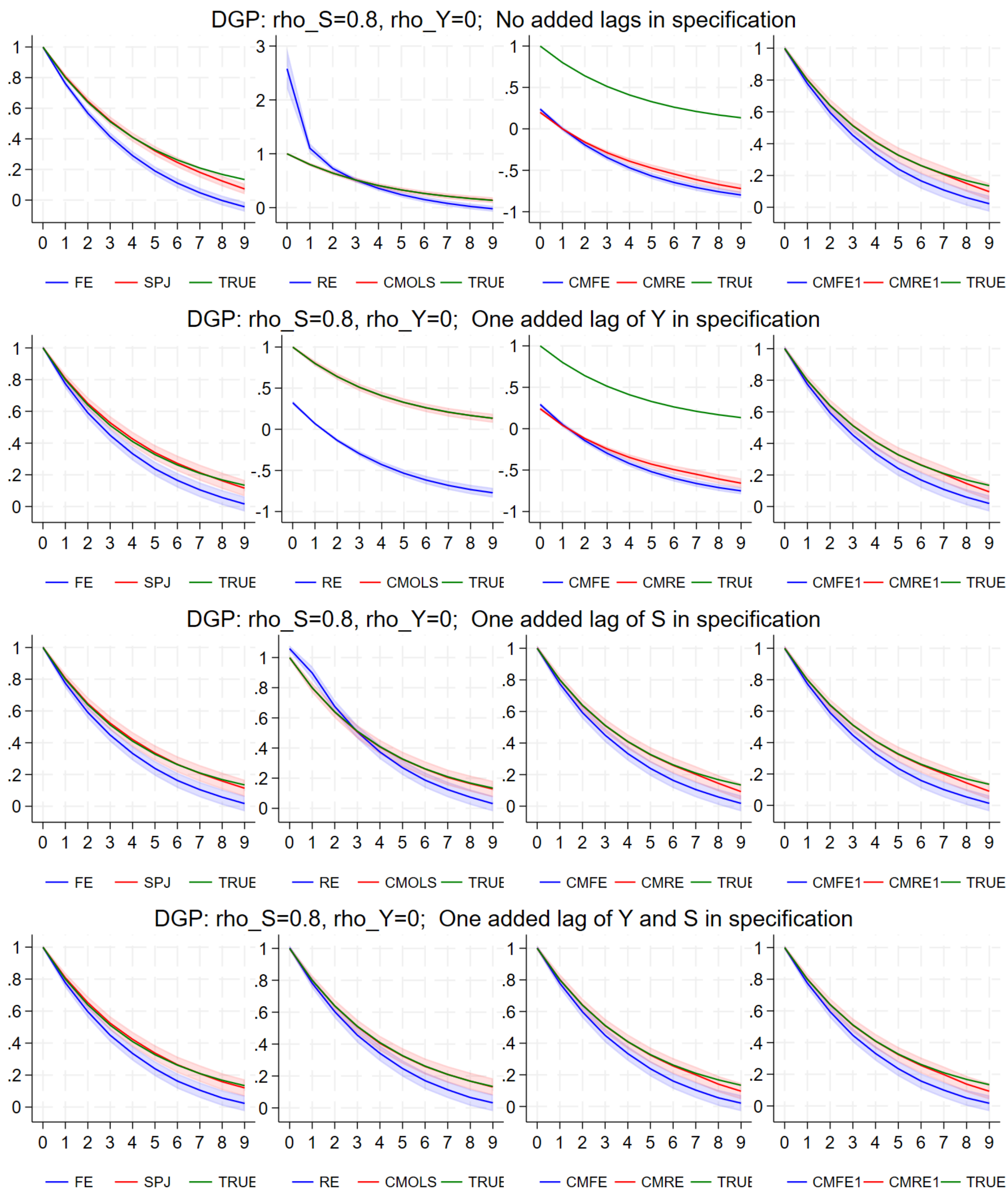


Figure 3: IRF, $N = 100, T = 50$ when $\rho_s = 0$ and $\rho_y = 0.8$

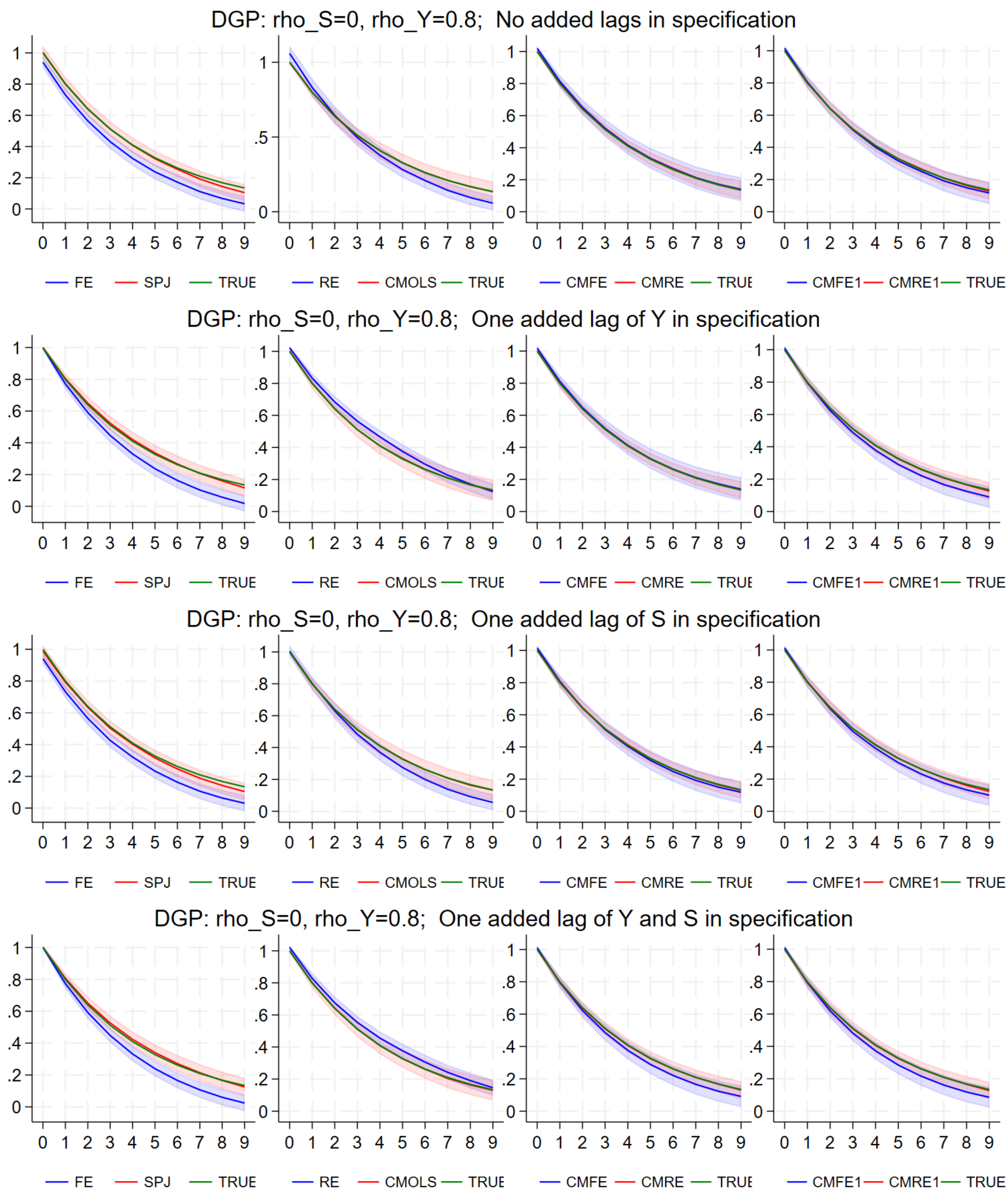


Figure 4: IRF, $N = 100, T = 50$ $\rho_s = 0.8$ and $\rho_y = 0.8$

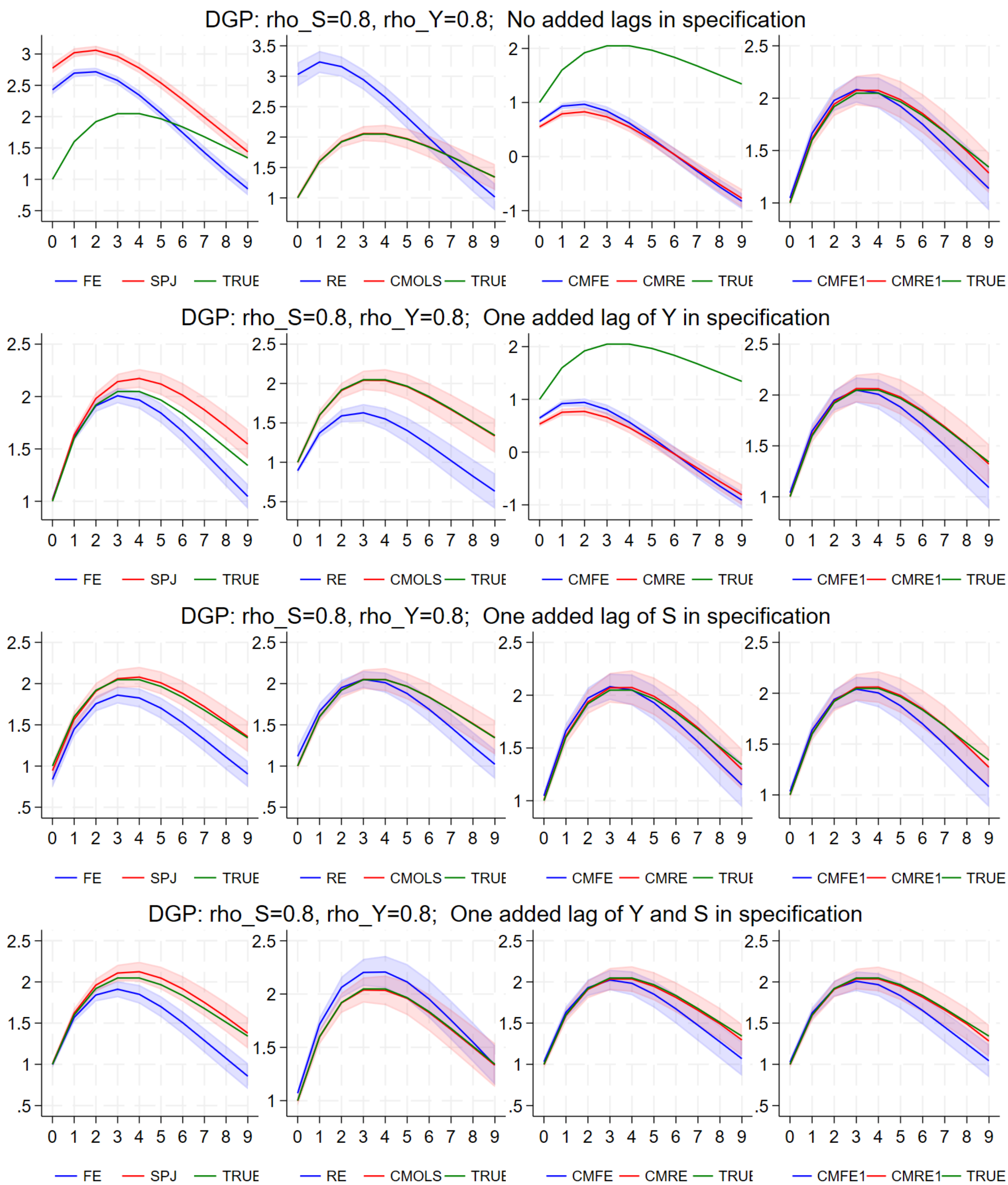


Table 1: DGP: $\rho_s = 0.8$ and $\rho_y = 0$ and SPEC: Lags S_t:0, Lags y_t:0

	Bias (in % of β)			Coverage Probability		
Estimator	Average	$h = 0$	$h = 9$	Average	$h = 0$	$h = 9$
CMOLS	0.04	-0.06	0.23	0.94	0.92	0.90
CMRE1	-0.51	-0.15	-3.62	0.92	0.98	0.69
SPJ	-1.36	-0.06	-6.14	0.58	0.89	0.27
CMFE1	-7.03	-0.15	-11.16	0.27	0.99	0.00
RE	12.82	158.08	-15.67	0.16	0.00	0.00
FE	-11.27	-0.06	-17.80	0.10	0.94	0.00
CMFE	-87.13	-76.13	-93.22	0.00	0.00	0.00
CMRE	-81.26	-80.09	-85.49	0.00	0.00	0.00

Table 2: DGP: $\rho_s = 0.8$ and $\rho_y = 0$ and SPEC: Lags S_t:+1, Lags y_t:0

	Bias (in % of β)			Coverage Probability		
Estimator	Average	$h = 0$	$h = 9$	Average	$h = 0$	$h = 9$
CMOLS	-0.27	0.00	-0.63	0.96	0.96	0.97
CMRE1	-0.90	0.14	-4.41	0.90	0.91	0.64
CMRE	-0.84	0.14	-4.18	0.90	0.90	0.66
SPJ	0.12	0.03	-2.06	0.89	0.95	0.88
RE	-2.63	5.92	-10.30	0.30	0.00	0.02
CMFE	-7.26	0.14	-11.63	0.25	0.92	0.01
CMFE1	-7.61	0.15	-12.13	0.23	0.91	0.01
FE	-7.36	0.05	-11.73	0.22	0.95	0.01

Table 3: DGP: $\rho_s = 0.8$ and $\rho_y = 0$ and SPEC: Lags S_t:0, Lags y_t:+1

	Bias (in % of β)			Coverage Probability		
Estimator	Average	$h = 0$	$h = 9$	Average	$h = 0$	$h = 9$
CMOLS	-0.08	-0.03	-0.07	0.96	0.95	0.98
CMRE1	-0.65	0.07	-4.09	0.89	0.90	0.66
SPJ	0.53	0.11	-1.84	0.82	0.90	0.78
CMFE1	-7.05	0.30	-11.45	0.26	0.92	0.01
FE	-7.32	0.26	-11.82	0.23	0.87	0.00
CMFE	-82.24	-70.76	-88.48	0.00	0.00	0.00
CMRE	-76.30	-75.89	-79.17	0.00	0.00	0.00
RE	-82.71	-67.68	-90.62	0.00	0.00	0.00

Table 4: DGP: $\rho_s = 0.8$ and $\rho_y = 0$ and SPEC: Lags S_t:+1, Lags y_t:+1

	Bias (in % of β)			Coverage Probability		
Estimator	Average	$h = 0$	$h = 9$	Average	$h = 0$	$h = 9$
CMOLS	-0.15	0.01	-0.30	0.95	0.94	0.93
CMRE	-0.83	0.02	-3.78	0.89	0.95	0.66
CMRE1	-0.93	-0.03	-4.12	0.88	0.95	0.61
SPJ	0.38	-0.03	-1.42	0.84	0.91	0.77
RE	-6.47	0.34	-10.24	0.33	0.89	0.05
CMFE	-7.23	0.25	-11.31	0.26	0.95	0.02
CMFE1	-7.55	-0.03	-11.70	0.25	0.95	0.02
FE	-7.16	-0.03	-11.09	0.25	0.94	0.01

Table 5: DGP: $\rho_s = 0$ and $\rho_y = 0.8$ and SPEC: Lags S_t:0, Lags y_t:0

	Bias (in % of β)			Coverage Probability		
Estimator	Average	$h = 0$	$h = 9$	Average	$h = 0$	$h = 9$
CMOLS	-0.08	-0.05	0.02	0.97	0.91	1.00
CMRE1	-0.00	0.10	-0.59	0.94	0.94	0.94
CMRE	0.18	0.12	0.18	0.94	0.90	0.92
CMFE1	-0.69	1.58	-1.79	0.92	0.44	0.95
CMFE	0.89	1.98	0.60	0.92	0.27	0.97
SPJ	-0.80	0.31	-3.02	0.75	0.84	0.70
RE	-2.66	6.01	-7.70	0.55	0.41	0.17
FE	-8.53	-5.96	-10.16	0.10	0.16	0.05

Table 6: DGP: $\rho_s = 0$ and $\rho_y = 0.8$ and SPEC: Lags S_t:+1, Lags y_t:0

	Bias (in % of β)			Coverage Probability		
Estimator	Average	$h = 0$	$h = 9$	Average	$h = 0$	$h = 9$
CMOLS	-0.07	-0.04	-0.12	0.97	0.97	0.99
CMRE	0.07	0.10	-0.36	0.93	0.93	0.90
CMRE1	-0.07	0.10	-1.06	0.93	0.96	0.89
CMFE	-0.58	1.60	-1.54	0.91	0.39	0.96
CMFE1	-1.84	1.33	-3.43	0.85	0.49	0.84
SPJ	-1.45	-1.21	-2.99	0.81	0.81	0.74
RE	-4.12	0.46	-7.84	0.55	0.91	0.09
FE	-8.80	-5.95	-10.37	0.06	0.05	0.03

Table 7: DGP: $\rho_s = 0$ and $\rho_y = 0.8$ and SPEC: Lags S_t:0, Lags y_t:+1

	Bias (in % of β)			Coverage Probability		
Estimator	Average	$h = 0$	$h = 9$	Average	$h = 0$	$h = 9$
CMOLS	0.06	0.15	-0.13	0.97	0.92	0.97
CMRE	-0.06	-0.02	0.01	0.95	0.96	0.95
CMRE1	-0.30	-0.06	-0.84	0.95	0.96	0.95
CMFE	0.62	1.82	0.53	0.92	0.33	0.98
SPJ	0.22	-0.00	-1.79	0.86	0.93	0.82
CMFE1	-2.72	1.04	-4.43	0.83	0.62	0.77
RE	3.02	2.25	-0.99	0.51	0.09	0.95
FE	-7.47	-0.16	-11.62	0.22	0.91	0.01

Table 8: DGP: $\rho_s = 0$ and $\rho_y = 0.8$ and SPEC: Lags S_t:+1, Lags y_t:+1

	Bias (in % of β)			Coverage Probability		
Estimator	Average	$h = 0$	$h = 9$	Average	$h = 0$	$h = 9$
CMOLS	-0.15	0.04	-0.40	0.98	0.97	0.98
CMRE	-0.23	-0.01	-0.39	0.95	0.93	0.95
CMRE1	-0.27	-0.01	-0.72	0.95	0.94	0.95
SPJ	0.65	0.14	-0.89	0.86	0.91	0.87
CMFE	-2.84	1.11	-4.30	0.81	0.63	0.81
CMFE1	-3.21	1.01	-4.87	0.78	0.68	0.74
RE	3.32	2.13	1.22	0.56	0.07	0.92
FE	-7.20	-0.01	-10.99	0.24	0.95	0.01

Table 9: DGP: $\rho_s = 0.8$ and $\rho_y = 0.8$ and SPEC: Lags S_t:0, Lags y_t:0

	Bias (in % of β)			Coverage Probability		
Estimator	Average	$h = 0$	$h = 9$	Average	$h = 0$	$h = 9$
CMRE1	0.74	0.77	-5.62	0.95	0.95	0.90
CMOLS	0.52	0.65	-0.19	0.94	0.98	0.97
CMFE1	-4.21	4.70	-20.45	0.74	0.54	0.53
RE	63.51	202.88	-32.84	0.24	0.00	0.19
FE	30.13	142.73	-49.46	0.10	0.00	0.00
SPJ	76.03	177.45	9.69	0.09	0.00	0.44
CMFE	-142.23	-35.09	-216.92	0.00	0.00	0.00
CMRE	-146.76	-45.02	-211.49	0.00	0.00	0.00

Table 10: DGP: $\rho_s = 0.8$ and $\rho_y = 0.8$ and SPEC: Lags S_t:+1, Lags y_t:0

	Bias (in % of β)			Coverage Probability		
Estimator	Average	$h = 0$	$h = 9$	Average	$h = 0$	$h = 9$
CMRE	0.85	0.64	-4.50	0.95	0.93	0.88
CMRE1	-0.34	0.12	-7.03	0.94	0.95	0.85
CMOLS	0.23	0.10	0.34	0.92	0.94	0.93
SPJ	1.19	-5.57	1.41	0.84	0.79	0.84
CMFE	-3.95	4.59	-19.24	0.77	0.50	0.60
CMFE1	-8.52	3.34	-26.05	0.70	0.67	0.34
RE	-8.48	11.74	-32.04	0.60	0.61	0.09
FE	-26.57	-16.34	-43.87	0.03	0.09	0.01

Table 11: DGP: $\rho_s = 0.8$ and $\rho_y = 0.8$ and SPEC: Lags S_t:0, Lags y_t:+1

	Bias (in % of β)			Coverage Probability		
Estimator	Average	$h = 0$	$h = 9$	Average	$h = 0$	$h = 9$
CMRE1	0.79	0.59	-2.10	0.96	0.93	0.94
CMOLS	-0.71	0.08	-0.83	0.96	0.96	0.99
CMFE1	-7.82	3.93	-25.12	0.71	0.58	0.34
FE	-11.51	1.96	-29.61	0.48	0.81	0.07
SPJ	12.57	1.05	20.40	0.42	0.89	0.30
CMFE	-147.07	-35.35	-225.38	0.00	0.00	0.00
CMRE	-152.39	-46.81	-215.06	0.00	0.00	0.00
RE	-48.12	-10.63	-70.90	0.00	0.00	0.00

Table 12: DGP: $\rho_s = 0.8$ and $\rho_y = 0.8$ and SPEC: Lags S_t:+1, Lags y_t:+1

	Bias (in % of β)			Coverage Probability		
Estimator	Average	$h = 0$	$h = 9$	Average	$h = 0$	$h = 9$
CMOLS	-0.75	-0.15	-0.94	0.95	0.98	0.96
CMRE1	-1.78	-0.40	-5.90	0.95	0.96	0.88
CMRE	-1.74	-0.43	-4.75	0.94	0.95	0.90
SPJ	5.38	0.55	3.63	0.79	0.98	0.76
CMFE	-10.08	3.02	-27.36	0.66	0.73	0.32
CMFE1	-11.75	2.59	-29.89	0.62	0.81	0.20
RE	10.14	6.97	-0.92	0.53	0.13	0.93
FE	-23.55	-0.24	-48.60	0.27	0.96	0.00

5.2 Very high autocorrelation

Simulations with higher autocorrelation are important because they are closer to the empirical persistence observed in many macroeconomic variables and because we know that the persistence amplifies the Nickell bias and because, as recognized by Mei, Sheng and Shi (2026) "the theoretical foundations of SPJ do not cover highly persistent regressors" and therefor, the reliability of the SPJ estimator diminishes.

Under this environment we can see that the bias of the FE deteriorates more sharply in the three DGPs considered. In some cases FE is clearly biased even at $t = 0$. In several cases the coverage probability is simply equal to zero, especially at the longest horizon.

The second most important result is that SPJ over-correction becomes more severe in the case of joint-persistence. This could be due to the underlying FE bias becoming too large causing over-correction. This deterioration under very high persistence suggests that the SPJ correction is not uniformly robust to highly persistent environments and may amplify finite-sample distortions when both shocks and outcomes exhibit strong serial correlation.

A third important result is that the bias in the estimator in cumulative differences when using RE becomes more relevant at higher horizons. For instance, we can see in Table 18 the CMRE1 displays a 10% attenuation bias at horizon $t = 9$ or the CMRE with one lag of $s_{i,t}$, (equivalent to CMRE1), an attenuation bias of 14%. This confirms that the any estimator relying on the within transformation is vulnerable to the Nickell bias.

Finally, CMOLS remains remarkable stable relative to competing estimators. Its bias is close to zero at all horizons as well as its coverage probability. Although stronger persistence worsens finite-sample performance across estimators, the deterioration of CMOLS is comparatively very limited. As a result, the relative advantage of cumulative-difference local projections estimated trhough pooled OLS becomes even more pronounced in highly persistent environments.

Figure 5: IRF, $N = 100, T = 50$ when $\rho_s = 0.9$ and $\rho_y = 0$

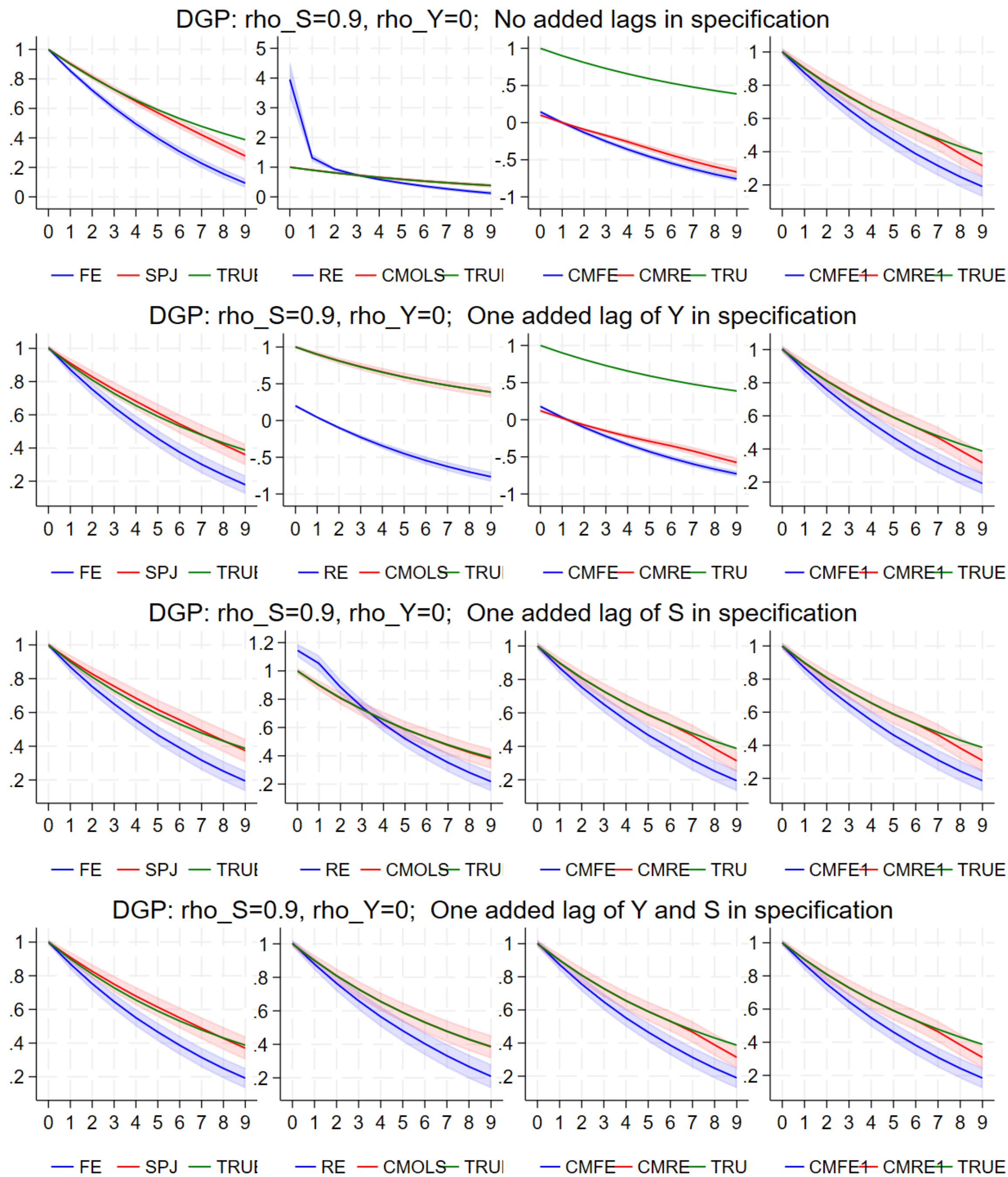


Figure 6: IRF, $N = 100, T = 50$ when $\rho_s = 0$ and $\rho_y = 0.9$

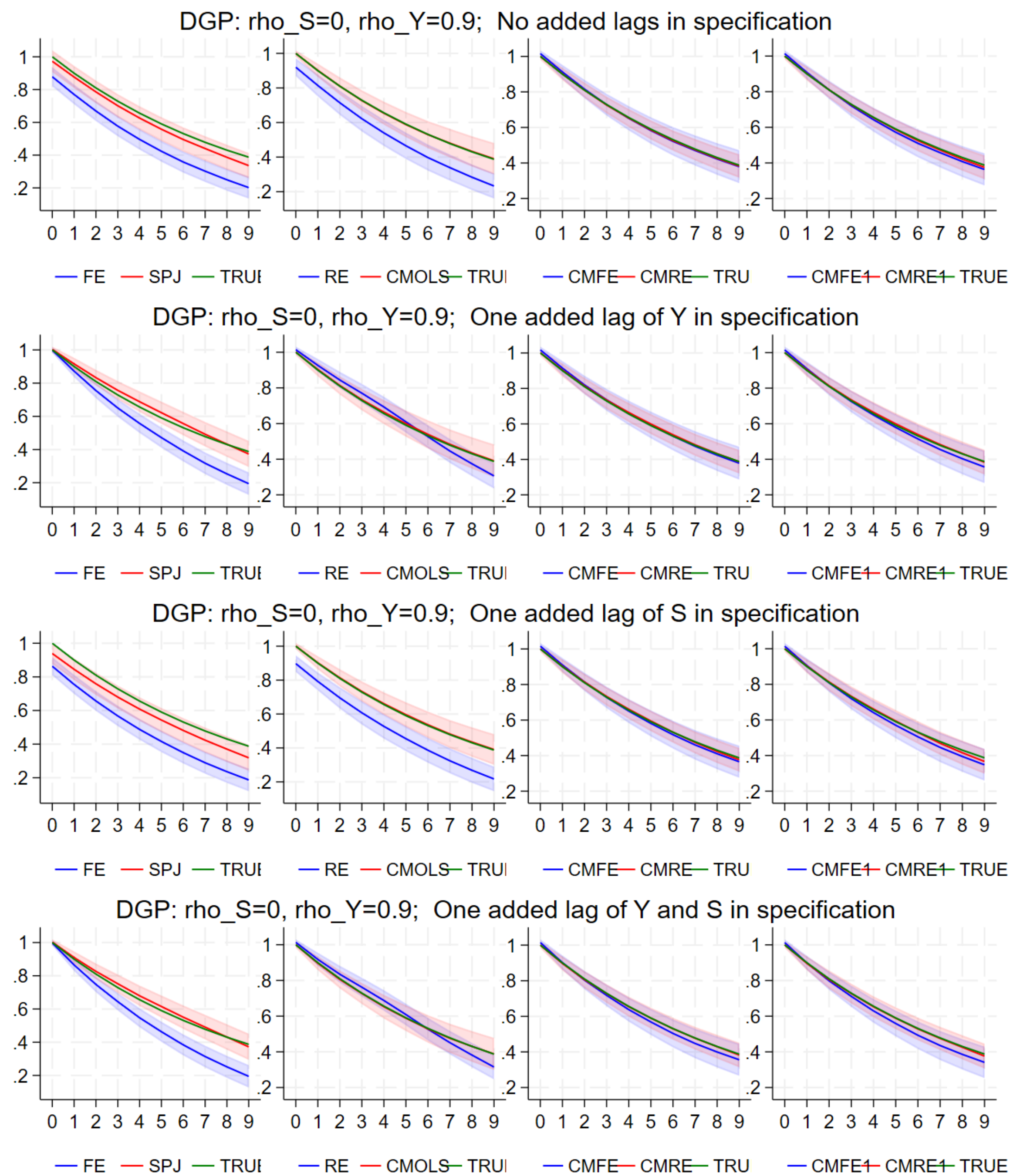


Figure 7: IRF, $N = 100, T = 50$ $\rho_s = 0.9$ and $\rho_y = 0.9$

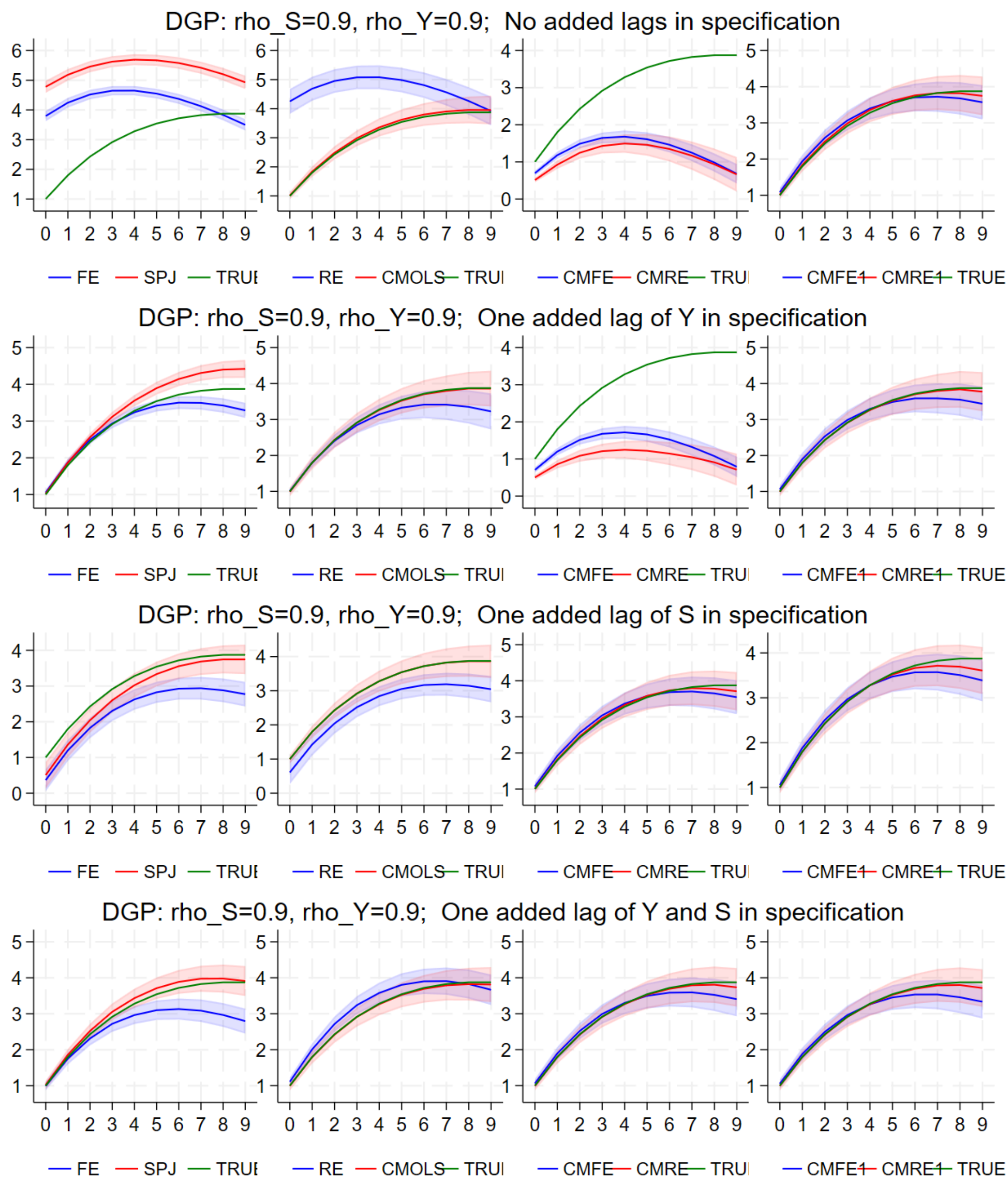


Table 13: DGP: $N = 100, T = 50$ when $\rho_s = 0.9$ and $\rho_y = 0$

	Bias (in % of β)			Coverage Probability		
Estimator	Average	$h = 0$	$h = 9$	Average	$h = 0$	$h = 9$
CMOLS	-0.04	0.04	-0.41	0.94	0.95	0.96
CMRE1	-1.26	0.04	-7.49	0.87	0.94	0.43
SPJ	0.03	-0.05	-4.19	0.73	0.94	0.64
CMRE	-46.79	-44.45	-54.01	0.43	0.47	0.21
CMFE1	-10.82	0.13	-19.93	0.22	0.94	0.00
FE	-12.36	0.06	-22.29	0.17	0.94	0.00
RE	-21.95	57.56	-44.03	0.17	0.23	0.00
CMFE	-55.56	-41.81	-66.28	0.11	0.48	0.00

Table 14: DGP: $N = 100, T = 50$ when $\rho_s = 0$ and $\rho_y = 0.9$

	Bias (in % of β)			Coverage Probability		
Estimator	Average	$h = 0$	$h = 9$	Average	$h = 0$	$h = 9$
CMOLS	0.18	0.04	0.27	0.97	0.94	0.98
CMRE	-0.01	0.04	-0.53	0.94	0.95	0.95
CMRE1	-0.15	0.04	-1.20	0.93	0.93	0.93
CMFE	-0.49	1.58	-1.75	0.92	0.59	0.96
CMFE1	-1.50	1.42	-3.50	0.90	0.64	0.93
SPJ	-1.50	-2.05	-3.74	0.74	0.79	0.70
RE	-6.36	-3.87	-11.97	0.43	0.36	0.23
FE	-13.61	-6.55	-19.29	0.11	0.47	0.00

Table 15: DGP: $N = 100, T = 50$ when $\rho_s = 0.9$ and $\rho_y = 0.9$

	Bias (in % of β)			Coverage Probability		
Estimator	Average	$h = 0$	$h = 9$	Average	$h = 0$	$h = 9$
CMRE1	-2.64	-0.05	-16.31	0.92	0.94	0.88
CMOLS	0.67	-0.05	-0.22	0.92	0.94	0.92
CMFE1	-7.76	6.26	-44.18	0.77	0.82	0.54
CMRE	-99.48	-24.52	-166.89	0.46	0.47	0.43
SPJ	61.91	83.35	37.77	0.44	0.52	0.47
RE	25.68	74.53	-40.94	0.42	0.47	0.52
CMFE	-89.15	-11.51	-176.78	0.39	0.40	0.31
FE	-3.96	55.10	-78.42	0.24	0.39	0.07

Table 16: DGP: $N = 100, T = 50$ when $\rho_s = 0.9$ and $\rho_y = 0$, Best specification

	Bias (in % of β)			Coverage Probability		
Estimator & Best Spec.	Average	$h = 0$	$h = 9$	Average	$h = 0$	$h = 9$
CMOLS: sl0, yl0	-0.05	-0.00	-0.22	0.96	0.98	0.99
CMRE1: sl0, yl0	-1.03	-0.00	-7.06	0.88	0.97	0.48
CMRE: sl1, yl0	-1.27	0.00	-7.35	0.87	0.97	0.44
SPJ: sl1, yl1	0.81	0.04	-1.31	0.83	0.96	0.83
RE: sl1, yl1	-2.50	0.41	-16.89	0.30	0.92	0.00
CMFE1: sl0, yl1	-10.44	-0.00	-19.58	0.24	0.98	0.00
CMFE: sl1, yl1	-10.59	-0.05	-19.29	0.22	0.97	0.00
FE: sl1, yl1	-10.64	-0.02	-19.31	0.20	0.97	0.00

Table 17: DGP: $N = 100, T = 50$ when $\rho_s = 0$ and $\rho_y = 0.9$, Best specification

	Bias (in % of β)			Coverage Probability		
Estimator & Best Spec.	Average	$h = 0$	$h = 9$	Average	$h = 0$	$h = 9$
CMOLS: sl0, yl0	0.02	0.03	0.08	0.97	0.95	1.00
CMRE: sl0, yl0	-0.00	0.05	-0.11	0.96	0.97	0.99
CMRE1: sl1, yl1	-0.26	0.03	-0.41	0.95	0.95	0.94
CMFE: sl0, yl0	-0.13	1.45	-0.80	0.95	0.66	1.00
CMFE1: sl0, yl0	-0.93	1.31	-2.40	0.93	0.72	0.97
SPJ: sl1, yl1	1.18	0.27	-1.43	0.85	0.94	0.83
RE: sl1, yl1	-0.03	1.35	-7.27	0.79	0.68	0.51
FE: sl0, yl1	-10.50	-0.14	-18.55	0.23	0.96	0.00

Table 18: DGP: $N = 100, T = 50$ when $\rho_s = 0.9$ and $\rho_y = 0.9$, Best specification

	Bias (in % of β)			Coverage Probability		
Estimator & Best Spec.	Average	$h = 0$	$h = 9$	Average	$h = 0$	$h = 9$
CMRE1: sl0, yl1	1.75	-0.40	-9.97	0.95	0.96	0.93
CMOLS: sl0, yl1	-0.24	-0.40	-1.15	0.94	0.97	0.94
CMRE: sl1, yl0	-0.72	-0.51	-14.01	0.92	0.97	0.90
SPJ: sl1, yl1	10.95	2.45	3.64	0.81	0.89	0.90
CMFE1: sl0, yl1	0.80	5.49	-30.49	0.80	0.88	0.67
CMFE: sl1, yl0	-1.28	6.29	-32.77	0.79	0.86	0.72
RE: sl0, yl1	14.89	0.94	4.66	0.72	0.92	0.95
FE: sl0, yl1	-15.27	-0.85	-37.62	0.46	0.91	0.19

5.3 Summary of results with high autocorrelation and N>T

A summary of the performance by estimator for the cases of autocorrelations betwen 0.8 and 0.9, would be the following:

1. CMOLS: Best overall performance

   The most robust result across all DGPs and specifications is the outstanding performance of CMOLS. CMOLS has in general the smallest absolute average bias, close to zero bias at either short or long horizons, and a coverage probability close to 95%.

   Importantly, this superior performance remains stable across all persistence structures and specifications. Even in the most difficult case, the joint persistence with (ρ_s=ρ_y=0.9), CMOLS maintains a close to zero bias and near-perfect coverage.

   This robustness is economically and econometrically important because it suggests that the cumulative-difference transformation combined with OLS and a simple lag addition largely neutralizes the distortions created by fixed-effects transformations in persistent environments.

2. CMRE1: Very strong but slightly inferior at long horizons

   The second-best estimator overall is CMRE1. In many specifications it performs almost as well as CMOLS, especially at short horizons. However, the results reveal a systematic deterioration at longer horizons. The coverage probability also declines noticeably at long horizons. This pattern becomes more pronounced under joint persistence, where the long-horizon bias becomes more relevant.

   The results strongly support the interpretation that the pseudo-differencing implicit in RE estimation leaves the estimator partially exposed to Nickell-type distortions, even after cumulative differencing. Thus, we can say that cumulative differencing alone is not sufficient, avoiding within/pseudo-within transformations also matters, which explains why CMOLS dominates CMRE1.

3. SPJ: Effective only in the benchmark Mei–Sheng–Shi environment

   The SPJ estimator performs very well in the specific environment analyzed by Mei, Sheng and Shi (2026), namely when only the shock variable is persistent and no additional persistence comes from the dependent variable.

In cases in which the persistence resides only in the shock, SPJ has essentially close zero average bias. However, once persistence in the dependent variable is introduced, the performance of SPJ deteriorates substantially in terms of bias and coverage probabilities.

More importantly, the results when there is joint persistence demonstrate the SPJ over-corrects and displays an upward bias, which in some cases could be ameliorated through lag augmentation, but it never disappear completely. Therefore, the results demonstrate that SPJ corrections are not uniformly robust across persistence structures and may over-correct in environments with joint persistence.

4. FE Estimator: persistent and unstable bias

   The FE estimator consistently performs poorly across almost all environments and several patterns emerge: (i) downward bias when persistence resides only in one of the variables, i.e. FE exhibits the attenuation bias emphasized by Mei, Sheng and Shi (2026). When both y_t and s_t are jointly persistent, the FE estimator becomes highly unstable. In some specifications, the bias becomes strongly positive, while in others it becomes severely negative.

   Coverage probabilities are generally extremely poor, often collapsing near zero at long horizons. These results suggest that FE panel LP estimators are highly sensitive to persistence structure, specification choice, and horizon length.

5. RE Estimator: Highly unstable even when individual effects are exogenous

   The RE estimator performs poorly throughout the simulations, as expected when individual effects are correlated with the shock. The results show very large positive biases in some cases, large negative biases in others, and generally poor coverage probabilities.

   Importantly, this instability persists even in the simulations where individual effects are uncorrelated with the shock variable. This strongly supports that RE inherits part of the Nickell-type problem through its pseudo-differencing transformation.

6. CMRE and CMFE poor performers due to inadequate lag augmentation

   The worst-performing estimators overall are CMRE and CMFE when the first lag of the shock is omitted. These estimators display extremely large negative biases together with very poor coverage probabilities. The results confirm the theoretical derivation in Table 3: once shocks are persistent, omitting the lag of the shock creates a severe omitted-variable problem in the cumulative differencing case. This shows that the latter alone is not enough; correct dynamic specification is also essential.

6 Empirical Applications

In this section we present a series of empirical exercises focusing on a comparison between fixed-effects, split-jackknife and cumulative-difference estimators, either with FE or by pooled OLS. We replicate some exercises based on a policy paper (Furceri et al. (2018)) and some of the examples used in Mei, Sheng and Shi (2026).

For the calculations we rely on the Stata command **locproj** that allows one to implement all the estimators considered here and on the stata command **xtlp** developed by Mei, Sheng and Shi (2026) based on their proposed correction. Estimating the cumulative differences OLS with one lag of the shock would require the following line when using the Stata command **locproj**:

locproj y s, m(reg) tr(cmlt) sl(1)

6.1 Impact of tariffs on real GDP and real Exports

We replicate some of the results in Furceri et al. (2018) in which they study the impact of a change in tariffs on GDP and other macroeconomic variables using a panel of annual data that spans 151 countries over 1963-2014. One of their main results is that they find empirically that tariff increases lead to declines of output in the medium term.

We additionally estimate the impulse response function of the same shock to local tariffs on real exports of the same local country, a variable that was not analyzed by Furceri et al. (2018), but that represents an interesting exercise given the clear exogeneity of local tariffs with respect to exports.

The original specification used in Furceri et al. (2018) is:

$$y_{i,t+h} - y_{i,t-1} = \alpha_i^h + \gamma_t^h + \beta_h \Delta T_{i,t} + \theta_h X_{i,t} + \epsilon_{i,t}; \qquad h = 0, ..., 5$$

Where $y_{i,t}$ is the outcome variable of interest, either real GDP or real Exports, α_i are country fixed effects to control for unobserved cross-country heterogeneity, γ_t are time fixed effects to control for global shocks, $\Delta T_{i,t}$ is the change in the tariff rate and $X_{i,t}$ is a vector of control variables.

Control variables include the trade-to-GDP ratio and the REER (Real Effective Exchange Rate). The models are estimated using a long-differences approach. The specification includes time fixed effects, two lags of the dependent variable, and two lags of the shock.

One important distinction between the original specification in Furceri et al. (2018) is that using our derivations in section (3) we assume that the individual effects α_i are eliminated by differentiating, and thus, the correct specification should be:

$$y_{i,t+h} - y_{i,t-1} = \gamma_t + \beta_h \Delta T_{i,t} + \theta X_{i,t} + \epsilon_{i,t}$$

However, for the comparison we used fixed-effects even though the models are in long-differences. In Figure 8 we can see that the IRF estimated with the CMOLS estimator in the case of real GDP displays a more severe impact than the one estimated by the cumulative-differences with fixed-effects (CMFE) estimator. However, the impact is smaller than the one estimated by the SPJ estimator, especially at longer horizons.

A similar result could be seen in the case where real exports are the response variable. In this case the difference between the CMFE and the CMOLS estimators is much smaller. However, the difference with the SPJ is significant.

These empirical results are consistent with the simulation evidence, in which SPJ tends to overcorrect in several specifications, especially when shocks and outcomes are jointly persistent.

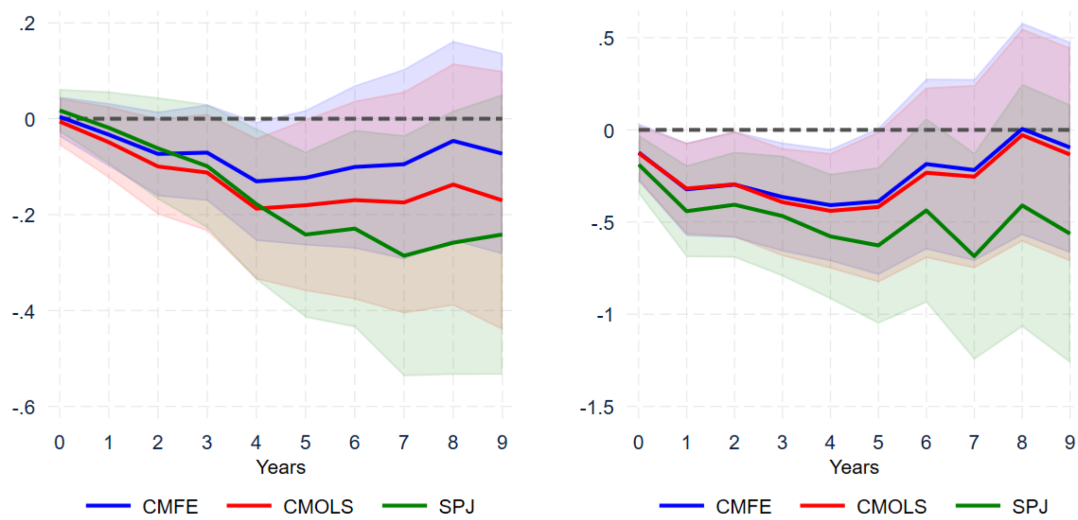


Figure 8: Impulse response of Real GDP & Exports to a change in tariffs

6.2 Impact of Currency Crises on Output Loss

We replicate the results in Mei, Sheng and Shi (2026) in which they examine the impact of currency crises on output loss. They used the data set from Cerra and Saxena (2008), which includes panel data on currency crises for 175 countries from 1965 to 2000. An exchange market pressure index (EMPI) is constructed as the sum of the percentage depreciation in the exchange rate and the percentage loss in foreign exchange reserves, allowing for cross-country comparability. A dummy variable for a currency crisis is assigned to a specific year and country if the EMPI is in the upper quartile of all observations within the panel. The panel local projection (LP) specification is as follows:

$$y_{i,t+h} - y_{i,t-1} = \alpha_{h,i} + \beta_h x_{i,t} + \sum_{j=1}^{4} (\theta_{h,j} x_{i,t-j} + \eta_{h,j} \Delta y_{i,t-j}) + \epsilon_{i,t}; \qquad h = 1, ..., 10$$

The dependent variable is the cumulative difference in the logarithm of real GDP. The shock $x_{i,t}$ is a dummy variable indicating a currency crisis.

Although the regression is still estimated through cumulative-differences, Cerra and Saxena (2008) and Mei, Sheng and Shi (2026) assume that the individual effects should still be included in the specification and proceed to estimate the IRF through fixed-effects.

In a similar way to the previous example, the IRF estimated by the SPJ estimator is

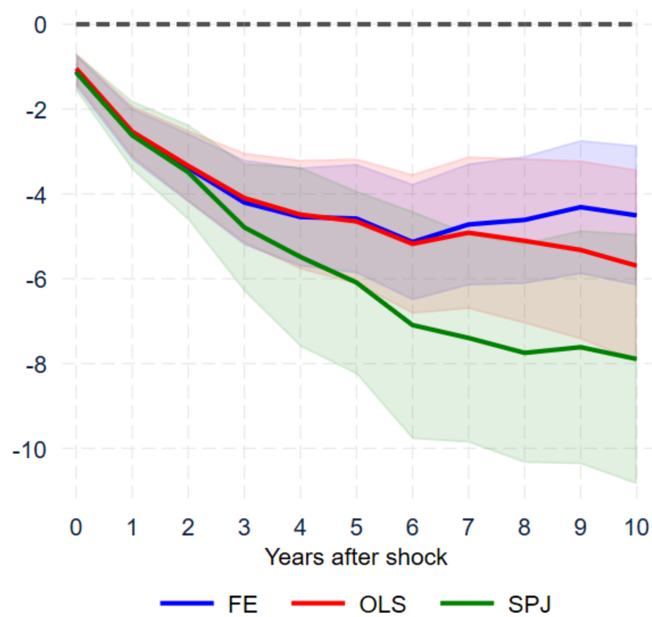


Figure 9: Impulse Responses of Real GDP to Currency Crises

significantly more severe than the one estimated by the CMFE estimator, which would indicate a significantly higher impact at longer horizons. However, the CMOLS only estimates a modest correction at the longest horizons with respect to the CMFE.

6.3 Impact of household and non-financial-firms debt, on economic output

Mian, Sufi and Verner (2017) explore the dynamics between household debt, non-financial firms debt, and economic fluctuations, with a cross-country panel via both VAR and LP. They find that a rise in the household debt to GDP ratio from four years ago to last year predicts a substantial decline in subsequent real GDP growth from the current year onward. By contrast, the output declines immediately following firm debt shocks, whereas recovers gradually afterward. They use an unbalanced panel of 30 countries from 1960 to 2012 and specify the LP regressions as follows:

$$y_{i,t+h} = \alpha_{i,h} + \beta_{h,HH} HH_{i,t-1} + \beta_{h,NF} NF_{i,t-1} + \sum_{j=2}^{5} (\theta_{h,j} HH_{i,t-j} + \omega_{h,j} NF_{i,t-j}) + \sum_{j=1}^{5} \eta_{h,j} y_{i,t-j} + \epsilon_{i,t}$$

The shock variables are the household debt to GDP ratio and the non-financial firm debt to GDP ratio included with one lag, i.e. $HH_{i,t-1}$ and $NF_{i,t-1}$. Control variables include four additional lags of household debt to GDP ratio and non-financial firm debt to GDP ratio, and five lags of the dependent variable.

The results in 10 show that when the shock is the household debt to GDP ratio, the CMOLS estimator finds a higher negative impact than the one estimated through CMFE at the longest horizons, but a smaller one than the estimated through SPJ. On the other hand, the impact estimate when the shock corresponds to the non-financial firm debt to GDP ratio is higher when estimated through CMOLS than either the FE or SPJ estimators, which surprisingly, are almost identical.

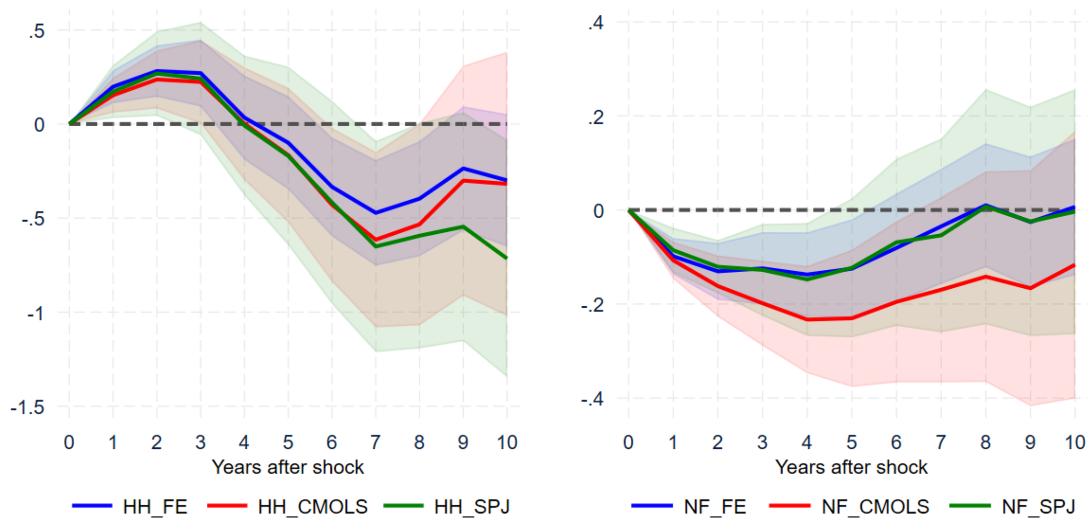


Figure 10: Impulse Responses of Real GDP to Household Debt and Nonfinancial Firm Debt

7 Conclusion

This paper studies the statistical properties of local projection estimators in panel data settings under alternative forms of serial persistence, alternative estimators, and alternative dynamic specifications. Motivated by recent evidence that fixed-effects panel local projections suffer from Nickell-type biases, we analyze whether these distortions can be avoided through alternative transformations of the dependent variable.

The central contribution of the paper is to show that cumulative-difference transformations provide a natural alternative to fixed-effects estimation in panel local projections. We demonstrate theoretically that cumulative differencing eliminates individual effects directly, thereby avoiding the within transformation that lies at the center of the incidental parameter problem. This allows impulse responses to be estimated consistently using pooled OLS.

Our Monte Carlo experiments confirm the unbiasedness of our proposed estimator and also reveal several important findings. First, the finite-sample behavior of panel LP estimators critically depends on the persistence structure of the data-generating process. While fixed-effects estimators typically exhibit attenuation bias when persistence resides only in the shock variable, both fixed-effects and split-panel jackknife estimators may exhibit substantial upward bias when shocks and outcomes are jointly persistent and no lags of the shock are included in the specification.

Second, dynamic specification choices play a crucial role in estimator performance. In particular, the inclusion of at least one lag of the shock variable is necessary to avoid omitted-variable bias whenever shocks are persistent, particularly when using a cumulative-difference (or simple difference) transformation of the dependent variable.

Most importantly, we show that cumulative-difference local projections estimated using pooled OLS and including one lag of the shock variable consistently provide the best overall finite-sample performance across the environments considered in this paper. Relative to conventional fixed-effects estimators, split-panel jackknife corrections, and random-effects alternatives, the proposed estimator generally exhibits substantially lower bias and significantly improved coverage probabilities across horizons, persistence structures, and sample dimensions.

The empirical applications reinforce these conclusions. Re-estimating several influential panel local projection studies using the alternative estimators considered in this paper reveals that the choice of estimator can materially affect the magnitude of the estimated impulse responses. Although empirical applications do not reveal the true impulse response, the observed differences closely mirror the patterns documented in the Monte Carlo experiments. In particular, the split-panel jackknife estimator frequently produces larger responses than cumulative-difference OLS in settings where our simulations predict upward over-correction under joint persistence. These findings suggest that methodological choices in panel local projections are not merely technical, but may influence the substantive economic conclusions drawn from empirical analyses.

These results suggest that many of the distortions emphasized in recent panel LP research are not inherent to local projections themselves, but instead arise from the interaction between within transformations and dynamic persistence. The findings therefore point toward specification design and variable transformation as central components of reliable panel local projection estimation.

We can summarize the theoretical derivations and simulation results regarding the different estimators considered throughout this paper in the following points:

- OLS-Cumulative-Difference estimator with one lag of the shock: Best overall performance, near zero bias and almost perfect coverage probability across different specifications and data generating processes.
- RE-Cumulative-Difference estimator with one lag of the shock: very strong performance, very similar to the OLS case, but slightly inferior at long horizons due to the pseudo within-transformation.
- SPJ estimator: Effective correction in the Mei-Sheng-Shi benchmark environment (persistence of the shock), but could perform poorly when both the shock and dependent variable are highly persistent.
- FE estimator: persistent and unstable negative bias due to the within-transformation.
- RE estimator: Highly unstable even when individual effects are exogenous
- FE-Cumulative-Difference estimator: It exhibits a similar negative bias as the FE one

due to the within-transformation. Moreover, it performs extremely poorly when the shock is persistent and no lags of it are included in the specification.

Two important points that need to be remark regarding the empirical application of the theoretical results presented here:

- In the theoretical framework and simulations, the autocorrelation structure is very simple. However, in reality, a variable could exhibit autocorrelation of order higher than one. Thus, in practical applications it would be important to include more lags of the shock if one considers that the shock could be correlated with higher order lags that could bias the estimation if they are omitted.
- We also avoid including other control variables in the theoretical results. However, in practical applications it would be the most common option to include them. We have to think that in such case we should apply the same specification to any control variable than the one applied to the shock. If the shock is included with one lag, we should also include the control variables with one lag. It we include two lags of the shock, the control variables should be included with two lags.

Several directions for future research remain open such as extending the analysis to nonlinear local projections, binary dependent variable, instrumental-variable settings, and unbalanced panels represents a promising avenue for future work.

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A Appendix

A.1 Cumulative Differences Estimator for h>0

We start with the $h = 1$ case. y_{t+1} is given by:

$$y_{i,t+1} = \rho_y y_{i,t} + \beta s_{i,t+1} + u_i + e_{i,t+1} \tag{26}$$

Replacing $s_{i,t+1} = \rho_s s_{i,t} + v_{i,t+1}$ and equation (15) into (26) and rearranging terms we get the following expression for $y_{i,t+1}$ as a function of $s_{i,t}$:

$$y_{i,t+1} = \sum_{k=1}^{T_0} \rho_y^{k+1}(\beta s_{i,t-k} + e_{i,t-k}) + \beta(\rho_y + \rho_s)s_{i,t} + e_{i,t+1} + \rho_y e_{i,t} + \beta v_{i,t+1} + \sum_{k=0}^{T_0+1} \rho_y^k u_i \tag{27}$$

Subtracting y_{t-1} as in equation (17) to obtain $y_{i,t+1} - y_{i,t-1}$, and using that the last term $\sum_{k=0}^{T_0+1} \rho_y^k u_i$ can be separated into $\sum_{k=T_0}^{T_0+1} \rho_y^k u_i + \sum_{k=0}^{T_0-1} \rho_y^k u_i$:

$$\begin{aligned} y_{i,t+1} - y_{i,t-1} = &\sum_{k=1}^{T_0} (\rho_y^{k+1} - \rho_y^{k-1})(\beta s_{i,t-k} + e_{i,t-k}) \\ &+ \beta(\rho_y + \rho_s)s_{i,t} + e_{i,t+1} + \rho_y e_{i,t} + \beta v_{i,t+1} + \sum_{k=T_0}^{T_0+1} \rho_y^k u_i \end{aligned} \tag{28}$$

Since the last term $\sum_{k=T}^{T_0+1} \rho_y^k u_i = \rho_y^{T_0+1} u_i + \rho_y^{T_0} u_i$, and since both $\rho_y^{T_0+1} u_i \simeq 0$ and $\rho_y^{T_0} u_i \simeq 0$, when $|p_y| < 1$ we have shown that individual effects have been eliminated by differentiation and that with the cumulative differencing in $h = 1$ we can recover the correct impulse response which in this case is $\beta(\rho_y + \rho_s)s_{i,t}$.

Thus we can avoid the within-transformation and estimate this local projection through OLS or RE using the following specification:

$$y_{i,t+1} - y_{i,t-1} = \beta_1 s_{i,t} + \gamma_1 s_{i,t-1} + \epsilon_{i,t+1} \tag{29}$$

Where $\beta_1 = \beta(\rho_y + \rho_s)$; $\gamma_1 = (\rho_y^2 - 1)\beta$;
and $\epsilon_{i,t+1} = e_{i,t+1} + \rho_y e_{i,t} + \beta v_{i,t+1} + \sum_{k=1}^{T_0} (\rho_y^{k+1} - \rho_y^{k-1}) e_{i,t-k} + \sum_{k=2}^{T_0} (\rho_y^{k+1} - \rho_y^{k-1}) \beta s_{i,t-k}$

When $h = 2$, y_{t+2} is given by:

$$y_{i,t+2} = \rho_y y_{i,t+1} + \beta s_{i,t+2} + u_i + e_{i,t+2} \tag{30}$$

Replacing $s_{i,t+2} = \rho_s s_{i,t+1} + v_{i,t+2}$ and then replacing the corresponding expression for s_{t+1} into the resulting equation, we would get $y_{i,t+2}$ as a function of $s_{i,t}$:

$$y_{i,t+2} = \rho_y y_{i,t+1} + \beta\rho^2 s_{i,t} + \beta v_{i,t+2} + \beta\rho_s v_{i,t+1} + u_i + e_{i,t+2} \tag{31}$$

Then we replace $y_{i,t+1}$ as in equation (27) and rearranging terms we get the following expression for $y_{i,t+2}$:

$$\begin{aligned} y_{i,t+2} = \sum_{k=1}^{T_0} \rho_y^{k+2}(\beta s_{i,t-k} + e_{i,t-k}) + \beta(\rho_y^2 + \rho_y + \rho_s + \rho_s^2)s_{i,t} \\ + e_{i,t+2} + \rho_y e_{i,t+1} + \rho_y^2 e_{i,t+1} + \beta(v_{i,t+2} + \rho_s v_{i,t+1}) + \sum_{k=0}^{T_0+2} \rho_y^k u_i \end{aligned} \tag{32}$$

Subtracting y_{t-1} as in equation (17) to obtain $y_{i,t+1} - y_{i,t-1}$, and using that the last term $\sum_{k=0}^{T_0+2} \rho_y^k u_i$ can be separated into $\sum_{k=T_0}^{T_0+2} \rho_y^k u_i + \sum_{k=0}^{T_0-1} \rho_y^k u_i$ we get the following expression for $y_{i,t+2} - y_{i,t-1}$;

$$\begin{aligned} y_{i,t+2} - y_{i,t-1} = \sum_{k=1}^{T_0} (\rho_y^{k+2} - \rho_y^{k-1})(\beta s_{i,t-k} + e_{i,t-k}) \\ + \beta(\rho_y^2 + \rho_y + \rho_s + \rho_s^2)s_{i,t} + e_{i,t+2} + \rho_y e_{i,t+1} + \rho_y^2 e_{i,t+1} + \\ \beta(v_{i,t+2} + \rho_s v_{i,t+1}) + \sum_{k=T_0}^{T_0+2} \rho_y^k u_i \end{aligned} \tag{33}$$

Since the last term $\sum_{k=T_0}^{T_0+2} \rho_y^k u_i \simeq 0$ since $|p_y| < 1$ and T_0, $T_0 + 1$ and $T_0 + 2$ are all very large powers, then equation (33) shows that differentiating has eliminated the individual effects. The same conclusions follow and the local projection specification when $h = 2$ would be given by:

$$y_{i,t+2} - y_{i,t-1} = \beta_2 s_{i,t} + \gamma_2 s_{i,t-1} + \epsilon_{i,t+2} \tag{34}$$

Where $\beta_2 = \beta(\rho_y^2 + \rho_y\rho_s + \rho_s^2)$; $\gamma_2 = (\rho_y^3 - 1)\beta$;

and $\epsilon_{i,t+2} =$
$e_{i,t+2} + \rho_y e_{i,t+1} + \rho_y^2 e_{i,t} + \sum_{k=1}^{T_0}(\rho_y^{k+2} - \rho_y^{k-1})e_{i,t-k} + \beta(v_{i,t+2} + \rho_s v_{i,t+1}) + \sum_{k=2}^{T_0}(\rho_y^{k+2} - \rho_y^{k-1})\beta s_{i,t-k}$

When $h = 3$, y_{t+3} we can follow the same recursive replacing to get the following specification:

$$y_{i,t+3} - y_{i,t-1} = \beta_3 s_{i,t} + \gamma_3 s_{i,t-1} + \epsilon_{i,t+3} \tag{35}$$

Where $\beta_3 = \beta(\rho_y^3 + \rho_y^2\rho_s + \rho_y\rho_s^2 + \rho_s^3)$; $\gamma_3 = (\rho_y^4 - 1)\beta$;
and $\epsilon_{i,t+3} = e_{i,t+3} + \rho_y e_{i,t+2} + \rho_y^2 e_{i,t+1} + \rho_y^3 e_{i,t} + \sum_{k=1}^{T_0}(\rho_y^{k+3} - \rho_y^{k-1})e_{i,t-k} + \beta(v_{i,t+3} + \rho_s v_{i,t+2} + \rho_s^2 v_{i,t+1}) + \sum_{k=2}^{T_0}(\rho_y^{k+3} - \rho_y^{k-1})\beta s_{i,t-k}$

A.2 Proof of Proposition 1: Unbiasedness of $\hat{\beta}_h$ when $0 < \rho_s < 1$

The formal result uses the Frisch–Waugh–Lovell theorem, which says that a multiple regression coefficient equals the regression of y on the part of that regressor orthogonal to the other regressors. Our dependent variable is given by equation (20).

$\hat{\beta}_h$ is obtained by first residualizing $s_{i,t}$ in $s_{i,t-1}$. Since: $s_{i,t} = \rho_s s_{i,t-1} + v_{i,t}$, and using Assumption 2 which implies that:

$$E[s_{i,t}|s_{i,t-1}, ..., s_{i,t-k}] = \rho_s s_{i,t-1}$$

Then the residual from projecting $s_{i,t}$ on $s_{i,t-1}$ is $v_{i,t}$, i.e.:

$$\tilde{s_{i,t}} = v_{i,t}$$

Therefore, following the Frisch–Waugh–Lovell theorem, the pooled OLS estimator of $\hat{\beta}_h$ would be given by:

$$\hat{\beta}_h = \frac{E[\tilde{s_{i,t}}(y_{i,t+h} - y_{i,t-1})]}{E[\tilde{s_{i,t}} s_{i,t}]]} = \frac{E[v_{i,t}(y_{i,t+h} - y_{i,t-1})]}{E[v_{i,t} s_{i,t}]]} \tag{36}$$

If we replace $y_{i,t+h} - y_{i,t-1}$ from equation (20):

$$E[v_{i,t}(y_{i,t+h} - y_{i,t-1})] = E[v_{i,t}(\beta_h s_{i,t} + \gamma_h s_{i,t-1} + \epsilon_{i,t+h})]$$

According to Assumption 1, $v_{i,t}$ is orthogonal to all past values of $s_{i,t}$ and to all other elements in $\epsilon_{i,t+h}$. Therefore, all terms vanish except the contemporaneous one:

$$E[v_{i,t}(y_{i,t+h} - y_{i,t-1})] = E[v_{i,t}(\beta_h s_{i,t})]$$

Thus, equation (36) becomes:

$$\hat{\beta_h} = \beta_h \frac{E[v_{i,t} s_{i,t}]}{E[v_{i,t} s_{i,t}]]} = \beta_h \tag{37}$$

A.3 Simulations when individual effects are not correlated to the shock

In Figures A1 to A3 we can see the case where we assume that the individual effects are not correlated to our shock variable $s_{i,t}$. The most important result in this case is that, unexpectedly, the RE estimator is also biased in most cases, especially at longer horizons.

This follows again from the pseudo within transformation that is implicit in the RE estimator which makes it also vulnerable to the Nickell-bias whenever the between variance is much higher than the within variance, which makes the RE estimator converge towards the FE one.

Figure A1: IRF, Uncorrelated individual effects, $N = 100, T = 50$ when $\rho_s = 0.8$ and $\rho_y = 0$

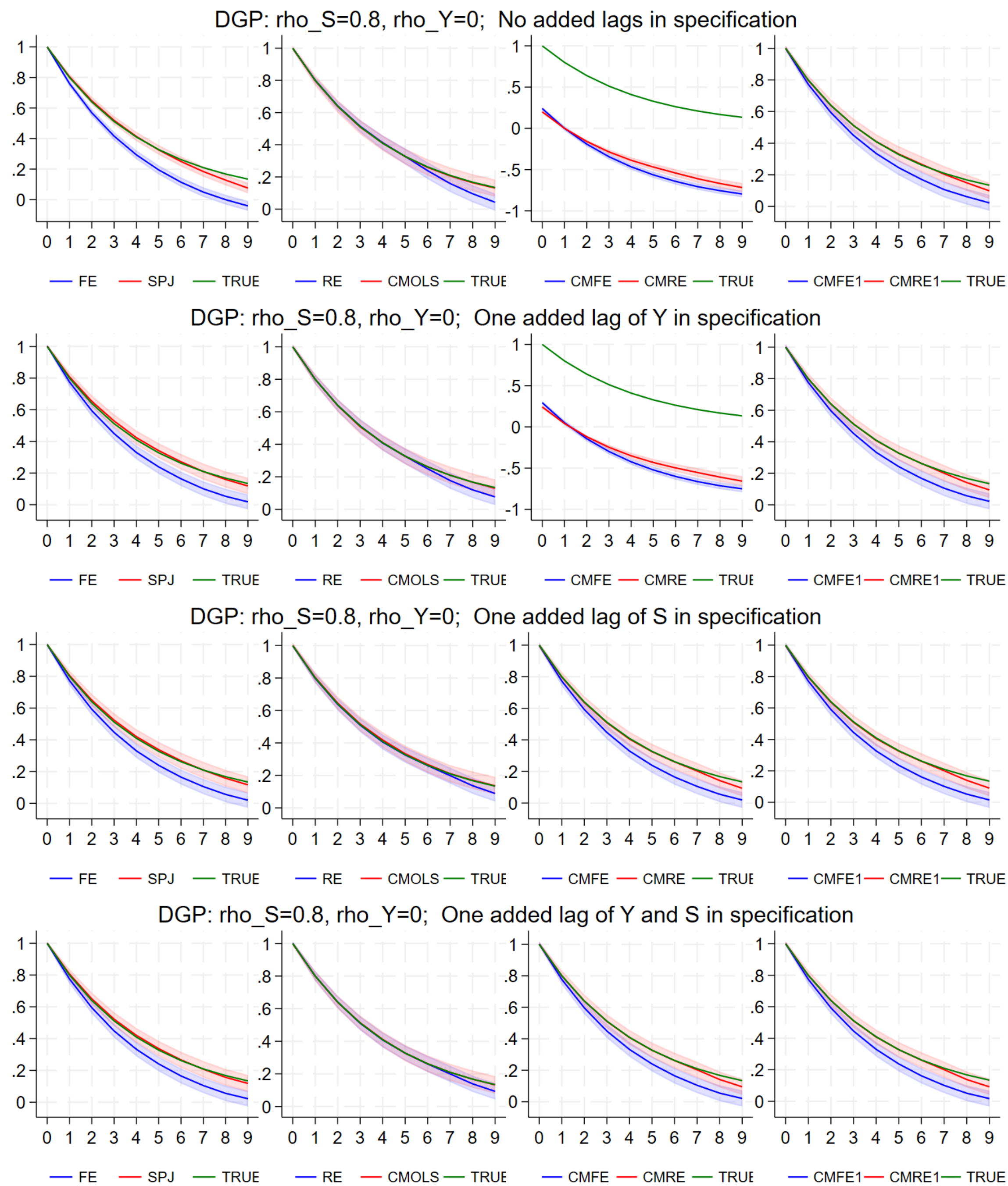

Figure A2: IRF, Uncorrelated individual effects, $N = 100, T = 50$ $\rho_s = 0$ and $\rho_y = 0.8$

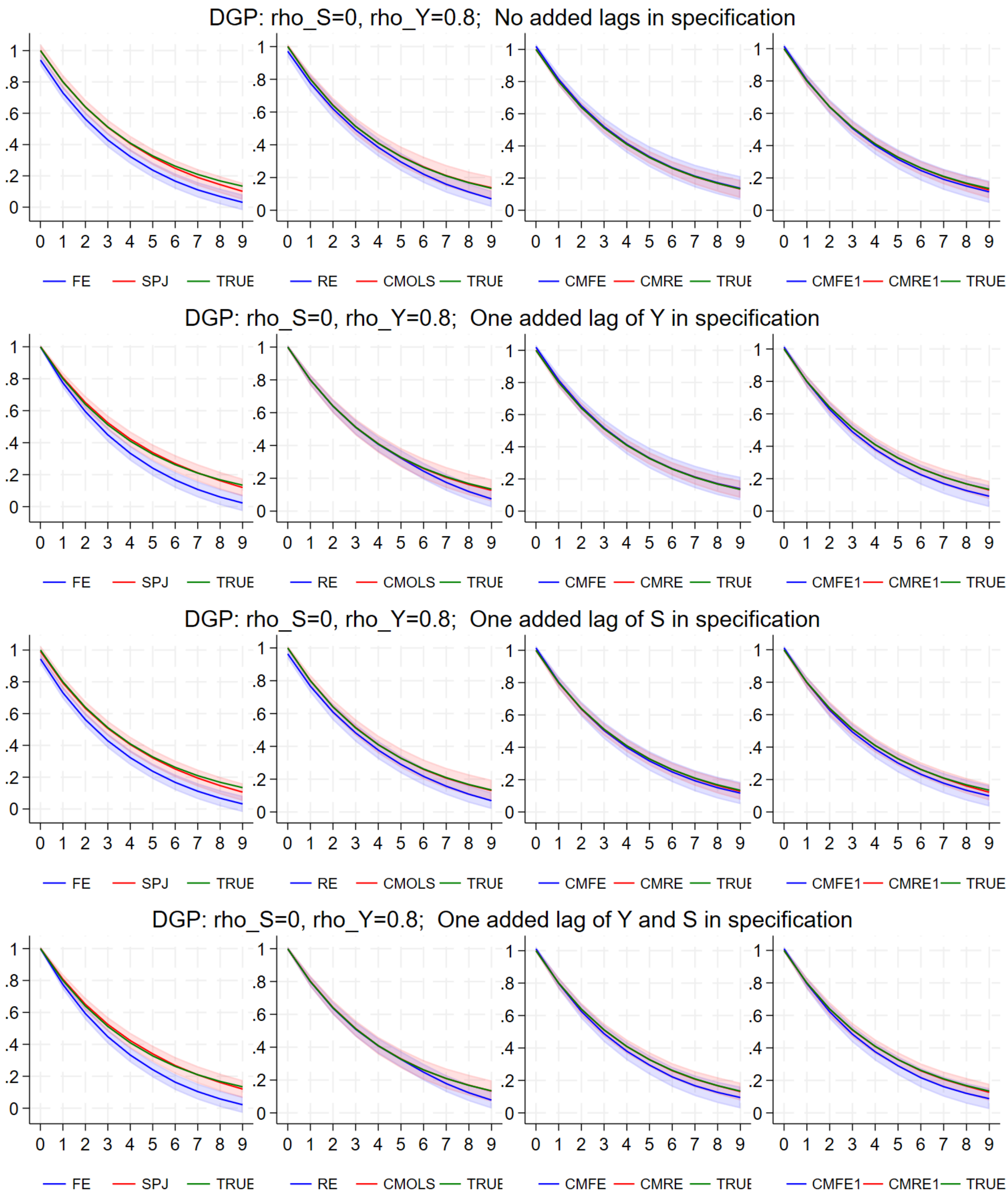

Figure A3: IRF, Uncorrelated individual effects, $N = 100, T = 50$ $\rho_s = 0.8$ and $\rho_y = 0.8$

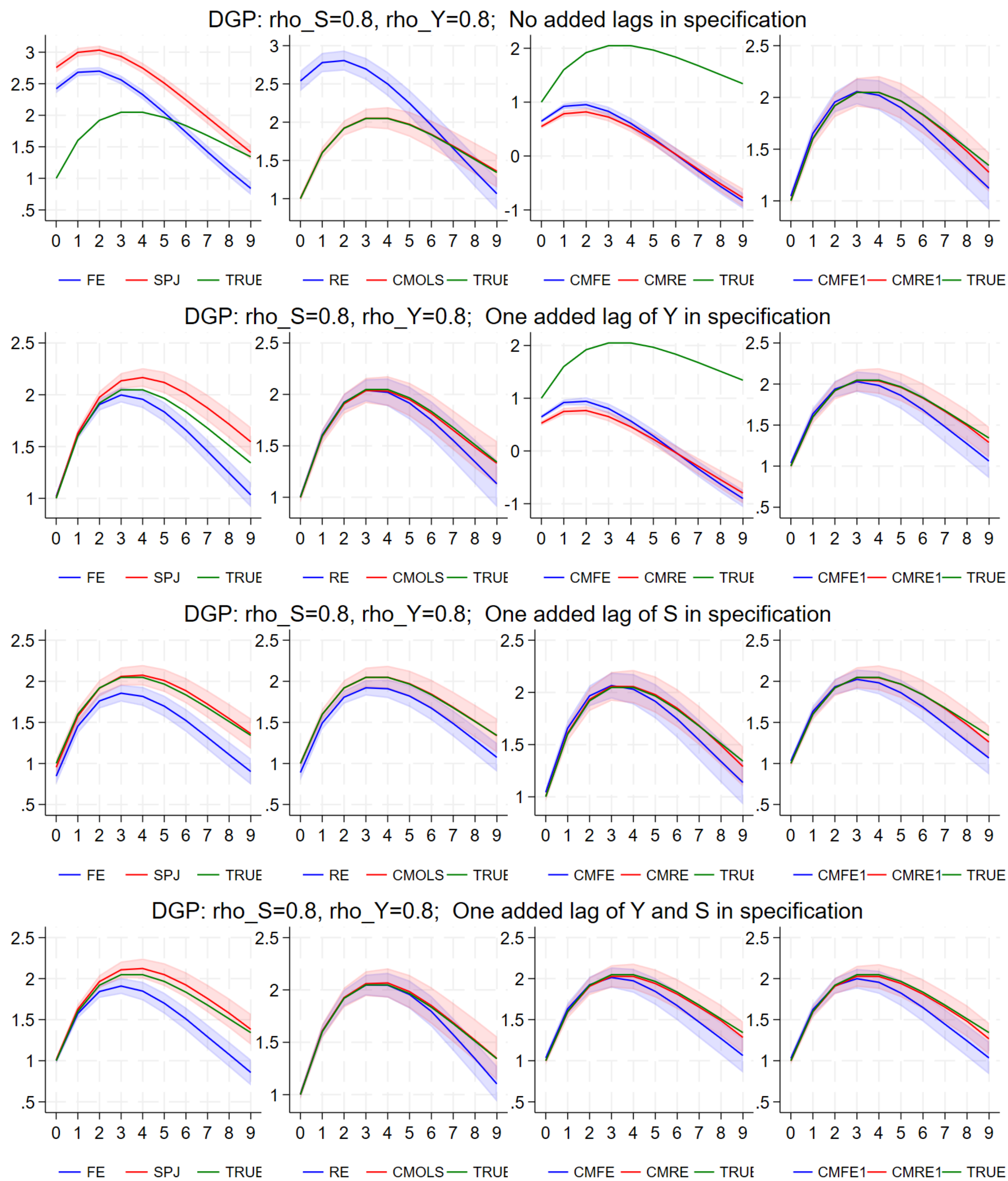

Table A1: DGP: $E[s_{i,t}|u_i] = 0$; $N = 100, T = 50$ when $\rho_s = 0.8$ and $\rho_y = 0$

	Bias (in % of β)			Coverage Probability		
Estimator	Average	$h = 0$	$h = 9$	Average	$h = 0$	$h = 9$
CMOLS	0.03	-0.02	-0.17	0.95	0.96	0.93
CMRE1	-0.79	-0.01	-4.03	0.90	0.93	0.65
RE	-1.41	0.01	-5.87	0.83	0.95	0.41
SPJ	-0.02	0.02	-2.69	0.80	0.93	0.67
CMRE	-39.78	-38.97	-43.08	0.45	0.47	0.33
CMFE1	-7.32	0.04	-11.50	0.25	0.94	0.01
FE	-8.24	0.05	-12.94	0.20	0.93	0.01
CMFE	-45.95	-36.63	-51.08	0.12	0.47	0.00

Table A2: DGP: $E[s_{i,t}|u_i] = 0$; $N = 100, T = 50$ when $\rho_s = 0$ and $\rho_y = 0.8$

	Bias (in % of β)			Coverage Probability		
Estimator	Average	$h = 0$	$h = 9$	Average	$h = 0$	$h = 9$
CMOLS	-0.00	0.03	-0.22	0.98	0.94	0.98
CMRE	-0.07	0.05	-0.24	0.95	0.95	0.95
CMRE1	-0.16	0.04	-0.83	0.95	0.94	0.94
CMFE	-0.49	1.60	-1.21	0.90	0.39	0.95
SPJ	-0.32	-0.11	-2.26	0.86	0.91	0.79
CMFE1	-2.06	1.23	-3.60	0.85	0.58	0.85
RE	-2.79	-1.60	-6.15	0.72	0.73	0.36
FE	-7.90	-2.92	-10.74	0.16	0.53	0.01

Table A3: DGP: $E[s_{i,t}|u_i] = 0$; $N = 100, T = 50$ when $\rho_s = 0.8$ and $\rho_y = 0.8$

	Bias (in % of β)			Coverage Probability		
Estimator	Average	$h = 0$	$h = 9$	Average	$h = 0$	$h = 9$
CMOLS	0.15	0.08	0.15	0.94	0.94	0.95
CMRE1	-1.45	0.16	-6.91	0.91	0.92	0.85
CMFE1	-9.51	3.50	-27.14	0.65	0.68	0.28
RE	4.66	36.02	-24.90	0.55	0.56	0.30
SPJ	23.27	43.23	8.40	0.54	0.62	0.61
CMRE	-75.39	-23.01	-109.13	0.45	0.47	0.44
CMFE	-76.33	-15.81	-122.58	0.34	0.31	0.20
FE	-8.34	32.16	-43.37	0.21	0.44	0.02

Table A4: DGP: $E[s_{i,t}|u_i] = 0$; $N = 100, T = 50$ when $\rho_s = 0.8$ and $\rho_y = 0$; Best specification

	Bias (in % of β)			Coverage Probability		
Estimator	Average	$h = 0$	$h = 9$	Average	$h = 0$	$h = 9$
CMOLS: sl1, yl1	-0.01	0.01	-0.17	0.96	0.98	0.98
SPJ: sl1, yl0	0.26	-0.01	-1.56	0.91	0.94	0.83
CMRE: sl1, yl1	-0.75	0.07	-3.92	0.91	0.95	0.67
CMRE1: sl0, yl0	-0.54	0.02	-3.55	0.90	0.94	0.70
RE: sl1, yl1	-0.83	0.01	-4.11	0.90	0.99	0.57
CMFE1: sl0, yl1	-7.04	0.03	-11.16	0.27	0.95	0.04
CMFE: sl1, yl1	-7.20	-0.16	-11.32	0.27	0.95	0.01
FE: sl1, yl1	-7.20	-0.00	-11.19	0.25	0.96	0.02

Table A5: DGP: $E[s_{i,t}|u_i] = 0$; $N = 100, T = 50$ when $\rho_s = 0$ and $\rho_y = 0.8$; Best specification

	Bias (in % of β)			Coverage Probability		
Estimator	Average	$h = 0$	$h = 9$	Average	$h = 0$	$h = 9$
CMOLS: sl0, yl0	-0.04	0.01	-0.16	0.98	0.96	1.00
CMRE: sl1, yl1	-0.00	-0.01	-0.19	0.96	0.96	0.96
CMRE1: sl0, yl0	0.01	0.00	-0.40	0.96	0.96	0.96
CMFE: sl1, yl0	0.67	1.15	0.30	0.93	0.61	0.99
CMFE1: sl0, yl0	-0.77	1.04	-2.04	0.93	0.65	0.97
SPJ: sl1, yl1	0.44	0.10	-1.43	0.88	0.96	0.80
RE: sl1, yl1	-1.55	0.00	-5.65	0.84	0.96	0.43
FE: sl0, yl1	-7.14	-0.02	-10.24	0.27	0.96	0.02

Table A6: DGP: $E[s_{i,t}|u_i] = 0$; $N = 100, T = 50$ when $\rho_s = 0.8$ and $\rho_y = 0.8$; Best specification

	Bias (in % of β)			Coverage Probability		
Estimator	Average	$h = 0$	$h = 9$	Average	$h = 0$	$h = 9$
CMOLS: sl1, yl0	0.20	-0.12	-0.42	0.95	0.97	0.96
CMRE: sl1, yl0	0.11	-0.10	-5.14	0.94	0.94	0.90
CMRE1: sl1, yl0	-1.01	-0.14	-5.38	0.93	0.93	0.87
RE: sl0, yl1	-5.47	0.53	-21.07	0.83	0.91	0.56
SPJ: sl1, yl0	1.56	0.87	2.02	0.83	0.86	0.87
CMFE: sl1, yl0	-5.02	3.28	-20.52	0.72	0.70	0.52
CMFE1: sl0, yl0	-6.22	2.79	-22.02	0.69	0.80	0.46
FE: sl0, yl1	-12.30	0.25	-30.83	0.42	0.91	0.08

A.4 Simulation results for sample with more time periods than individuals

In Figures A4 to A6 we can see the case when we have much longer time-periods than individuals. In this case, we can observe that the bias of all estimators decrease compared to the case with more individuals than time-periods, which is also noticed by Mei, Sheng and Shi (2026). The main results highlighted in the previous section continue to hold.

Figure A4: IRF, $N = 30, T = 60$ when $\rho_s = 0.8$ and $\rho_y = 0$

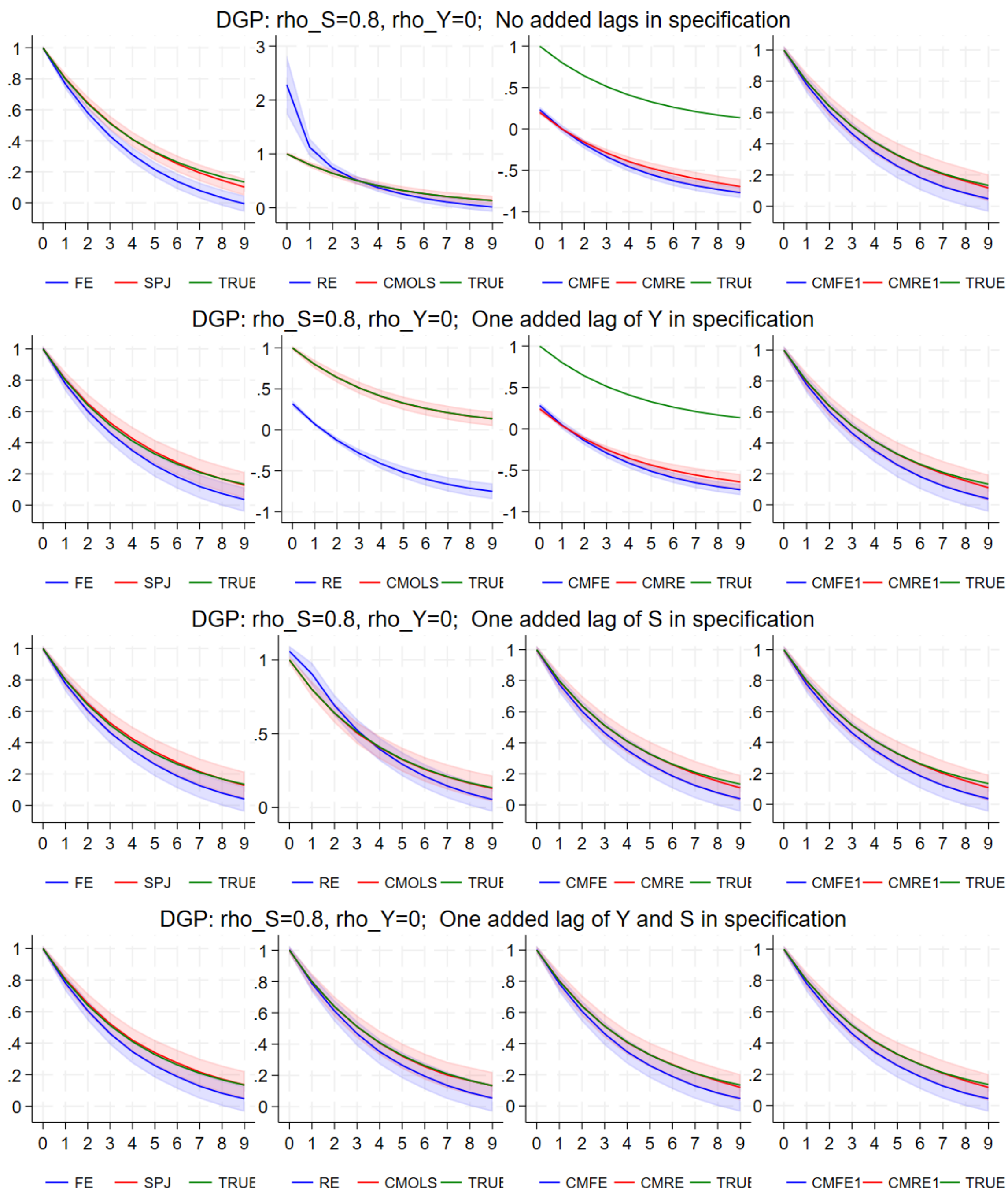

Figure A5: IRF, $N = 30, T = 60$ when $\rho_s = 0$ and $\rho_y = 0.8$

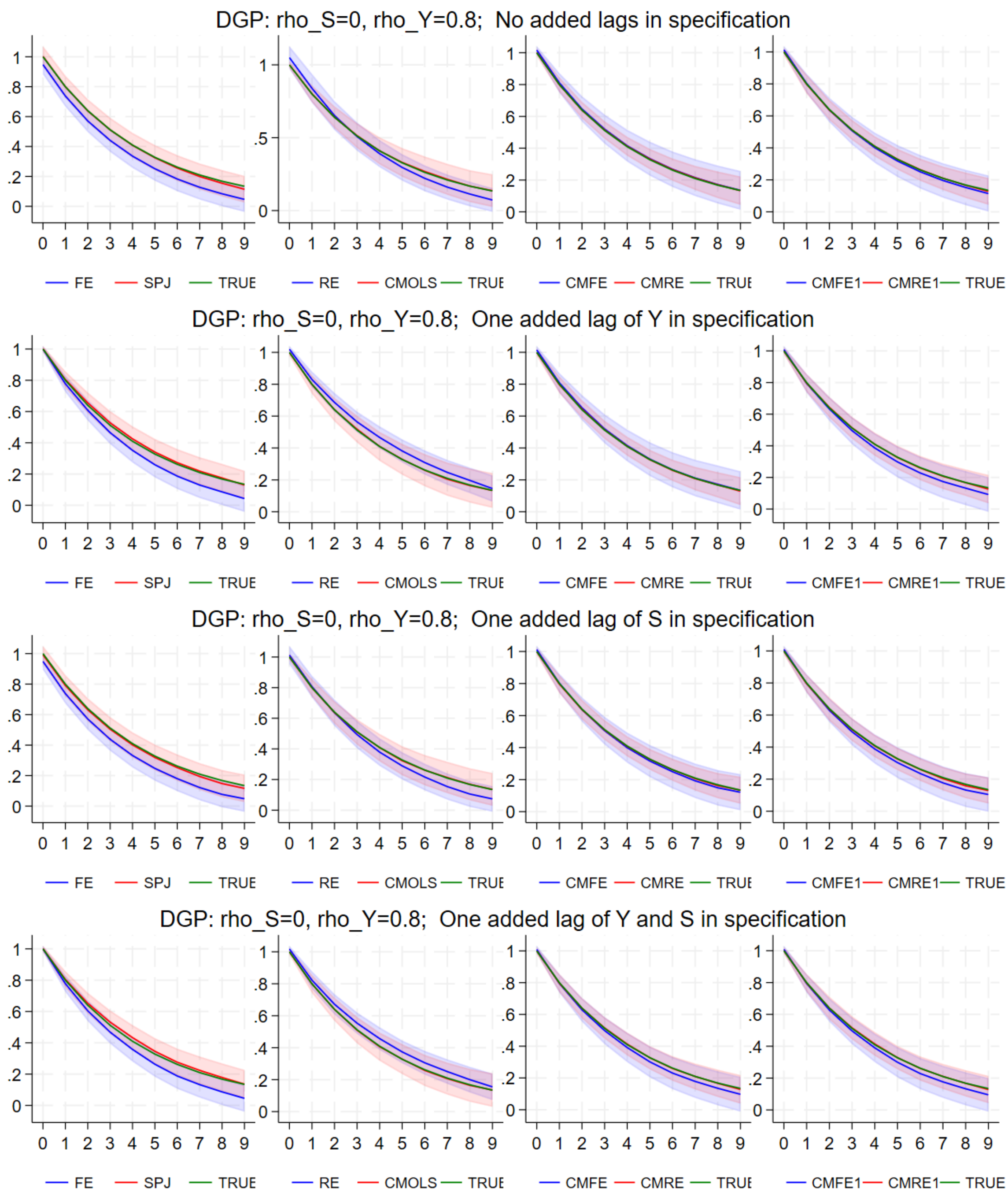

Figure A6: IRF, $N = 30, T = 60$ when $\rho_s = 0.8$ and $\rho_y = 0.8$

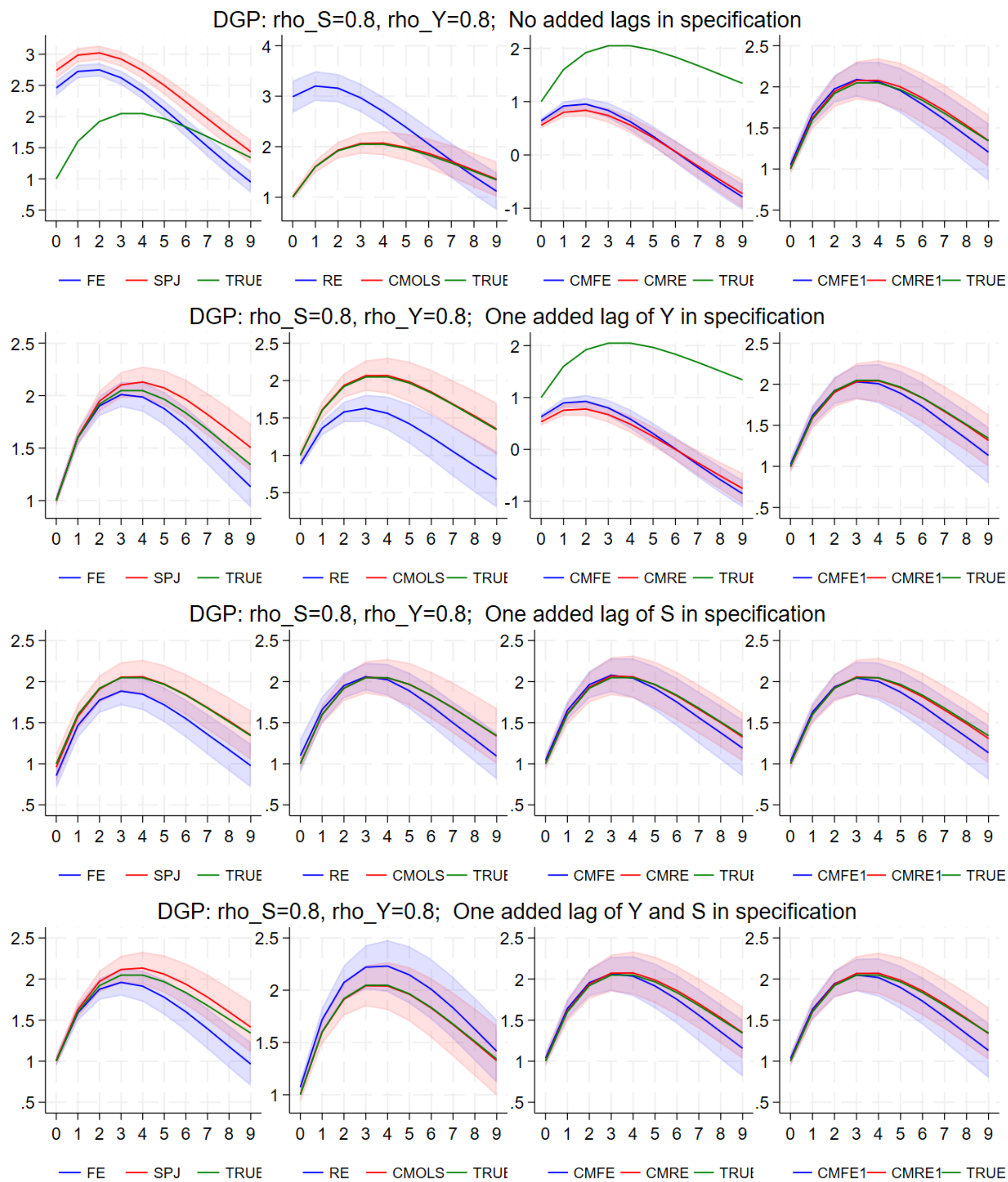

Table A7: DGP: $N = 30, T = 60$ when $\rho_s = 0.8$ and $\rho_y = 0$

	Bias (in % of β)			Coverage Probability		
Estimator	Average	$h = 0$	$h = 9$	Average	$h = 0$	$h = 9$
CMOLS	-0.16	-0.01	-0.02	0.95	0.94	0.94
CMRE1	-0.50	-0.09	-2.14	0.94	0.95	0.92
SPJ	0.33	-0.04	-1.12	0.84	0.94	0.76
CMFE1	-5.87	-0.04	-9.25	0.63	0.97	0.40
FE	-6.66	-0.01	-10.50	0.51	0.96	0.28
CMRE	-39.47	-38.98	-41.08	0.47	0.47	0.45
RE	-18.84	16.63	-29.08	0.45	0.25	0.35
CMFE	-44.65	-37.08	-48.78	0.33	0.48	0.20

Table A8: DGP: $N = 30, T = 60$ when $\rho_s = 0$ and $\rho_y = 0.8$

	Bias (in % of β)			Coverage Probability		
Estimator	Average	$h = 0$	$h = 9$	Average	$h = 0$	$h = 9$
CMOLS	-0.01	0.02	0.09	0.98	0.96	0.99
CMFE	-0.36	1.32	-1.23	0.96	0.78	0.97
CMFE1	-1.74	0.99	-3.27	0.95	0.84	0.96
CMRE1	-0.15	-0.00	-0.65	0.95	0.95	0.94
CMRE	-0.05	0.01	-0.32	0.94	0.93	0.94
SPJ	0.10	-0.08	-1.03	0.88	0.92	0.91
RE	0.68	2.52	-2.25	0.77	0.66	0.80
FE	-6.48	-2.58	-8.85	0.59	0.78	0.47

Table A9: DGP: $N = 30, T = 60$ when $\rho_s = 0.8$ and $\rho_y = 0.8$

	Bias (in % of β)			Coverage Probability		
Estimator	Average	$h = 0$	$h = 9$	Average	$h = 0$	$h = 9$
CMOLS	0.66	0.40	0.10	0.93	0.93	0.95
CMRE1	0.40	0.46	-1.60	0.93	0.96	0.92
CMFE1	-5.69	3.30	-19.12	0.86	0.85	0.79
SPJ	22.12	42.69	8.44	0.62	0.69	0.66
FE	-3.13	33.24	-33.56	0.48	0.62	0.28
RE	7.06	51.12	-26.57	0.48	0.33	0.59
CMRE	-73.18	-22.45	-104.38	0.47	0.48	0.46
CMFE	-73.72	-16.43	-116.62	0.44	0.43	0.43

Table A10: DGP: $N = 30, T = 60$ when $\rho_s = 0.8$ and $\rho_y = 0$; Best specification

	Bias (in % of β)			Coverage Probability		
Estimator &Best Spec.	Average	$h = 0$	$h = 9$	Average	$h = 0$	$h = 9$
CMOLS: sl0, yl0	0.05	-0.03	-0.00	0.96	0.97	0.96
CMRE1: sl0, yl0	-0.33	-0.05	-1.64	0.95	0.97	0.94
CMRE: sl1, yl0	-0.17	0.03	-1.52	0.94	0.95	0.91
SPJ: sl1, yl0	0.63	0.03	0.15	0.91	0.97	0.89
RE: sl1, yl1	-0.89	0.35	-7.92	0.73	0.95	0.55
CMFE: sl1, yl1	-5.52	-0.14	-8.66	0.67	0.97	0.44
CMFE1: sl0, yl0	-5.69	-0.05	-8.60	0.65	0.98	0.47
FE: sl1, yl1	-5.67	0.00	-8.72	0.64	0.98	0.41

Table A11: DGP: $N = 30, T = 60$ when $\rho_s = 0$ and $\rho_y = 0.8$; Best specification

	Bias (in % of β)			Coverage Probability		
Estimator &Best Spec.	Average	$h = 0$	$h = 9$	Average	$h = 0$	$h = 9$
CMOLS: sl0, yl0	-0.05	0.02	0.06	0.98	0.97	1.00
CMFE: sl0, yl1	0.59	0.91	-0.04	0.97	0.88	1.00
CMRE1: sl0, yl1	-0.01	0.05	-0.52	0.97	0.99	0.95
CMFE1: sl0, yl1	-0.69	0.84	-1.95	0.96	0.93	1.00
CMRE: sl0, yl1	-0.07	0.03	-0.03	0.95	0.98	0.96
SPJ: sl0, yl1	-0.55	0.08	0.17	0.92	0.98	0.92
RE: sl1, yl0	-1.59	1.25	1.15	0.83	0.94	0.91
FE: sl1, yl1	-5.39	-0.00	-8.61	0.67	0.98	0.54

Table A12: DGP: $N = 30, T = 60$ when $\rho_s = 0.8$ and $\rho_y = 0$; Best specification

	Bias (in % of β)			Coverage Probability		
Estimator &Best Spec.	Average	$h = 0$	$h = 9$	Average	$h = 0$	$h = 9$
CMRE1: sl1, yl1	-1.00	0.25	0.21	0.96	0.97	0.95
CMRE: sl1, yl1	0.09	0.75	0.52	0.96	0.96	0.95
CMOLS: sl1, yl1	0.02	0.17	-0.47	0.95	0.95	0.98
CMFE: sl1, yl1	-3.73	3.52	-15.18	0.91	0.87	0.88
CMFE1: sl1, yl1	-1.59	2.43	-13.72	0.89	0.93	0.90
SPJ: sl1, yl1	-0.23	-0.13	0.73	0.86	0.93	0.84
RE: sl1, yl0	-6.71	7.15	7.53	0.77	0.86	0.91
FE: sl0, yl1	-8.62	0.61	-21.00	0.65	0.95	0.46

A.5 Simulations with lower autocorrelation

In Figures A7 to A9 we can see the case when our series have a lower autocorrelation, in this case, for either $y_{i,t}$ and $s_{i,t}$ we assume an autocorrelation coefficient of 0.8 instead of 0.8. Again, we can notice that the bias of all the estimators also decreases compared to the first case, and is almost unnoticeable in most cases.

Figure A7: IRF, $N = 100, T = 50$ when $\rho_s = 0.5$ and $\rho_y = 0$

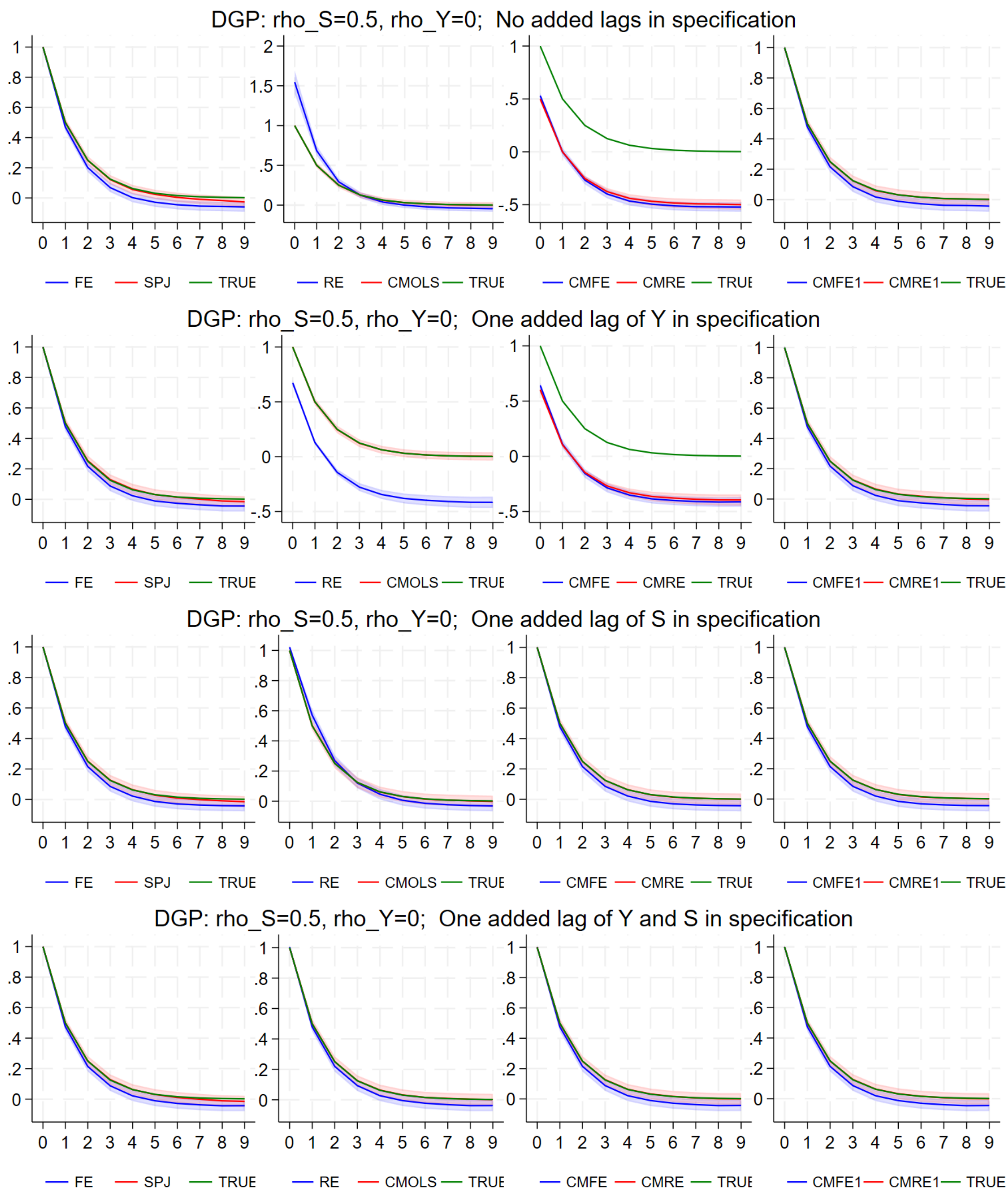

Figure A8: IRF, $N = 100, T = 50$ $\rho_s = 0$ and $\rho_y = 0.5$

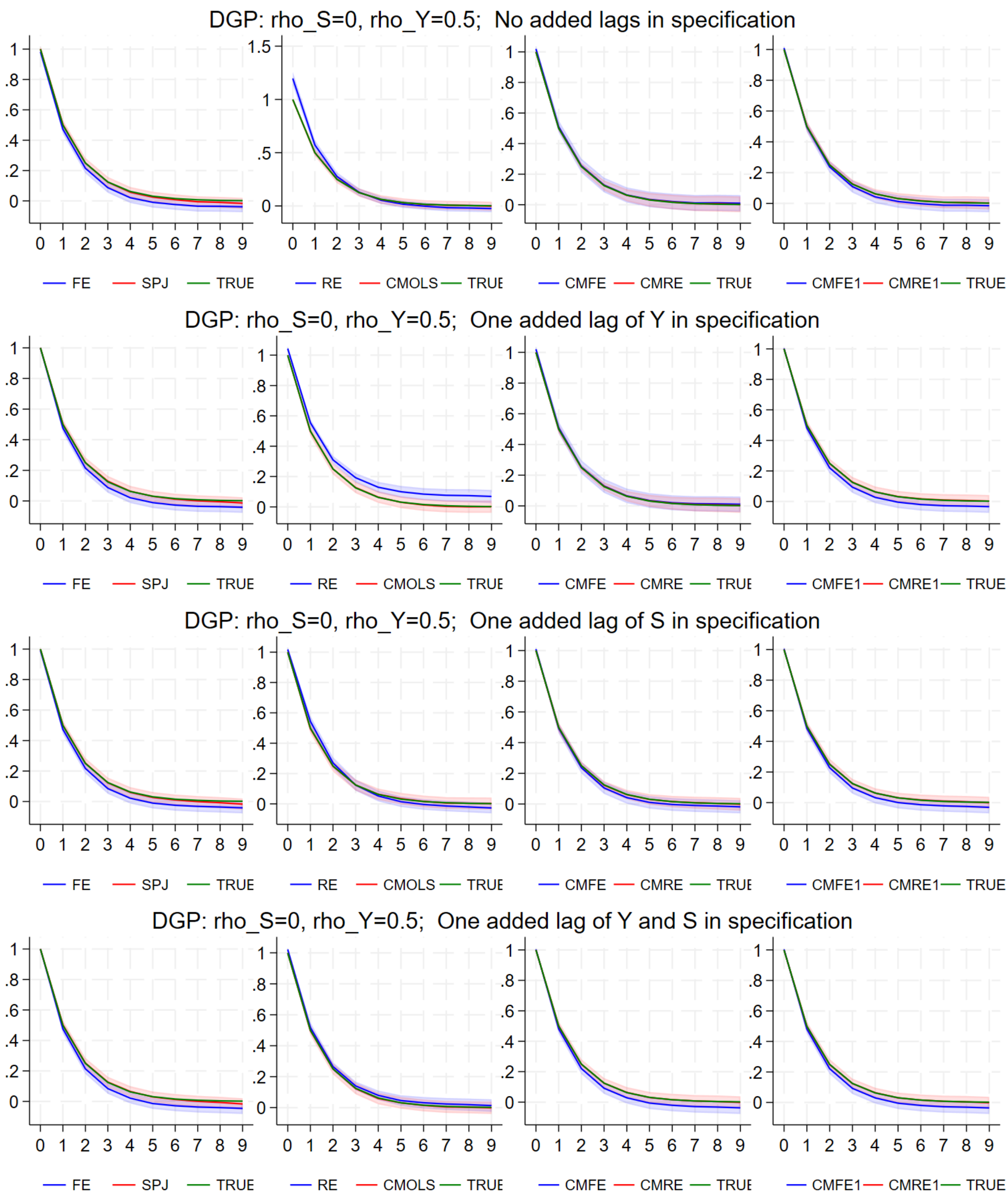

Figure A9: IRF, $N = 100, T = 50$ $\rho_s = 0.5$ and $\rho_y = 0.5$

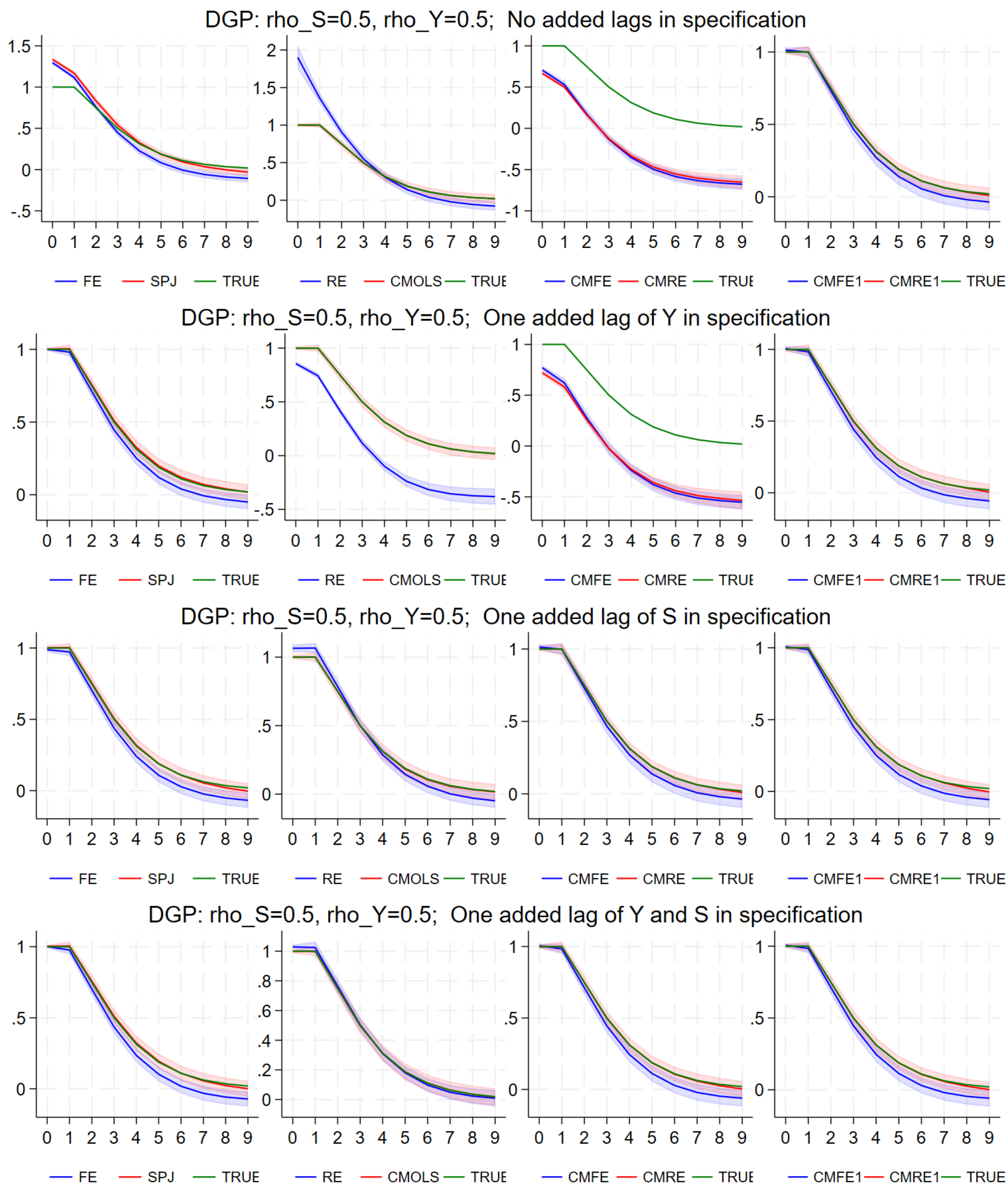

Table A13: DGP: $N = 100, T = 50$ when $\rho_s = 0.5$ and $\rho_y = 0$

	Bias (in % of β)			Coverage Probability		
Estimator	Average	$h = 0$	$h = 9$	Average	$h = 0$	$h = 9$
CMOLS	-0.03	-0.02	-0.11	0.95	0.96	0.95
CMRE1	-0.06	-0.02	-0.27	0.94	0.95	0.94
SPJ	-0.49	0.02	-1.95	0.87	0.94	0.77
CMRE	-22.43	-22.43	-22.52	0.47	0.48	0.47
CMFE1	-3.66	0.01	-4.57	0.44	0.95	0.30
RE	-9.50	6.19	-13.43	0.38	0.22	0.35
FE	-3.92	0.02	-4.88	0.37	0.94	0.24
CMFE	-24.86	-20.62	-25.67	0.23	0.48	0.19

Table A14: DGP: $N = 100, T = 50$ when $\rho_s = 0$ and $\rho_y = 0.5$

	Bias (in % of β)			Coverage Probability		
Estimator	Average	$h = 0$	$h = 9$	Average	$h = 0$	$h = 9$
CMOLS	-0.09	-0.01	-0.20	0.96	0.95	0.95
CMRE1	0.03	0.02	-0.15	0.95	0.95	0.94
CMRE	0.02	0.01	-0.13	0.95	0.94	0.94
SPJ	-0.41	0.05	-1.75	0.91	0.94	0.83
CMFE	-0.74	1.32	-1.06	0.83	0.57	0.82
CMFE1	-2.36	0.57	-3.06	0.72	0.80	0.70
RE	2.35	7.01	0.60	0.54	0.07	0.59
FE	-3.57	-0.67	-4.34	0.43	0.77	0.33

Table A15: DGP: $N = 100, T = 50$ when $\rho_s = 0.5$ and $\rho_y = 0.5$

	Bias (in % of β)			Coverage Probability		
Estimator	Average	$h = 0$	$h = 9$	Average	$h = 0$	$h = 9$
CMOLS	-0.13	0.00	-0.17	0.96	0.95	0.96
CMRE1	-0.28	0.06	-1.62	0.94	0.95	0.88
SPJ	1.39	8.50	-2.37	0.77	0.68	0.75
CMFE1	-4.97	0.83	-7.19	0.50	0.78	0.33
CMRE	-27.68	-15.26	-31.37	0.47	0.46	0.44
RE	-6.70	21.28	-14.44	0.40	0.01	0.34
FE	-5.33	7.20	-9.38	0.28	0.64	0.12
CMFE	-30.12	-12.56	-35.15	0.27	0.38	0.19

Table A16: DGP: $N = 100, T = 50$ when $\rho_s = 0.5$ and $\rho_y = 0$; Best specification

	Bias (in % of β)			Coverage Probability		
Estimator	Average	$h = 0$	$h = 9$	Average	$h = 0$	$h = 9$
CMOLS: sl0, yl1	-0.03	0.01	-0.03	0.96	0.99	0.98
CMRE1: sl1, yl1	-0.01	0.02	-0.13	0.95	0.97	0.95
CMRE: sl1, yl1	-0.05	0.02	-0.12	0.94	0.96	0.95
SPJ: sl1, yl0	-0.24	0.02	-1.59	0.90	0.98	0.87
RE: sl1, yl0	-0.60	0.40	-3.30	0.56	0.88	0.59
CMFE1: sl0, yl1	-3.53	0.02	-4.43	0.48	0.97	0.31
CMFE: sl1, yl1	-3.58	0.01	-4.37	0.46	0.96	0.39
FE: sl0, yl1	-3.53	-0.00	-4.33	0.45	0.99	0.33

Table A17: DGP: $N = 100, T = 50$ when $\rho_s = 0$ and $\rho_y = 0.5$; Best specification

	Bias (in % of β)			Coverage Probability		
Estimator	Average	$h = 0$	$h = 9$	Average	$h = 0$	$h = 9$
CMOLS: sl0, yl0	-0.01	0.02	-0.06	0.98	0.98	0.98
CMRE1: sl0, yl1	0.04	-0.01	0.04	0.96	0.98	0.95
CMRE: sl0, yl0	-0.06	-0.01	0.08	0.95	0.97	0.96
SPJ: sl1, yl1	-0.26	-0.02	-1.47	0.92	0.98	0.85
CMFE: sl0, yl0	0.72	0.35	0.83	0.92	0.93	0.93
CMFE1: sl0, yl0	-1.31	0.37	-1.69	0.89	0.91	0.89
RE: sl1, yl1	-0.39	1.81	1.15	0.75	0.28	0.90
FE: sl0, yl1	-3.48	0.01	-4.04	0.45	0.98	0.38

Table A18: DGP: $N = 100, T = 50$ when $\rho_s = 0.5$ and $\rho_y = 0.5$; Best specification

	Bias (in % of β)			Coverage Probability		
Estimator	Average	$h = 0$	$h = 9$	Average	$h = 0$	$h = 9$
CMOLS: sl0, yl0	-0.04	-0.00	0.11	0.97	0.96	0.99
CMRE1: sl0, yl0	-0.03	0.02	-0.99	0.95	0.99	0.93
CMRE: sl1, yl1	-0.12	0.04	-1.11	0.94	0.93	0.90
SPJ: sl1, yl0	0.06	0.07	-0.17	0.89	0.92	0.86
RE: sl1, yl1	0.16	2.92	-1.04	0.82	0.06	0.93
CMFE1: sl0, yl0	-3.52	0.56	-5.57	0.70	0.87	0.59
CMFE: sl1, yl0	-3.56	0.58	-5.62	0.68	0.87	0.58
FE: sl0, yl1	-3.09	0.12	-6.98	0.42	0.94	0.23

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