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Online Supplement for Testing Identification via Heteroskedasticity in Structural Vector Autoregressive Models

The simulations are performed as described in Section 4 of the paper.

S1. Comparison of volatility change points

Table S1. Comparison of relative rejection frequencies of tests for DGP1 with Gaussian errors and different volatility change points (nominal significance level 5%).

		VAR(0)		VAR(4)	
(λ_1, λ_2)	T	$Q_2(0,0)$	$Q_2(\tilde{\kappa}_1, \tilde{\kappa}_2)$	$Q_2(0,0)$	$Q_2(\tilde{\kappa}_1, \tilde{\kappa}_2)$
			$\tau = 0.5$		
(2,2)	100	0.067	0.064	0.144	0.148
(size)	250	0.050	0.044	0.079	0.075
	500	0.050	0.048	0.060	0.062
(2,1)	100	0.338	0.323	0.443	0.429
(power)	250	0.678	0.677	0.707	0.702
	500	0.946	0.946	0.948	0.946
			$\tau = 0.2$		
(2,2)	100	0.051	0.054	0.136	0.130
(size)	250	0.052	0.050	0.073	0.072
	500	0.058	0.059	0.067	0.070
(2,1)	100	0.312	0.305	0.431	0.423
(power)	250	0.672	0.668	0.701	0.693
	500	0.946	0.940	0.945	0.943

Note. The DGP is a bivariate Gaussian VAR(0) process with independent $u_t \sim \mathcal{N}(0, I)$ for $t = 1, \ldots, \tau T$ and independent $u_t \sim \mathcal{N}(0, \mathrm{diag}(\lambda_1, \lambda_2))$ for $t = \tau T + 1, \ldots, T$. The correct volatility change point τT is used in all simulations.

Table S2. Comparison of relative rejection frequencies of tests for DGP1 with t-distributed errors and different volatility change points (nominal significance level 5%).

		VAR(0)		VAR(4)	
(λ_1, λ_2)	T	$Q_2(0,0)$	$Q_2(\tilde{\kappa}_1, \tilde{\kappa}_2)$	$Q_2(0,0)$	$Q_2(\tilde{\kappa}_1, \tilde{\kappa}_2)$
			$\tau = 0.5$		
(2,2)	100	0.173	0.047	0.266	0.123
	250	0.187	0.048	0.229	0.067
	500	0.214	0.048	0.231	0.060
(2,1)	100	0.400	0.195	0.475	0.294
	250	0.618	0.391	0.646	0.425
	500	0.802	0.598	0.819	0.627
			$\tau = 0.2$		
(2,2)	100	0.175	0.046	0.280	0.149
	250	0.216	0.060	0.244	0.086
	500	0.259	0.067	0.277	0.078
(2,1)	100	0.406	0.235	0.481	0.329
	250	0.614	0.389	0.644	0.433
	500	0.822	0.611	0.828	0.636

Note. The DGP is a bivariate VAR(0) process with temporally and contemporaneously independent t-distributed errors $u_{kt} \sim t(5)$ for $t = 1, \ldots, \tau T$ and $u_{kt} \sim \sqrt{\lambda_k} \times t(5)$ for $t = \tau T + 1, \ldots, T$. The correct volatility change point τT is used in all simulations.

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Table S3. Relative rejection frequencies of tests for DGP4 (nominal significance level 5%).

		VAR(1)			VAR(4)	
(λ_1, λ_2)	T	$Q_2(0,0)$	$Q_2(\tilde{\kappa}_1, \tilde{\kappa}_2)$		$Q_2(0,0)$	$Q_2(\tilde{\kappa}_1, \tilde{\kappa}_2)$
				$a = 0.5$		
(2,2)	100	0.067	0.063		0.119	0.120
	250	0.052	0.053		0.067	0.070
	500	0.047	0.047		0.057	0.056
(2,1)	100	0.362	0.348		0.440	0.430
	250	0.692	0.680		0.707	0.699
	500	0.932	0.934		0.939	0.937
				$a = 0.9$		
(2,2)	100	0.069	0.068		0.121	0.129
	250	0.067	0.066		0.082	0.083
	500	0.054	0.058		0.062	0.061
(2,1)	100	0.333	0.331		0.421	0.439
	250	0.699	0.698		0.715	0.720
	500	0.942	0.942		0.943	0.943

Note. The DGP is a bivariate Gaussian VAR(1) process with $\tau = 0.5$, independent $u_t \sim \mathcal{N}(0, I)$ for $t = 1, \ldots, \tau T$, and independent $u_t \sim \mathcal{N}(0, \mathrm{diag}(\lambda_1, \lambda_2))$ for $t = \tau T + 1, \ldots, T$. The correct volatility change point τT is used in the simulations.

S2. Persistence of VAR process

To explore the impact of the persistence of the VAR process on the small-sample properties of the identification tests, we have also considered the following bivariate Gaussian VAR(1) process. The corresponding simulation results are presented in Table S3.

DGP4: A bivariate Gaussian VAR(1) process,

$$y_t = \begin{bmatrix} a & 0 \\ 0 & 0 \end{bmatrix} y_{t-1} + u_t,$$

with $a = 0.5$ and 0.9. For $a = 0.9$, the process has one persistent variable. The error process u_t is the same Gaussian process as for DGP1, with τ fixed at 0.5 and

$$\Lambda = \mathrm{diag}(\lambda_1, \lambda_2) \quad \text{with} \quad (\lambda_1, \lambda_2) = (2, 2), (2, 1).$$

S3. Five-dimensional DGP

To explore the impact of the dimension of the VAR process on the small-sample properties of the identification tests, we consider the following five-dimensional Gaussian VAR(1) process. Simulation results are presented in Table S4.

DGP5: The fifth DGP is a five-dimensional ($K = 5$) VAR(1) process,

$$y_t = \begin{bmatrix} a_1 & 0 & 0 & 0 & 0 \\ 0 & a_2 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} y_{t-1} + u_t,$$

where $a_1 = 0.9$ and $a_2 = 0.5$. The error process is again Gaussian with independent $u_t \sim \mathcal{N}(0, \Sigma_m)$, and the volatility change occurs in the middle of the sample, $\tau = 0.5$. Moreover,

$$\Lambda = \mathrm{diag}(\lambda_1, \ldots, \lambda_5) \quad \text{with}$$

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Table S4. Relative rejection frequencies of individual tests for DGP5 (nominal significance level 5%).

$(\lambda_1, \ldots, \lambda_5)$	$\mathbb{H}_0$	$Q_r(0, 0)$	$Q_r(\tilde{\kappa}_1, \tilde{\kappa}_2)$
$T = 100$			
(2,2,2,2,2) (size)	$\lambda_1 = \lambda_2 = \lambda_3 = \lambda_4 = \lambda_5$	0.228	0.218
(5,4,3,2,1) (power)	$\lambda_1 = \lambda_2 = \lambda_3 = \lambda_4 = \lambda_5$	0.902	0.889
	$\lambda_1 = \lambda_2 = \lambda_3 = \lambda_4$	0.466	0.447
	$\lambda_2 = \lambda_3 = \lambda_4 = \lambda_5$	0.706	0.677
	$\lambda_1 = \lambda_2 = \lambda_3$	0.181	0.176
	$\lambda_3 = \lambda_4 = \lambda_5$	0.454	0.428
	$\lambda_1 = \lambda_2$	0.052	0.049
	$\lambda_4 = \lambda_5$	0.256	0.247
$T = 250$			
(2,2,2,2,2) (size)	$\lambda_1 = \lambda_2 = \lambda_3 = \lambda_4 = \lambda_5$	0.098	0.102
(5,4,3,2,1) (power)	$\lambda_1 = \lambda_2 = \lambda_3 = \lambda_4 = \lambda_5$	0.999	0.999
	$\lambda_1 = \lambda_2 = \lambda_3 = \lambda_4$	0.764	0.763
	$\lambda_2 = \lambda_3 = \lambda_4 = \lambda_5$	0.992	0.989
	$\lambda_1 = \lambda_2 = \lambda_3$	0.292	0.281
	$\lambda_3 = \lambda_4 = \lambda_5$	0.908	0.909
	$\lambda_1 = \lambda_2$	0.075	0.073
	$\lambda_4 = \lambda_5$	0.646	0.641
$T = 500$			
(2,2,2,2,2) (size)	$\lambda_1 = \lambda_2 = \lambda_3 = \lambda_4 = \lambda_5$	0.086	0.085
(5,4,3,2,1) (power)	$\lambda_1 = \lambda_2 = \lambda_3 = \lambda_4 = \lambda_5$	1.000	1.000
	$\lambda_1 = \lambda_2 = \lambda_3 = \lambda_4$	0.987	0.987
	$\lambda_2 = \lambda_3 = \lambda_4 = \lambda_5$	1.000	1.000
	$\lambda_1 = \lambda_2 = \lambda_3$	0.570	0.570
	$\lambda_3 = \lambda_4 = \lambda_5$	1.000	1.000
	$\lambda_1 = \lambda_2$	0.154	0.150
	$\lambda_4 = \lambda_5$	0.916	0.915

Note. The DGP is a five-dimensional Gaussian VAR(1) process with $\tau = 0.5$, independent $u_t \sim \mathcal{N}(0, I_5)$ for $t = 1, \ldots, \tau T$, and independent $u_t \sim \mathcal{N}(0, \mathrm{diag}(\lambda_1, \ldots, \lambda_5))$ for $t = \tau T + 1, \ldots, T$. The correct volatility change point τT is used in the simulations.

$$(\lambda_1, \ldots, \lambda_5) = (2, 2, 2, 2, 2) \quad \text{and} \quad (5, 4, 3, 2, 1).$$

The first set of λ_ks allows us to study the size of the tests, and the second set of λ_ks is chosen to investigate the power.

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