

Nickell-Type Bias in Panel Quantile Local Projections with a Revision of Macroeconomic Tail Risk Estimate

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The views expressed are those of the authors and do not necessarily reflect those of the Bank of Spain or the Eurosystem.

Motivation

Macroeconomic risk is about the tails of the distribution.

Panel quantile local projections measure how financial conditions today predict growth at different horizons and quantiles.

- Many studies use panel quantile LP: Adrian et al. (2022), Amado et al. (2026), Banerjee et al. (2024), Clark et al. (2024), Galán (2024), Adrian et al. (2025), Furceri et al. (2025).
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- Canay (2011) and MSS (2019) use **demeaning** to remove country fixed effects.
- At horizon h , the usable time dimension falls to $T_h = T - h$.
- Estimating fixed effects can correlate the transformed regressor with the future forecast error.

The resulting bias can change the estimated path of downside risk

What we do

1. Identify an LP-specific Nickell-type distortion in the quantile score.
2. Trace how the standard within-transformation (demeaning) in Canay (2011) and MSS (2019) transmits the LP bias, and apply SPJ.
3. Use Monte Carlo designs to separate short- T bias from estimator misspecification.
4. Revisit Growth-at-Risk and the role of credit booms in future downside risk.

Contribution to the literature

Literature	This paper
Nickell (1981): dynamic FE bias Mei, Sheng and Shi (2026 JIE): panel mean LPs with SPJ	Extends the LP timing mechanism to quantile scores and moment-based estimators.
Galvão (2011): dynamic panel QR Zheng, Shin and Chen (2024): interactive effects	Targets horizon-specific predictive quantiles. Bias can arise even without a lagged outcome regressor.
Dhaene and Jochmans (2015) Galvão and Kato (2016) Machado and Santos Silva (2019)	Uses existing SPJ logic to isolate and cancel the additional LP-specific inverse-time term.

Panel quantile local projections

For each horizon h and quantile τ ,

$$Q_{\tau}(Y_{i,t+h} \mid \mathcal{F}_{it}, \alpha_{i,h}) = \alpha_{i,h}(\tau) + W'_{it}\theta_h(\tau), \quad t = 1, \dots, T_h.$$

- W_{it} contains the predictor of interest and controls.
- $\alpha_{i,h}(\tau)$ captures unit heterogeneity at each horizon and quantile.
- $\theta_h(\tau)$ is a predictive conditional-quantile coefficient.

Define $u_{i,t+h}(\tau) = Y_{i,t+h} - \alpha_{i,h}(\tau) - W'_{it}\theta_h(\tau)$ and the quantile score

$$Z_{i,t+h}(\tau) = \tau - \mathbf{1}\{u_{i,t+h}(\tau) \leq 0\}.$$

Canay and MSS remove fixed effects by demeaning

Both estimators use the **standard within-transformation (demeaning)** in their preliminary estimation steps:

$$\widetilde{Y}_{i,t+h} = Y_{i,t+h} - \bar{Y}_{i,h}, \quad \widetilde{W}_{it} = W_{it} - \bar{W}_{i,h}.$$

The bars are unit averages over the usable horizon-specific time block.

- **Canay (2011):** demean the mean regression to estimate unit location effects, then run pooled QR after subtracting the estimated effects.
- **MSS (2019):** demean the location and scale equations, then recover quantile slopes from the estimated location, scale and residual quantile.

Demeaning uses the whole time block, including observations after date t .

Where Nickell bias comes from

The date- t moment can be valid before removing fixed effects:

$$\mathbb{E}[Z_{i,t+h} \mid \mathcal{G}_{it}] = 0 \implies \mathbb{E}[W_{it}Z_{i,t+h}] = 0.$$

The **demeaning step in Canay and MSS** uses a unit time average,

$$\widetilde{W}_{it} = W_{it} - \bar{W}_{i,h}, \quad \bar{W}_{i,h} = \frac{1}{T_h} \sum_{s=1}^{T_h} W_{is}.$$

Therefore,

$$\mathbb{E}[\widetilde{W}_{it}Z_{i,t+h}] = -\frac{1}{T_h} \sum_{s>t} \mathbb{E}[W_{is}Z_{i,t+h}],$$

which need not equal zero under predeterminedness.

Future regressors inside $\bar{W}_{i,h}$ share innovations with the horizon- h forecast error.

A one-period example

Consider the location model behind DGP A:

$$x_{i,t+1} = \mu_i + \rho(x_{it} - \mu_i) + \varepsilon_{i,t+1}, \quad y_{it} = \alpha_i + \beta_0 x_{it} + u_{it}.$$

Substituting the regressor equation gives

$$y_{i,t+1} = \underbrace{\alpha_i + \beta_0(1 - \rho)\mu_i}_{\alpha_{i,1}: \text{unit intercept}} + \beta_0 \rho x_{it} + \underbrace{\beta_0 \varepsilon_{i,t+1} + u_{i,t+1}}_{V_{i,t,1}: \text{forecast error}}.$$

Conditional on the unit effect,

$$\text{Cov}(x_{it}, V_{i,t,1}) = 0, \quad \text{Cov}(x_{i,t+1}, V_{i,t,1}) = \beta_0 \text{Var}(\varepsilon_{i,t+1}) \neq 0.$$

The **standard within-transformation (demeaning)** subtracts $\bar{x}_i$, which includes $x_{i,t+1}$. This contaminates the valid date- t moment and can transmit to the quantile score.

The estimators, briefly

Estimator	How it works	Key restriction
Canay (2011)	Demean the mean regression to estimate unit effects. Run pooled QR on the adjusted outcome.	Unit effects are common location shifts across quantiles.
MSS (2019)	Demean location and scale equations , then estimate the standardized residual quantile. $\hat{\theta}_h(\tau) = \hat{\beta}_h + \hat{\delta}_h \hat{q}_h(\tau).$	A common location–scale structure.
Koenker (2004)	Estimate slopes and unit effects jointly using quantile loss and an FE penalty.	Flexible quantile-specific unit effects.

Split-panel jackknife: implementation

For each (h, τ) , split the **usable origin dates** into two approximately equal consecutive blocks of lengths $T_{h,a}$ and $T_{h,b}$.

1. Estimate the model on the full horizon-specific sample.
2. Recompute **demeaning and every subsequent estimation stage** on each half.
3. Combine the estimates:

$$\hat{\theta}_{h,\text{SPJ}}^m(\tau) = 2\hat{\theta}_h^m(\tau) - \frac{T_{h,a}}{T_h}\hat{\theta}_{h,a}^m(\tau) - \frac{T_{h,b}}{T_h}\hat{\theta}_{h,b}^m(\tau)$$

For equal halves, the weights are $1/2$ and $1/2$.

Why the half-panel LP bias doubles

Fix h , τ , N and the estimator. On a time block of length L ,

$$\hat{\theta}_{h,L} - \theta_h = S_{h,L} + \boxed{\frac{B_h^{\text{LP}}}{L}} + A_{h,L} + r_{h,L}.$$

$$\text{Full panel: } L = T_h \implies \frac{B_h^{\text{LP}}}{L} = \frac{B_h^{\text{LP}}}{T_h},$$

$$\text{Each half: } L = T_h/2 \implies \frac{B_h^{\text{LP}}}{L} = \frac{B_h^{\text{LP}}}{T_h/2} = \frac{2B_h^{\text{LP}}}{T_h}.$$

The average of the half-panel estimates retains this common LP component:

$$\frac{1}{2} \left(\frac{2B_h^{\text{LP}}}{T_h} + \frac{2B_h^{\text{LP}}}{T_h} \right) = \frac{2B_h^{\text{LP}}}{T_h}.$$

What the jackknife removes

With a common target and a stable LP coefficient B_h across blocks,

$$\text{full-panel LP bias} = \frac{B_h}{T_h}, \quad \text{half-panel LP bias} = \frac{2B_h}{T_h}.$$

Thus, for equal halves,

$$2\frac{B_h}{T_h} - \frac{1}{2} \left(\frac{2B_h}{T_h} + \frac{2B_h}{T_h} \right) = 0.$$

- SPJ cancels the leading LP-specific $1/T_h$ component.
- Other short- T terms can remain after correction.
- Half-sample estimation can raise variance. Misspecification can remain.

Monte Carlo design

Configurations

- $h = 0, \dots, 10$
- $\tau \in \{0.1, 0.5, 0.9\}$
- $\rho \in \{0, 0.5, 0.9\}$
- 1,000 replications

Panel sizes

N,T: (200, 50, 200) and (50, 200, 200).

Canay, MSS, and their SPJ variants.

RMSE plots also include Koenker.

$$\text{Absolute bias}_h(\tau) = \left| \frac{1}{R} \sum_{r=1}^R (\hat{\theta}_{h,r}(\tau) - \theta_h(\tau)) \right|,$$

$$\text{RMSE}_h(\tau) = \sqrt{\frac{1}{R} \sum_{r=1}^R (\hat{\theta}_{h,r}(\tau) - \theta_h(\tau))^2}.$$

DGP A: a location-shift benchmark

$$x_{it} = \mu_i + \rho(x_{i,t-1} - \mu_i) + \varepsilon_{it}, \quad y_{it} = \alpha_i + \beta_0 x_{it} + u_{it},$$

with $\varepsilon_{it} \sim \chi_1^2 - 1$, $u_{it} \sim N(0, 1)$ and $\beta_0 = -0.6$.

The analytical quantile slope is

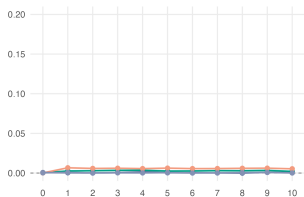
$$\theta_h^A(\tau) = \beta_0 \rho^h \quad \text{for every } \tau.$$

- Canay and MSS both match the conditional quantile structure.
- Differences across raw and SPJ estimates reveal finite-sample distortions and the cost of correction.

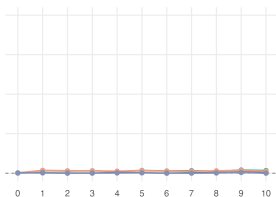
DGP A: absolute bias

$\rho = 0$, $N = 50$, $T = 200$

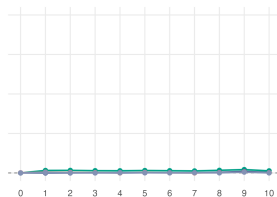
$\tau = 0.1$



$\tau = 0.5$



$\tau = 0.9$



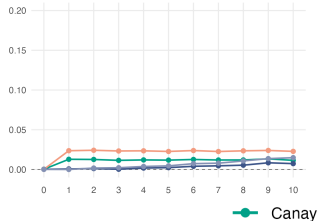
Canay MSS Canay + SPJ MSS + SPJ

Horizon $h = 0, \dots, 10$. Native selected panels from the paper.

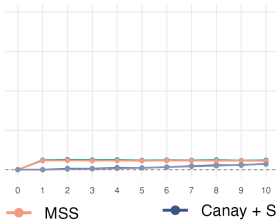
DGP A: absolute bias and RMSE

$\rho = 0$, $N = 200$, $T = 50$

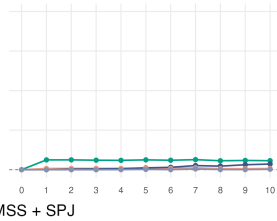
Absolute bias $\tau = 0.1$



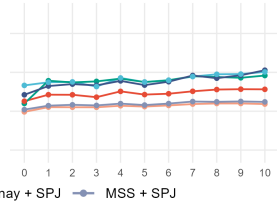
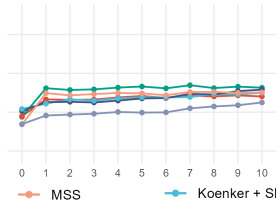
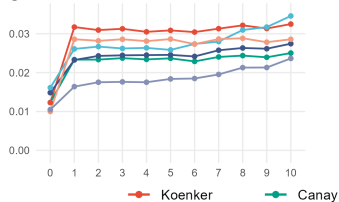
$\tau = 0.5$



$\tau = 0.9$



RMSE

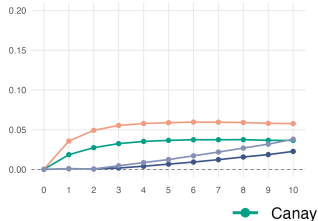


Horizon $h = 0, \dots, 10$. Native panels and legends from the paper; OLS panel omitted.

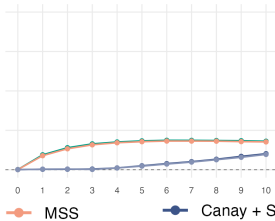
DGP A: absolute bias and RMSE

$\rho = 0.5$, $N = 200$, $T = 50$

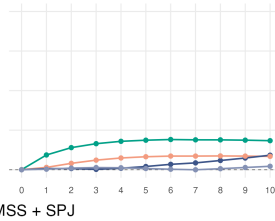
Absolute bias $\tau = 0.1$



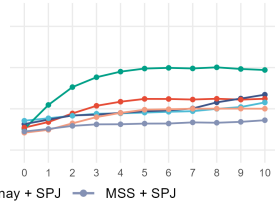
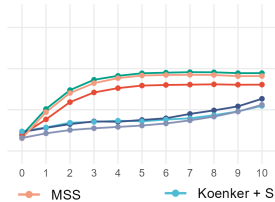
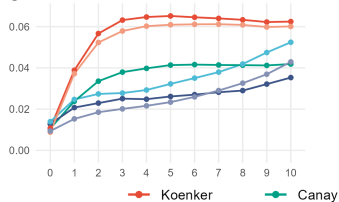
$\tau = 0.5$



$\tau = 0.9$



RMSE

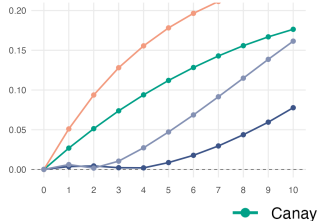


Horizon $h = 0, \dots, 10$. Native panels and legends from the paper; OLS panel omitted.

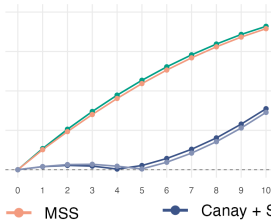
DGP A: absolute bias and RMSE

$\rho = 0.9$, $N = 200$, $T = 50$

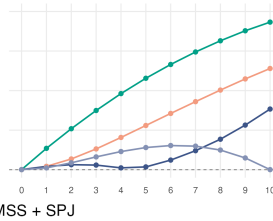
Absolute bias $\tau = 0.1$



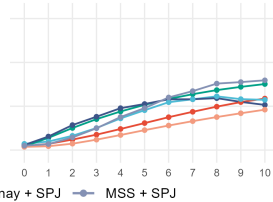
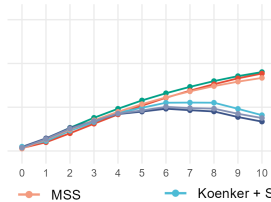
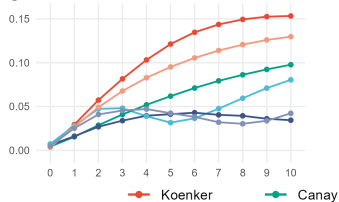
$\tau = 0.5$



$\tau = 0.9$



RMSE

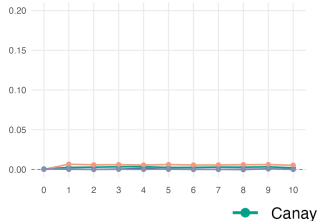


Horizon $h = 0, \dots, 10$. Native panels and legends from the paper; OLS panel omitted.

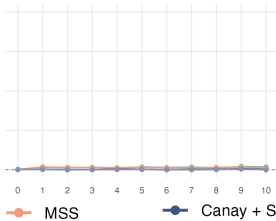
DGP A: absolute bias and RMSE

$\rho = 0$, $N = 50$, $T = 200$

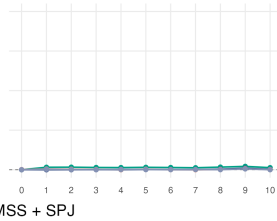
Absolute bias $\tau = 0.1$



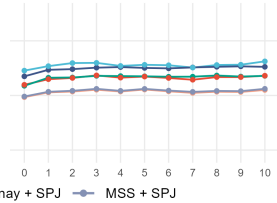
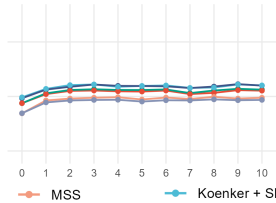
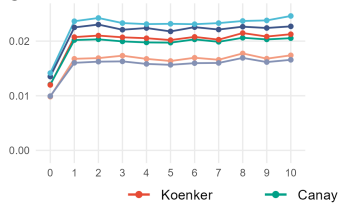
$\tau = 0.5$



$\tau = 0.9$



RMSE

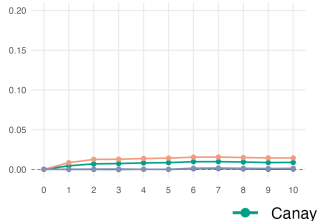


Horizon $h = 0, \dots, 10$. Native panels and legends from the paper; OLS panel omitted.

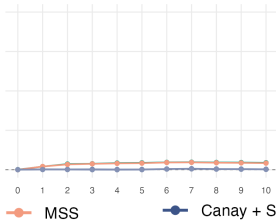
DGP A: absolute bias and RMSE

$\rho = 0.5$, $N = 50$, $T = 200$

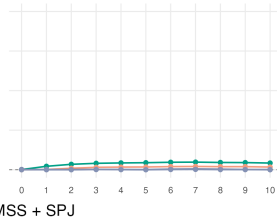
Absolute bias $\tau = 0.1$



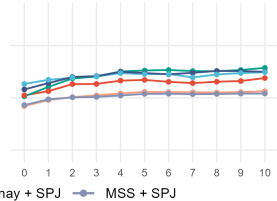
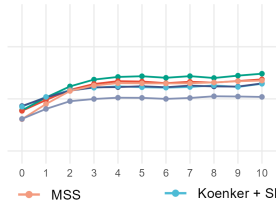
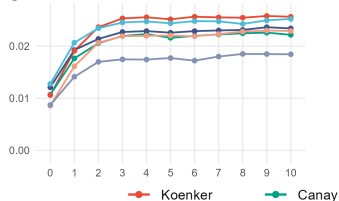
$\tau = 0.5$



$\tau = 0.9$



RMSE

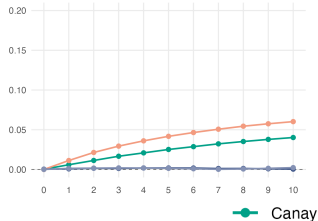


Horizon $h = 0, \dots, 10$. Native panels and legends from the paper; OLS panel omitted.

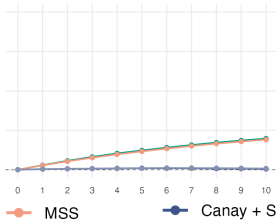
DGP A: absolute bias and RMSE

$\rho = 0.9$, $N = 50$, $T = 200$

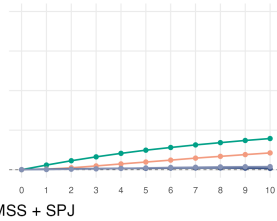
Absolute bias $\tau = 0.1$



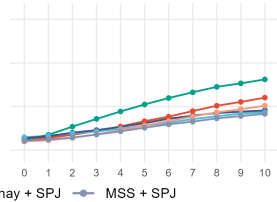
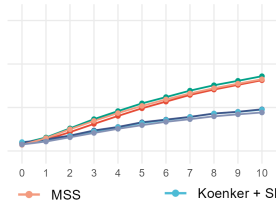
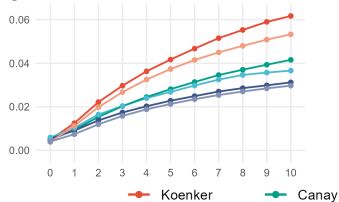
$\tau = 0.5$



$\tau = 0.9$



RMSE

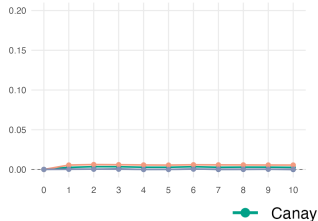


Horizon $h = 0, \dots, 10$. Native panels and legends from the paper; OLS panel omitted.

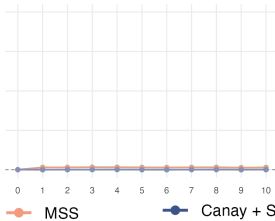
DGP A: absolute bias and RMSE

$\rho = 0$, $N = 200$, $T = 200$

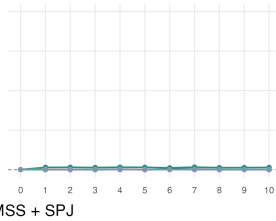
Absolute bias $\tau = 0.1$



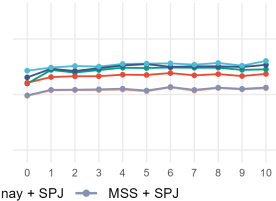
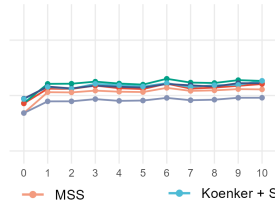
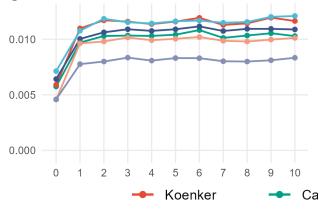
$\tau = 0.5$



$\tau = 0.9$



RMSE

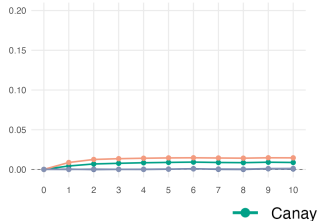


Horizon $h = 0, \dots, 10$. Native panels and legends from the paper; OLS panel omitted.

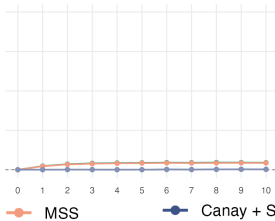
DGP A: absolute bias and RMSE

$\rho = 0.5$, $N = 200$, $T = 200$

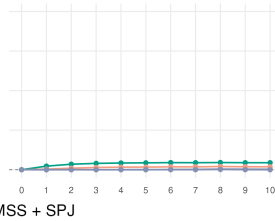
Absolute bias $\tau = 0.1$



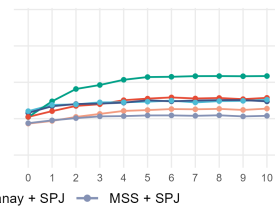
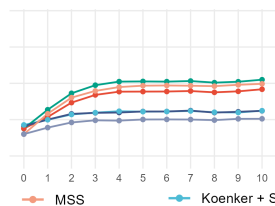
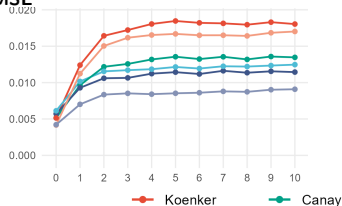
$\tau = 0.5$



$\tau = 0.9$



RMSE

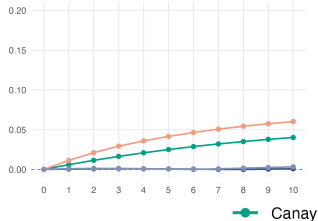


Horizon $h = 0, \dots, 10$. Native panels and legends from the paper; OLS panel omitted.

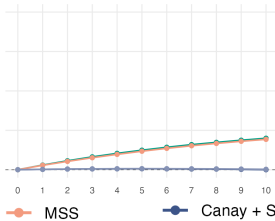
DGP A: absolute bias and RMSE

$\rho = 0.9$, $N = 200$, $T = 200$

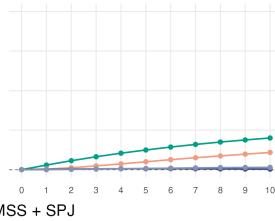
Absolute bias $\tau = 0.1$



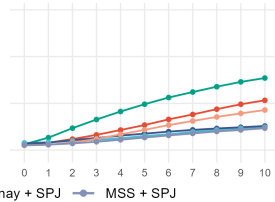
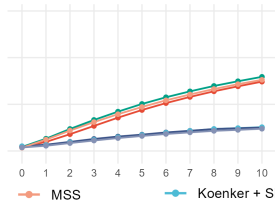
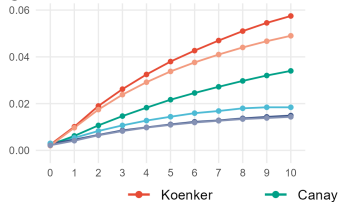
$\tau = 0.5$



$\tau = 0.9$



RMSE



Horizon $h = 0, \dots, 10$. Native panels and legends from the paper; OLS panel omitted.

DGP B: heterogeneous location and scale

$$x_{it} = \mu_i + \rho(x_{i,t-1} - \mu_i) + \sigma_i \varepsilon_{it}, \quad y_{it} = \alpha_i + \beta_0 x_{it} + \sigma_i u_{it}.$$

The scale σ_i varies across units and is related to α_i .

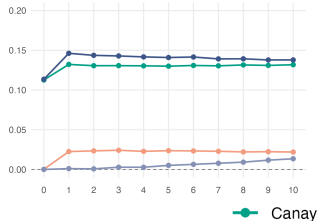
$$Q_\tau(y_{i,t+h} \mid x_{it}, i) = \alpha_{i,h} + \sigma_i Q_\tau(V_h) + \beta_0 \rho^h x_{it}, \quad \theta_h^B(\tau) = \beta_0 \rho^h.$$

- MSS matches the location–scale structure.
- Canay's common location-shift restriction fails when the unit quantile effect varies with τ .

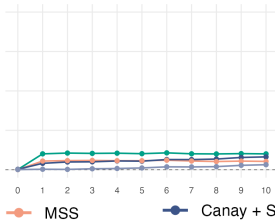
DGP B: absolute bias and RMSE

$\rho = 0$, $N = 200$, $T = 50$

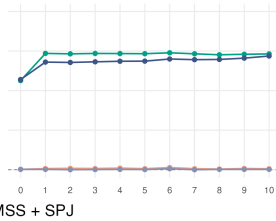
Absolute bias $\tau = 0.1$



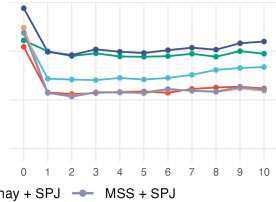
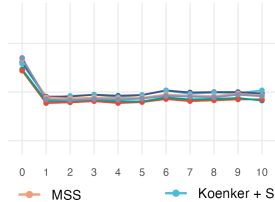
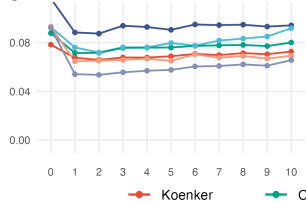
$\tau = 0.5$



$\tau = 0.9$



RMSE

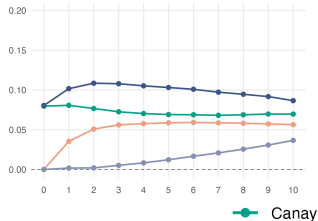


Horizon $h = 0, \dots, 10$. Native panels and legends from the paper; OLS panel omitted.

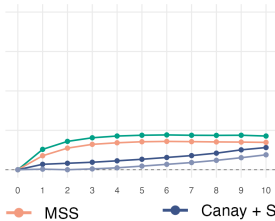
DGP B: absolute bias and RMSE

$\rho = 0.5$, $N = 200$, $T = 50$

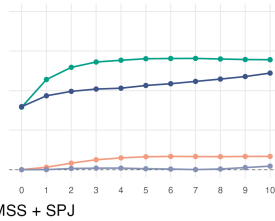
Absolute bias $\tau = 0.1$



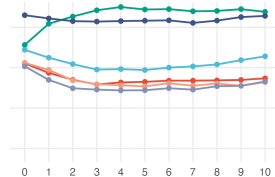
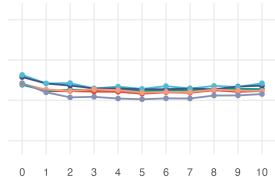
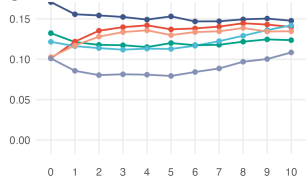
$\tau = 0.5$



$\tau = 0.9$



RMSE

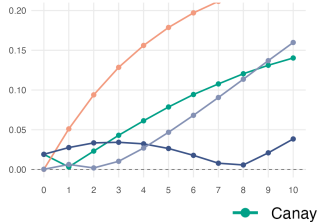


Horizon $h = 0, \dots, 10$. Native panels and legends from the paper; OLS panel omitted.

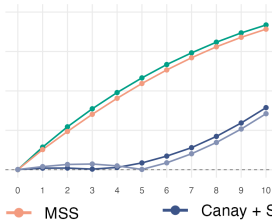
DGP B: absolute bias and RMSE

$\rho = 0.9$, $N = 200$, $T = 50$

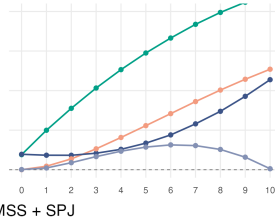
Absolute bias $\tau = 0.1$



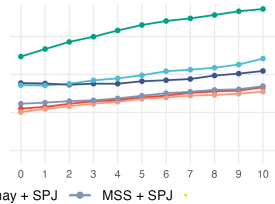
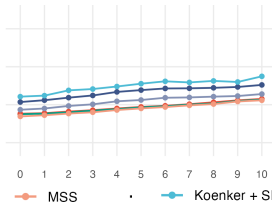
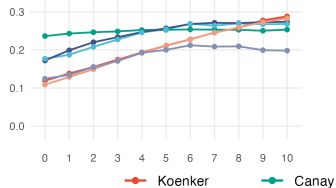
$\tau = 0.5$



$\tau = 0.9$



RMSE

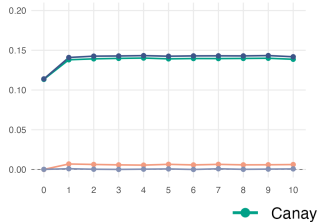


Horizon $h = 0, \dots, 10$. Native panels and legends from the paper; OLS panel omitted.

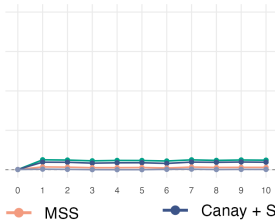
DGP B: absolute bias and RMSE

$\rho = 0$, $N = 50$, $T = 200$

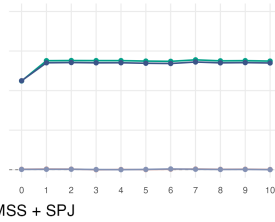
Absolute bias $\tau = 0.1$



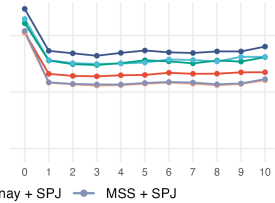
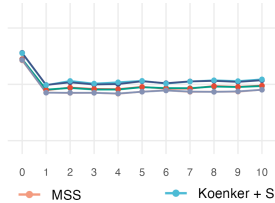
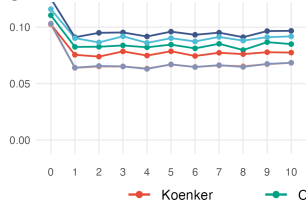
$\tau = 0.5$



$\tau = 0.9$



RMSE

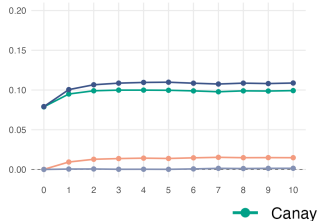


Horizon $h = 0, \dots, 10$. Native panels and legends from the paper; OLS panel omitted.

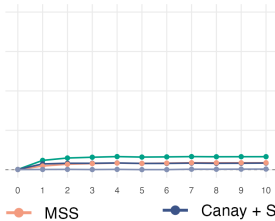
DGP B: absolute bias and RMSE

$\rho = 0.5$, $N = 50$, $T = 200$

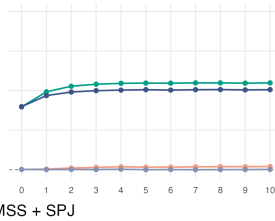
Absolute bias $\tau = 0.1$



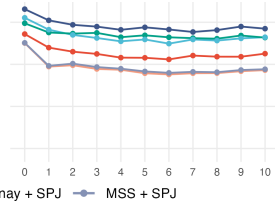
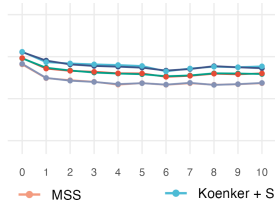
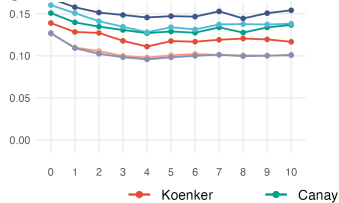
$\tau = 0.5$



$\tau = 0.9$



RMSE

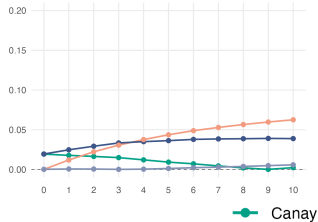


Horizon $h = 0, \dots, 10$. Native panels and legends from the paper; OLS panel omitted.

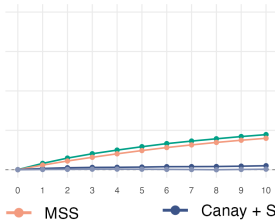
DGP B: absolute bias and RMSE

$\rho = 0.9$, $N = 50$, $T = 200$

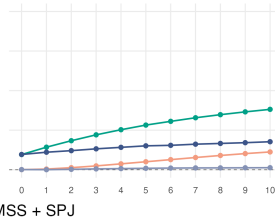
Absolute bias $\tau = 0.1$



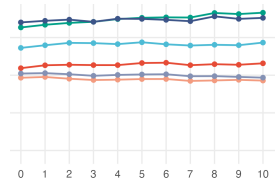
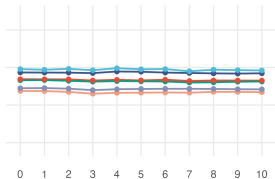
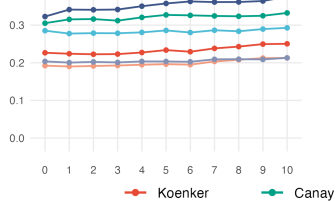
$\tau = 0.5$



$\tau = 0.9$



RMSE

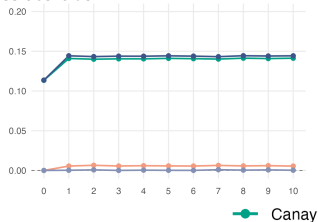


Horizon $h = 0, \dots, 10$. Native panels and legends from the paper; OLS panel omitted.

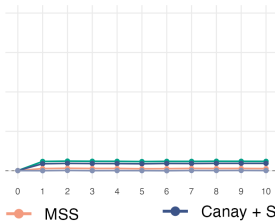
DGP B: absolute bias and RMSE

$\rho = 0$, $N = 200$, $T = 200$

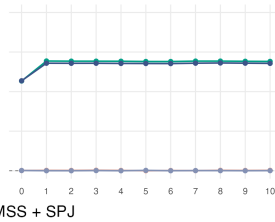
Absolute bias $\tau = 0.1$



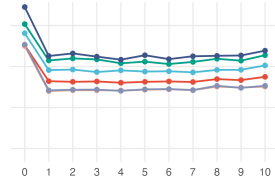
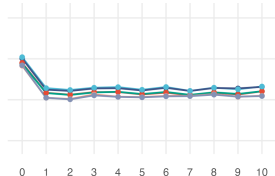
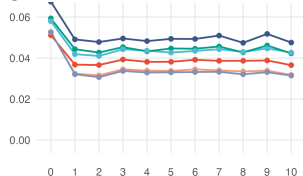
$\tau = 0.5$



$\tau = 0.9$



RMSE

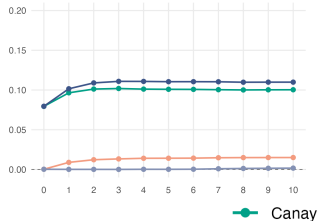


Horizon $h = 0, \dots, 10$. Native panels and legends from the paper; OLS panel omitted.

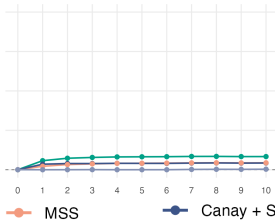
DGP B: absolute bias and RMSE

$\rho = 0.5$, $N = 200$, $T = 200$

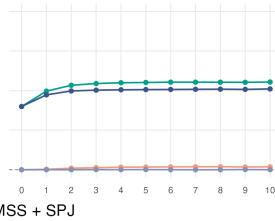
Absolute bias $\tau = 0.1$



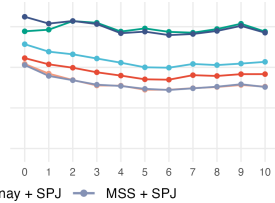
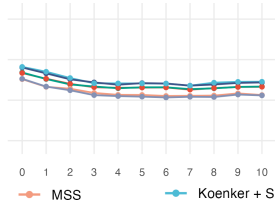
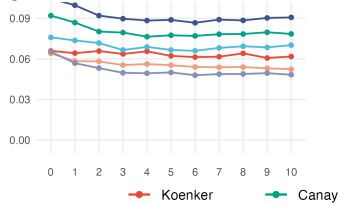
$\tau = 0.5$



$\tau = 0.9$



RMSE

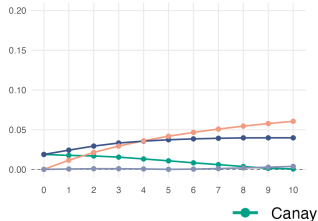


Horizon $h = 0, \dots, 10$. Native panels and legends from the paper; OLS panel omitted.

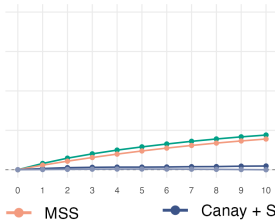
DGP B: absolute bias and RMSE

$\rho = 0.9$, $N = 200$, $T = 200$

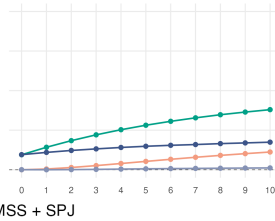
Absolute bias $\tau = 0.1$



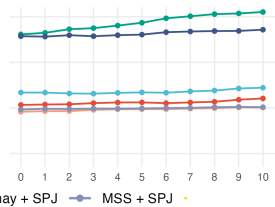
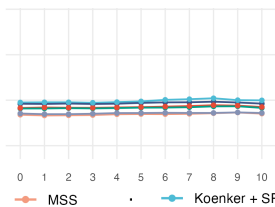
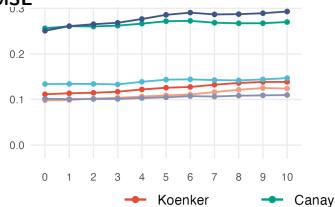
$\tau = 0.5$



$\tau = 0.9$



RMSE



Horizon $h = 0, \dots, 10$. Native panels and legends from the paper; OLS panel omitted.

DGP C: distributional shape changes

A binary Markov regressor has persistence ρ and $\Pr(x_{it} = 1) = 1/2$:

$$y_{it} = \alpha_i + \beta_0 x_{it} + e_{it}, \quad \begin{cases} e_{it} \mid x_{it} = 0 \sim N(0, 1), \\ e_{it} \mid x_{it} = 1 \sim \text{Logistic}(0, \sqrt{3}/\pi). \end{cases}$$

The innovations have equal means and variances, but different shapes.

$$\theta_h^C(\tau) = q_{1,h}(\tau) - q_{0,h}(\tau),$$

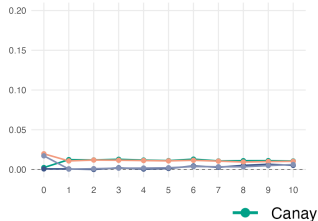
where $q_{s,h}(\tau)$ is the quantile of $y_{i,t+h} - \alpha_i$ conditional on $x_{it} = s$.

- Canay matches the additive location-shift structure.
- MSS generally imposes the wrong distributional shape.

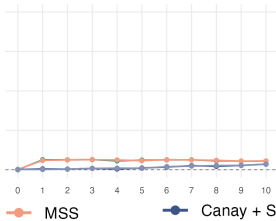
DGP C: absolute bias and RMSE

$\rho = 0$, $N = 200$, $T = 50$

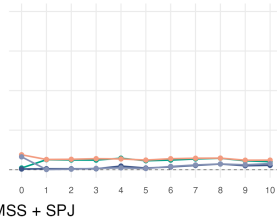
Absolute bias $\tau = 0.1$



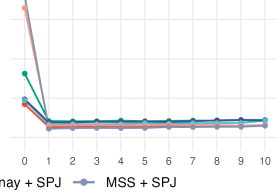
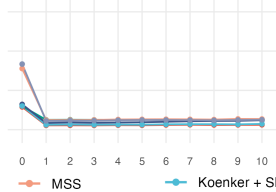
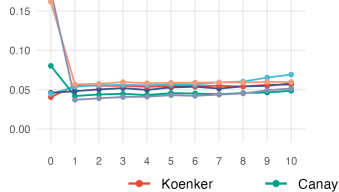
$\tau = 0.5$



$\tau = 0.9$



RMSE

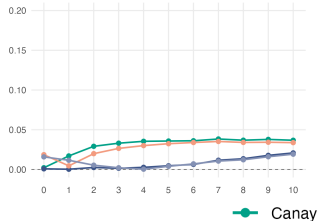


Horizon $h = 0, \dots, 10$. Native panels and legends from the paper; OLS panel omitted.

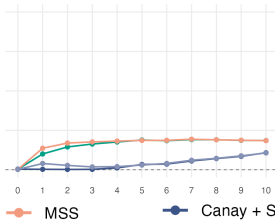
DGP C: absolute bias and RMSE

$\rho = 0.5$, $N = 200$, $T = 50$

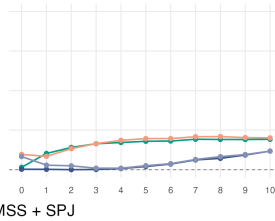
Absolute bias $\tau = 0.1$



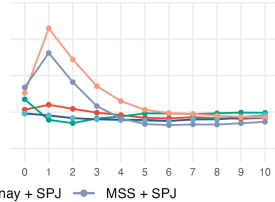
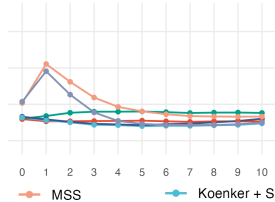
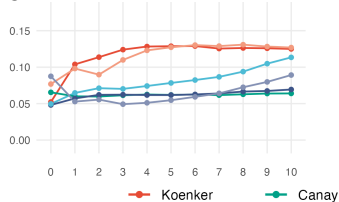
$\tau = 0.5$



$\tau = 0.9$



RMSE

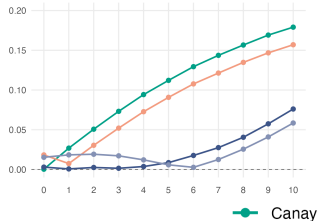


Horizon $h = 0, \dots, 10$. Native panels and legends from the paper; OLS panel omitted.

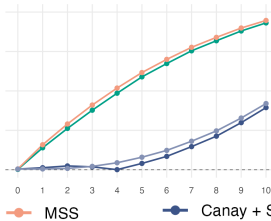
DGP C: absolute bias and RMSE

$\rho = 0.9$, $N = 200$, $T = 50$

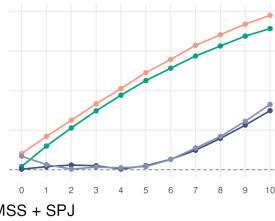
Absolute bias $\tau = 0.1$



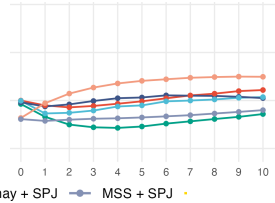
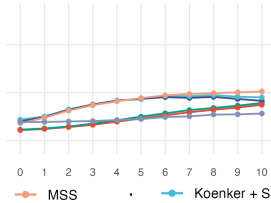
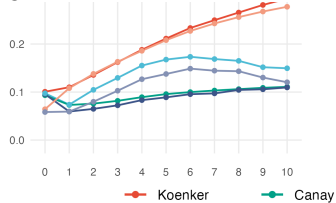
$\tau = 0.5$



$\tau = 0.9$



RMSE

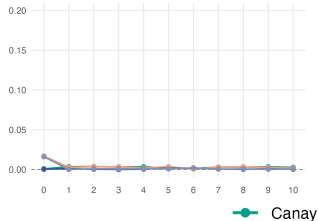


Horizon $h = 0, \dots, 10$. Native panels and legends from the paper; OLS panel omitted.

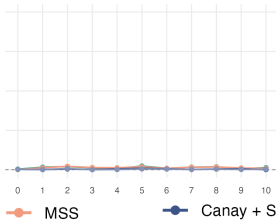
DGP C: absolute bias and RMSE

$\rho = 0$, $N = 50$, $T = 200$

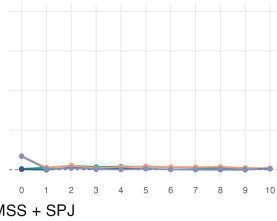
Absolute bias $\tau = 0.1$



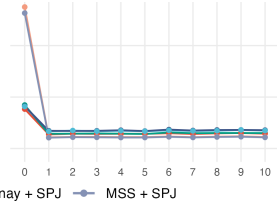
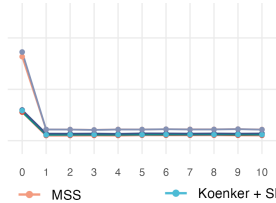
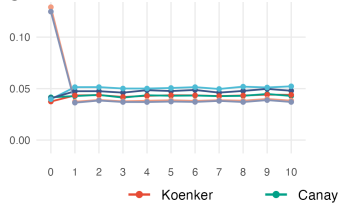
$\tau = 0.5$



$\tau = 0.9$



RMSE

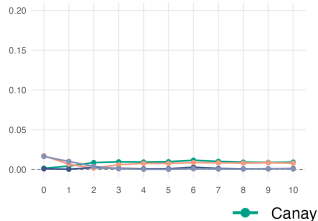


Horizon $h = 0, \dots, 10$. Native panels and legends from the paper; OLS panel omitted.

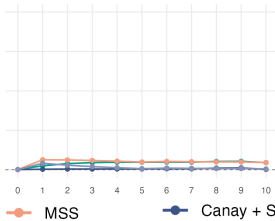
DGP C: absolute bias and RMSE

$\rho = 0.5$, $N = 50$, $T = 200$

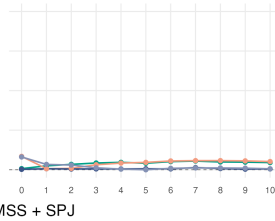
Absolute bias $\tau = 0.1$



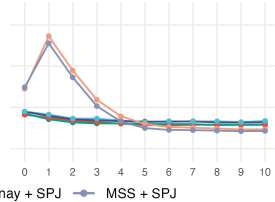
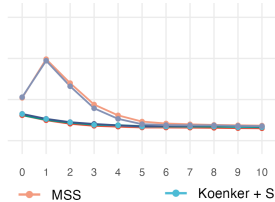
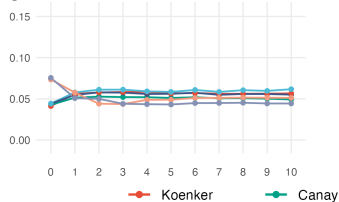
$\tau = 0.5$



$\tau = 0.9$



RMSE

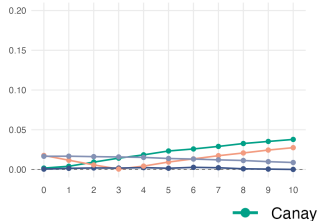


Horizon $h = 0, \dots, 10$. Native panels and legends from the paper; OLS panel omitted.

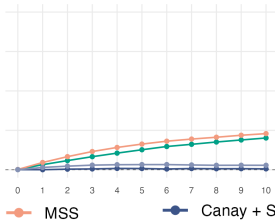
DGP C: absolute bias and RMSE

$\rho = 0.9$, $N = 50$, $T = 200$

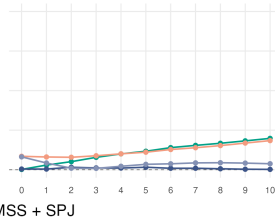
Absolute bias $\tau = 0.1$



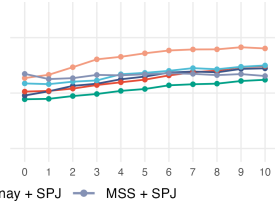
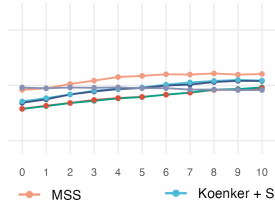
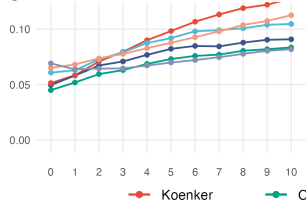
$\tau = 0.5$



$\tau = 0.9$



RMSE

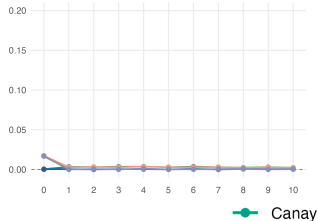


Horizon $h = 0, \dots, 10$. Native panels and legends from the paper; OLS panel omitted.

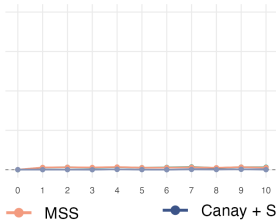
DGP C: absolute bias and RMSE

$\rho = 0$, $N = 200$, $T = 200$

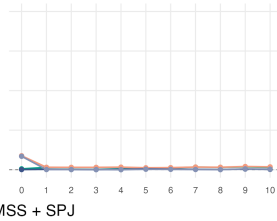
Absolute bias $\tau = 0.1$



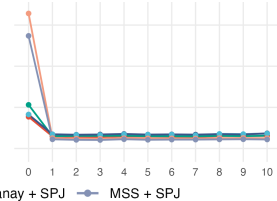
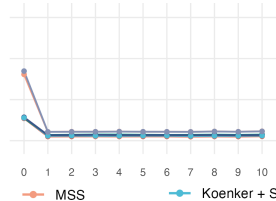
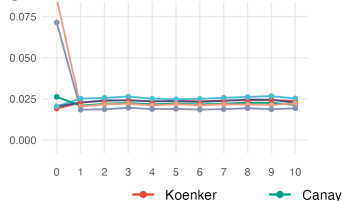
$\tau = 0.5$



$\tau = 0.9$



RMSE

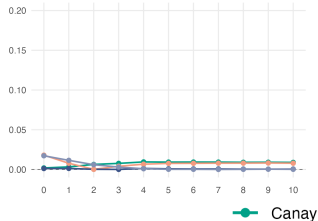


Horizon $h = 0, \dots, 10$. Native panels and legends from the paper; OLS panel omitted.

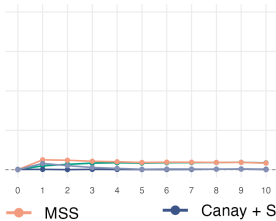
DGP C: absolute bias and RMSE

$\rho = 0.5$, $N = 200$, $T = 200$

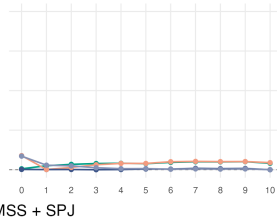
Absolute bias $\tau = 0.1$



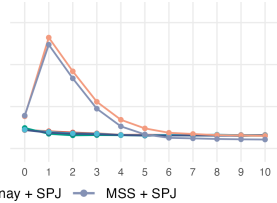
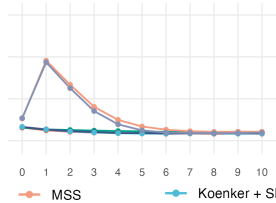
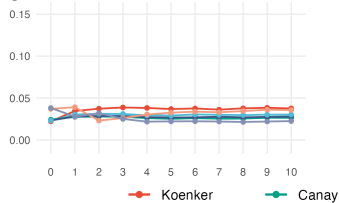
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$\tau = 0.9$



RMSE

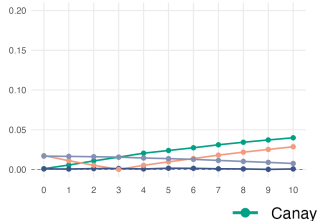


Horizon $h = 0, \dots, 10$. Native panels and legends from the paper; OLS panel omitted.

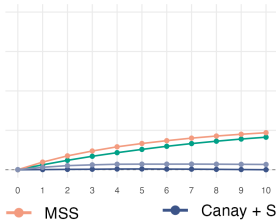
DGP C: absolute bias and RMSE

$\rho = 0.9$, $N = 200$, $T = 200$

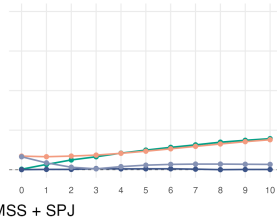
Absolute bias $\tau = 0.1$



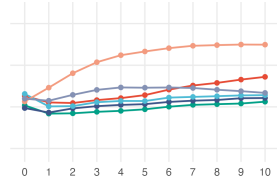
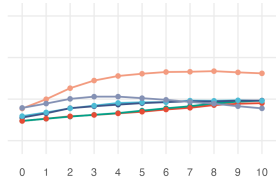
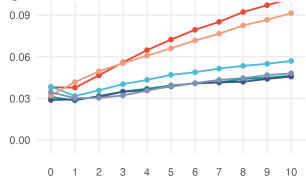
$\tau = 0.5$



$\tau = 0.9$



RMSE



Koenker Canay MSS Koenker + SPJ Canay + SPJ MSS + SPJ

Horizon $h = 0, \dots, 10$. Native panels and legends from the paper; OLS panel omitted.

Monte Carlo: bias reduction and its cost

- **Correct specification matters.** DGP A isolates finite-sample distortions. DGPs B and C separate these distortions from incorrect quantile restrictions.
- **SPJ can reduce bias while increasing RMSE.** Half panels are particularly short at long horizons when $T = 50$.
- **Longer panels make correction more reliable.** Longer T makes more reliable SPJ.

Growth-at-Risk: the original evidence

Adrian et al. (2022) study 11 advanced economies using quarterly data over 1975–2017.

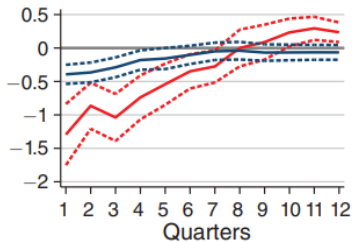
Panel quantile projections relate future GDP growth to financial conditions, credit-to-GDP growth and a credit-boom indicator.

- Looser financial conditions support near-term growth but can worsen downside risk further ahead.
- Credit booms predict a lower fifth percentile of growth from about quarter 5 onward.
- The original approach uses pooled quantile regressions with country dummies.

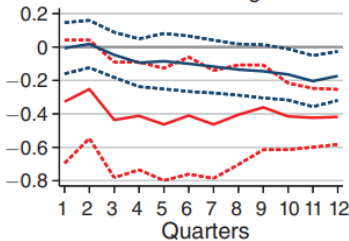
Original Growth-at-Risk estimates

Adrian et al. (2022), fifth percentile and median

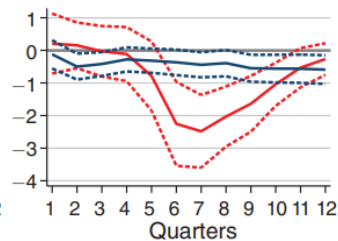
Panel A. FCI



Panel B. Credit-to-GDP growth



Panel C. Credit boom



— Fifth percentile — Median

The original estimates connect credit booms to weaker medium-term downside growth. FCI coefficients turn positive at longer horizons.

Growth-at-Risk: our comparison

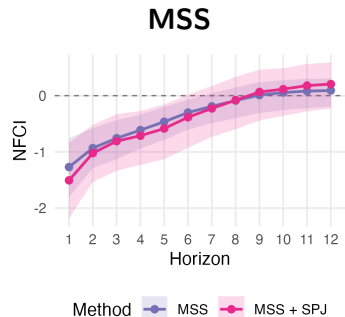
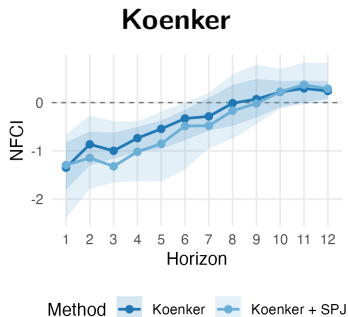
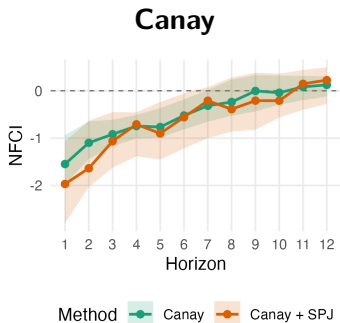
- Re-estimate the horizon-specific regressions using Canay, Koenker and MSS, with and without SPJ.
- The application estimates the 5th, 50th and 95th percentiles. Here we focus on Growth-at-Risk at the 5th percentile, over 1–12 quarters.
- Focus on whether SPJ changes the role of credit booms in downside growth risk.

Two comparisons matter:

Changing the estimator relative to Adrian et al. changes the benchmark. Comparing raw and SPJ within an estimator isolates the effect of the correction in that implementation.

Financial conditions and downside growth

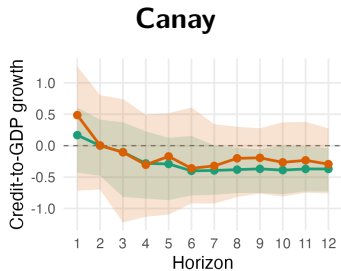
Fifth percentile, baseline and SPJ



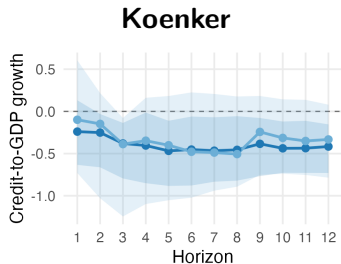
The coefficients rise with the horizon. Some estimates turn positive at longer horizons, with uncertainty around the timing and magnitude.

Credit growth and downside growth

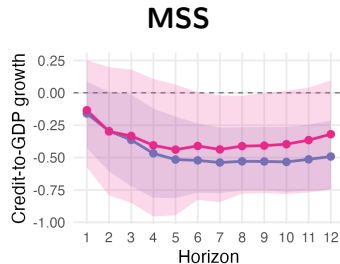
Fifth percentile, baseline and SPJ



Method ● Canay ● Canay + SPJ



Method ● Koenker ● Koenker + SPJ

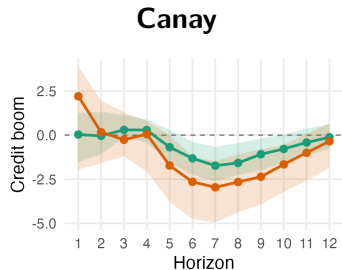


Method ● MSS ● MSS + SPJ

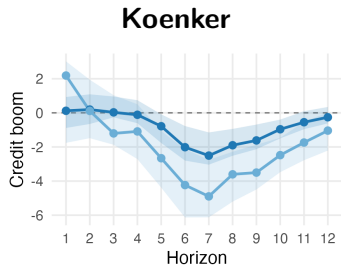
Credit-to-GDP growth generally predicts lower downside growth beyond the shortest horizons. The correction varies across estimators.

Credit booms and downside growth risk

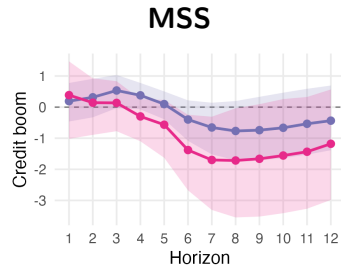
Fifth percentile, baseline and SPJ



Method ■ Canay ■ Canay + SPJ



Method ■ Koenker ■ Koenker + SPJ



Method ■ MSS ■ MSS + SPJ

From quarter 3 onward, SPJ coefficients lie below the baseline for all three estimators. The correction restores a negative medium-term effect under MSS.

Credit-boom estimates at six quarters

Fifth percentile of annualized average GDP growth

Estimator	Baseline	SPJ	SPJ 90% interval
Canay	-1.314	-2.651	$[-4.766, -1.220]$
Koenker	-2.014	-4.235	$[-6.132, -2.136]$
MSS / MM-QR	-0.399	-1.380	$[-2.674, -0.246]$

SPJ implies stronger medium-term downside risk from credit booms.

Every corrected interval excludes zero at this horizon. The original Model 3 coefficient is -2.264, but estimator changes also affect comparisons with that benchmark.

Conclusions

1. The **standard within-transformation (demeaning)** used by Canay and MSS can cause Nickell-type bias.
2. We provide a generic bias expansion for panel QLP estimators and show in different simulations that that a simple split-panel jackknife removes the leading LP-specific bias.
3. In the Growth-at-Risk exercise, the correction points to a stronger adverse association between credit booms and future downside growth.

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