vec — Vector error-correction models

Description
vec fits a type of vector autoregression in which some of the variables are cointegrated by using Johansen’s (1995) maximum likelihood method. Constraints may be placed on the parameters in the cointegrating equations or on the adjustment terms. See [TS] vec intro for a list of commands that are used in conjunction with vec.

Quick start
Vector error-correction model for y1, y2, and y3 using tsset data
vec y1 y2 y3

Use 4 lags for the underlying VAR model
vec y1 y2 y3, lags(4)

Use 2 cointegrating equations
vec y1 y2 y3, lags(4) rank(2)

Add a linear trend in the cointegrating equations and a quadratic trend in the undifferenced data
vec y1 y2 y3, lags(4) rank(2) trend(trend)

As above, but without a trend or a constant
vec y1 y2 y3, lags(4) rank(2) trend(none)

Menu
Statistics > Multivariate time series > Vector error-correction model (VECM)


**vec** 

*depvarlist*  
[ *if* ]  
[ *in* ]  
[ , *options* ]

**options**

<table>
<thead>
<tr>
<th>Description</th>
<th>Model</th>
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<tr>
<td>use # cointegrating equations; default is rank(1)</td>
<td><em>rank(#)</em></td>
</tr>
<tr>
<td>use # for the maximum lag in underlying VAR model</td>
<td><em>lags(#)</em></td>
</tr>
<tr>
<td>include an unrestricted constant in model; the default</td>
<td><em>trend(constant)</em></td>
</tr>
<tr>
<td>include a restricted constant in model</td>
<td><em>trend(rconstant)</em></td>
</tr>
<tr>
<td>include a linear trend in the cointegrating equations and a quadratic trend in the undifferenced data</td>
<td><em>trend(trend)</em></td>
</tr>
<tr>
<td>include a restricted trend in model</td>
<td><em>trend(rtrend)</em></td>
</tr>
<tr>
<td>do not include a trend or a constant</td>
<td><em>trend(none)</em></td>
</tr>
<tr>
<td>place constraints_bc on cointegrating vectors</td>
<td><em>bconstraints(constraints_bc)</em></td>
</tr>
<tr>
<td>place constraints_ac on adjustment parameters</td>
<td><em>acconstraints(constraints_ac)</em></td>
</tr>
</tbody>
</table>

| Include normalized seasonal indicator variables *varlist*_si | *sindicators(varlist*_si)* |
| do not perform checks and corrections for collinearity among lags of dependent variables | *noreduce* |

<table>
<thead>
<tr>
<th>Description</th>
<th>Reporting</th>
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<tr>
<td>set confidence level; default is level(95)</td>
<td><em>level(#)</em></td>
</tr>
<tr>
<td>do not report parameters in the cointegrating equations</td>
<td><em>nobot</em></td>
</tr>
<tr>
<td>do not report the likelihood-ratio test of overidentifying restrictions</td>
<td><em>noid</em></td>
</tr>
<tr>
<td>report adjustment parameters in separate table</td>
<td><em>alpha</em></td>
</tr>
<tr>
<td>report parameters in ( \Pi = \alpha \beta' )</td>
<td><em>pi</em></td>
</tr>
<tr>
<td>do not report elements of ( \Pi ) matrix</td>
<td><em>nopt</em></td>
</tr>
<tr>
<td>report parameters in the moving-average impact matrix</td>
<td><em>mai</em></td>
</tr>
<tr>
<td>do not report adjustment and short-run parameters</td>
<td><em>noetable</em></td>
</tr>
<tr>
<td>force reporting of short-run, beta, and alpha parameters when the parameters in beta are not identified; advanced option</td>
<td><em>dforce</em></td>
</tr>
<tr>
<td>do not display constraints</td>
<td><em>nocnsreport</em></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Description</th>
<th>Maximization</th>
</tr>
</thead>
<tbody>
<tr>
<td>control the maximization process; seldom used</td>
<td><em>maximize_options</em></td>
</tr>
<tr>
<td>display legend instead of statistics</td>
<td><em>coeflegend</em></td>
</tr>
</tbody>
</table>

vec does not allow gaps in the data.
You must *tsset* your data before using vec; see [TS] tsset.
*varlist* must contain at least two variables and may contain time-series operators; see [U] 11.4.4 Time-series varlists.
by, fp, rolling, statsby, and *xi* are allowed; see [U] 11.1.10 Prefix commands.
*coeflegend* does not appear in the dialog box.
See [U] 20 Estimation and postestimation commands for more capabilities of estimation commands.
Options

Model

- `rank(#)` specifies the number of cointegrating equations; `rank(1)` is the default.

- `lags(#)` specifies the maximum lag to be included in the underlying VAR model. The maximum lag in a VECM is one smaller than the maximum lag in the corresponding VAR in levels; the number of lags must be greater than zero but small enough so that the degrees of freedom used up by the model are fewer than the number of observations. The default is `lags(2)`.

- `trend(trend_spec)` specifies which of Johansen’s five trend specifications to include in the model. These specifications are discussed in Specification of constants and trends below. The default is `trend(constant)`.

- `bconstraints(constraintsbc)` specifies the constraints to be placed on the parameters of the cointegrating equations. When no constraints are placed on the adjustment parameters—that is, when the `aconstraints()` option is not specified—the default is to place the constraints defined by Johansen’s normalization on the parameters of the cointegrating equations. When constraints are placed on the adjustment parameters, the default is not to place constraints on the parameters in the cointegrating equations.

- `aconstraints(constraintsac)` specifies the constraints to be placed on the adjustment parameters. By default, no constraints are placed on the adjustment parameters.

Adv. model

- `sindicators(varlistsi)` specifies the normalized seasonal indicator variables to include in the model. The indicator variables specified in this option must be normalized as discussed in Johansen (1995). If the indicators are not properly normalized, the estimator of the cointegrating vector does not converge to the asymptotic distribution derived by Johansen (1995). More details about how these variables are handled are provided in Methods and formulas. `sindicators()` cannot be specified with `trend(none)` or with `trend(rconstant)`.

- `noreduce` causes `vec` to skip the checks and corrections for collinearity among the lags of the dependent variables. By default, `vec` checks to see whether the current lag specification causes some of the regressions performed by `vec` to contain perfectly collinear variables; if so, it reduces the maximum lag until the perfect collinearity is removed.

Reporting

- `level(#); see [R] Estimation options.`

- `nobtable` suppresses the estimation table for the parameters in the cointegrating equations. By default, `vec` displays the estimation table for the parameters in the cointegrating equations.

- `noiidtest` suppresses the likelihood-ratio test of the overidentifying restrictions, which is reported by default when the model is overidentified.

- `alpha` displays a separate estimation table for the adjustment parameters, which is not displayed by default.

- `pi` displays a separate estimation table for the parameters in \( \Pi = \alpha \beta' \), which is not displayed by default.

- `noptable` suppresses the estimation table for the elements of the \( \Pi \) matrix, which is displayed by default when the parameters in the cointegrating equations are not identified.

- `mai` displays a separate estimation table for the parameters in the moving-average impact matrix, which is not displayed by default.
noetable suppresses the main estimation table that contains information about the estimated adjustment parameters and the short-run parameters, which is displayed by default.

dforce displays the estimation tables for the short-run parameters and \( \alpha \) and \( \beta \)—if the last two are requested—when the parameters in \( \beta \) are not identified. By default, when the specified constraints do not identify the parameters in the cointegrating equations, estimation tables are displayed only for \( \Pi \) and the MAI.

nocnsreport; see [R] Estimation options.

display options: noci, nopvalues, vsquish, cformat(\%fmt), pformat(\%fmt), sformat(\%fmt), and nolstretch; see [R] Estimation options.

Maximization

maximize options: iterate(#), [no]log, trace, toltrace, tolerance(#), ltolerance(#), afro\(m\)atrix\(a\), and b\(f\)rom\(m\)atrix\(b\); see [R] Maximize.

toltrace displays the relative differences for the log likelihood and the coefficient vector at every iteration. This option cannot be specified if no constraints are defined or if nolog is specified.

afro\(m\)atrix\(a\) specifies a \(1 \times (K \ast r)\) row vector with starting values for the adjustment parameters, where \(K\) is the number of endogenous variables and \(r\) is the number of cointegrating equations specified in the \(\text{rank()}\) option. The starting values should be ordered as they are reported in \(e(\alpha)\). This option cannot be specified if no constraints are defined.

b\(f\)rom\(m\)atrix\(b\) specifies a \(1 \times (m_1 \ast r)\) row vector with starting values for the parameters of the cointegrating equations, where \(m_1\) is the number of variables in the trend-augmented system and \(r\) is the number of cointegrating equations specified in the \(\text{rank()}\) option. (See Methods and formulas for more details about \(m_1\).) The starting values should be ordered as they are reported in \(e(\beta)\). As discussed in Methods and formulas, for some trend specifications, \(e(\beta)\) contains parameter estimates that are not obtained directly from the optimization algorithm. b\(f\)rom() should specify only starting values for the parameters reported in \(e(\beta)\). This option cannot be specified if no constraints are defined.

The following option is available with vec but is not shown in the dialog box:

coefflegend; see [R] Estimation options.

Remarks and examples

Remarks are presented under the following headings:

Introduction
Specification of constants and trends
Collinearity

Introduction

VECMs are used to model the stationary relationships between multiple time series that contain unit roots. vec implements Johansen’s approach for estimating the parameters of a VECM.

[TS] vec intro reviews the basics of integration and cointegration and highlights why we need special methods for modeling the relationships between processes that contain unit roots. This manual entry assumes familiarity with the material in [TS] vec intro and provides examples illustrating how to use the vec command. See Johansen (1995), Hamilton (1994), and Becketti (2020) for more in-depth introductions to cointegration analysis.
Example 1

This example uses annual data on the average per-capita disposable personal income in the eight U.S. Bureau of Economic Analysis (BEA) regions of the United States. We use data from 1948–2002 in logarithms. Unit-root tests on these series fail to reject the null hypothesis that per-capita disposable income in each region contains a unit root. Because capital and labor can move easily between the different regions of the United States, we would expect that no one series will diverge from all the remaining series and that cointegrating relationships exist.

Below we graph the natural logs of average disposal income in the New England and the Southeast regions.

```
use https://www.stata-press.com/data/r16/rdinc
line ln_ne ln_se year
```

![Graph showing natural logs of average disposal income in New England and Southeast regions.](image)

The graph indicates a differential between the two series that shrinks between 1960 and about 1980 and then grows until it stabilizes around 1990. We next estimate the parameters of a bivariate VECM with one cointegrating relationship.
vector ln_ne ln_se

Vector error-correction model

Sample: 1950 - 2002
Number of obs = 53
AIC = -11.00462
Log likelihood = 300.6224
HQIC = -10.87595
Det(Sigma_ml) = 4.06e-08
SBIC = -10.67004

<table>
<thead>
<tr>
<th>Equation</th>
<th>Parms</th>
<th>RMSE</th>
<th>R-sq</th>
<th>chi2</th>
<th>P&gt;chi2</th>
</tr>
</thead>
<tbody>
<tr>
<td>D Ln_ne</td>
<td>4</td>
<td>.017896</td>
<td>0.9313</td>
<td>664.4668</td>
<td>0.0000</td>
</tr>
<tr>
<td>D Ln_se</td>
<td>4</td>
<td>.018723</td>
<td>0.9292</td>
<td>642.7179</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

| Coef. | Std. Err. | z    | P>|z| | [95% Conf. Interval] |
|-------|-----------|------|-----|----------------------|
| D Ln_ne _ce1 L1. | - .4337524 | .0721365 | -6.01 | 0.000 | -.5751373 -.2923675 |
| ln_ne LD. | .7168658 | .1889085 | 3.79 | 0.000 | .3466119 1.08712 |
| ln_se LD. | -.6748754 | .2117975 | -3.19 | 0.001 | -1.089991 -.2597599 |
| _cons | -.0019846 | .0080291 | -0.25 | 0.805 | -.0177214 .0137521 |

| D Ln_se _ce1 L1. | -.3543935 | .0754725 | -4.70 | 0.000 | -.5023168 -.2064701 |
| ln_ne LD. | .3366786 | .1976448 | 1.70 | 0.088 | -.050698 .7240553 |
| ln_se LD. | -.1605811 | .2215922 | -0.72 | 0.469 | -.5948939 .2737317 |
| _cons | .002429 | .0084004 | 0.29 | 0.772 | -.0140355 .0188936 |

Cointegrating equations

<table>
<thead>
<tr>
<th>Equation</th>
<th>Parms</th>
<th>chi2</th>
<th>P&gt;chi2</th>
</tr>
</thead>
<tbody>
<tr>
<td>_ce1</td>
<td>1</td>
<td>29805.02</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

Identification: beta is exactly identified

Johansen normalization restriction imposed

| beta | Coef. | Std. Err. | z    | P>|z| | [95% Conf. Interval] |
|------|-------|-----------|------|-----|----------------------|
| _ce1 | ln_ne | 1 | . | . | . |
|     | ln_se | -.9433708 | .0054643 | -172.64 | 0.000 | -.9540807 -.9326609 |
|     | _cons | -.8964065 | . | . | . |

The default output has three parts. The header provides information about the sample, the model fit, and the identification of the parameters in the cointegrating equation. The main estimation table contains the estimates of the short-run parameters, along with their standard errors and confidence intervals. The second estimation table reports the estimates of the parameters in the cointegrating equation, along with their standard errors and confidence intervals.
The results indicate strong support for a cointegrating equation such that

\[ \ln(ne) - 0.943 \ln(se) - 0.896 \]

should be a stationary series. Identification of the parameters in the cointegrating equation is achieved by constraining some of them to be fixed, and fixed parameters do not have standard errors. In this example, the coefficient on \( \ln(ne) \) has been normalized to 1, so its standard error is missing. As discussed in \textit{Methods and formulas}, the constant term in the cointegrating equation is not directly estimated in this trend specification but rather is backed out from other estimates. Not all the elements of the VCE that correspond to this parameter are readily available, so the standard error for the \texttt{cons} parameter is missing.

To get a better idea of how our model fits, we predict the cointegrating equation and graph it over time:

\begin{verbatim}
. predict ce, ce
. line ce year
\end{verbatim}

![Graph of Predicted Cointegrated Equation](image)

Although the predicted cointegrating equation has the right appearance for the time before the mid-1960s, afterward the predicted cointegrating equation does not look like a stationary series. A better model would account for the trends in the size of the differential.

As discussed in \textit{[TS] vec intro}, simply normalizing one of the coefficients to be one is sufficient to identify the parameters of the single cointegrating vector. When there is more than one cointegrating equation, more restrictions are required.

\textbf{Example 2}

We have data on monthly unemployment rates in Indiana, Illinois, Kentucky, and Missouri from January 1978 through December 2003. We suspect that factor mobility will keep the unemployment rates in equilibrium. The following graph plots the data.
The graph shows that although the series do appear to move together, the relationship is not as clear as in the previous example. There are periods when Indiana has the highest rate and others when Indiana has the lowest rate. Although the Kentucky rate moves closely with the other series for most of the sample, there is a period in the mid-1980s when the unemployment rate in Kentucky does not fall at the same rate as the other series.

We will model the series with two cointegrating equations and no linear or quadratic time trends in the original series. Because we are focusing on the cointegrating vectors, we use the `noetable` option to suppress displaying the short-run estimation table.
. vec missouri indiana kentucky illinois, trend(rconstant) rank(2) lags(4)
> noetable
Vector error-correction model
Sample: 1978m5 - 2003m12  
Number of obs = 308
AIC = -2.306048
Log likelihood = 417.1314  HQIC = -2.005818
Det(Sigma_ml) = 7.83e-07  SBIC = -1.555184

Cointegrating equations

<table>
<thead>
<tr>
<th>Equation</th>
<th>Parms</th>
<th>chi2</th>
<th>P&gt;chi2</th>
</tr>
</thead>
<tbody>
<tr>
<td>_ce1</td>
<td>2</td>
<td>133.3885</td>
<td>0.0000</td>
</tr>
<tr>
<td>_ce2</td>
<td>2</td>
<td>195.6324</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

Identification: beta is exactly identified
Johansen normalization restrictions imposed

| beta     | Coef. | Std. Err. | z    | P>|z| | [95% Conf. Interval] |
|----------|-------|-----------|------|-----|-----------------------|
| _ce1     | missouri | 1 | . | . | . | . | . | . | . |
|          | indiana   | 0 (omitted) | . | . | . | . | . | . | . |
|          | kentucky  | .3493902 | .2005537 | 1.74 | 0.081 | -.0436879 | .742663 |
|          | illinois  | -1.135152 | .2069063 | -5.49 | 0.000 | -1.540681 | -0.7296235 |
|          | _cons     | -.3880707 | .4974323 | -0.78 | 0.435 | -1.36302 | .5868787 |
| _ce2     | missouri | -1.11e-16 | . | . | . | . | . | . | . |
|          | indiana   | 1 | . | . | . | . | . | . | . |
|          | kentucky  | .2059473 | .2718678 | 0.76 | 0.449 | -0.3269038 | .7387985 |
|          | illinois  | -1.51962 | .2804792 | -5.42 | 0.000 | -2.069349 | -.9698907 |
|          | _cons     | 2.92857 | .6743122 | 4.34 | 0.000 | 1.606942 | 4.250197 |

Except for the coefficients on kentucky in the two cointegrating equations and the constant term in the first, all the parameters are significant at the 5% level. We can refit the model with the Johansen normalization and the overidentifying constraint that the coefficient on kentucky in the second cointegrating equation is zero.

. constraint define 1 [ _ce1]missouri = 1
. constraint define 2 [ _ce1]indiana = 0
. constraint define 3 [ _ce2]missouri = 0
. constraint define 4 [ _ce2]indiana = 1
. constraint define 5 [ _ce2]kentucky = 0
. vec missouri indiana kentucky illinois, trend(rconstant) rank(2) 
> lags(4) noetable bconstraints(1/5)

Iteration 1: log likelihood = 416.97177
(output omitted)
Iteration 20: log likelihood = 416.9744

Vector error-correction model

Sample: 1978m5 - 2003m12 Number of obs = 308
AIC = -2.311522
Log likelihood = 416.9744 HQIC = -2.016134
Det(Sigma_ml) = 7.84e-07 SBIC = -1.572769

Cointegrating equations

<table>
<thead>
<tr>
<th>Equation</th>
<th>Parms</th>
<th>chi2</th>
<th>P&gt;chi2</th>
</tr>
</thead>
<tbody>
<tr>
<td>_ce1</td>
<td>2</td>
<td>145.233</td>
<td>0.0000</td>
</tr>
<tr>
<td>_ce2</td>
<td>1</td>
<td>209.9344</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

Identification: beta is overidentified

( 1) [ _ce1]missouri = 1
( 2) [ _ce1]indiana = 0
( 3) [ _ce2]missouri = 0
( 4) [ _ce2]indiana = 1
( 5) [ _ce2]kentucky = 0

| beta | Coef. | Std. Err. | z    | P>|z| | [95% Conf. Interval] |
|------|-------|-----------|------|-----|---------------------|
| _ce1 | missouri | 1 | . | . | . | . | . |
|      | indiana  | 0 (omitted) |
|      | kentucky | .2521685 | .1649653 | 1.53 | 0.126 | -.0711576 | .5754946 |
|      | illinois | -1.037453 | .1734165 | -5.98 | 0.000 | -1.377343 | -.6975626 |
|      | _cons    | -.3891102 | .4726968 | -0.82 | 0.410 | -1.315579 | .5373586 |
| _ce2 | missouri | 0 (omitted) |
|      | indiana  | 1 |
|      | kentucky | 0 (omitted) |
|      | illinois | -1.314265 | .0907071 | -14.49 | 0.000 | -1.492048 | -1.136483 |
|      | _cons    | 2.937016 | .6448924 | 4.55 | 0.000 | 1.67305 | 4.200982 |

LR test of identifying restrictions: chi2(1) = .3139 Prob > chi2 = 0.575

The test of the overidentifying restriction does not reject the null hypothesis that the restriction is valid, and the p-value on the coefficient on kentucky in the first cointegrating equation indicates that it is not significant. We will leave the variable in the model and attribute the lack of significance to whatever caused the kentucky series to temporarily rise above the others from 1985 until 1990, though we could instead consider removing kentucky from the model.

Next, we look at the estimates of the adjustment parameters. In the output below, we replay the previous results. We specify the alpha option so that vec will display an estimation table for the estimates of the adjustment parameters, and we specify nobtable to suppress the table for the parameters of the cointegrating equations because we have already looked at those.
. vec, alpha notable noetable

Vector error-correction model

Sample: 1978m5 - 2003m12  
Number of obs = 308
AIC = -2.311522  
Log likelihood = 416.9744  
HQIC = -2.016134  
Det(Sigma_ml) = 7.84e-07  
SBIC = -1.572769

Adjustment parameters

<table>
<thead>
<tr>
<th>Equation</th>
<th>Parms</th>
<th>chi2</th>
<th>P&gt;chi2</th>
</tr>
</thead>
<tbody>
<tr>
<td>D_missouri</td>
<td>2</td>
<td>19.39607</td>
<td>0.0001</td>
</tr>
<tr>
<td>D_indiana</td>
<td>2</td>
<td>6.426086</td>
<td>0.0402</td>
</tr>
<tr>
<td>D_kentucky</td>
<td>2</td>
<td>8.524901</td>
<td>0.0141</td>
</tr>
<tr>
<td>D_illinois</td>
<td>2</td>
<td>22.32893</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

| alpha       | Coef.  | Std. Err. | z     | P>|z| | [95% Conf. Interval] |
|-------------|--------|-----------|-------|------|----------------------|
| D_missouri  |        |           |       |      |                      |
| _ce1 L1.    | -.0683152 | .0185763 | -3.68 | 0.000 | -.1047242 -.0319063 |
| _ce2 L1.    | .0405613  | .0112417  | 3.61  | 0.000 | .018528 .0625946   |
| D_indiana   |        |           |       |      |                      |
| _ce1 L1.    | -.0342096 | .0220955 | -1.55 | 0.122 | -.0775159 .0090967 |
| _ce2 L1.    | .0325804  | .0133713  | 2.44  | 0.015 | .0063732 .0587877  |
| D_kentucky  |        |           |       |      |                      |
| _ce1 L1.    | -.0482012 | .0231633 | -2.08 | 0.037 | -.0936004 -.0028021 |
| _ce2 L1.    | .0374395  | .0140175  | 2.67  | 0.008 | .0099657 .0649133  |
| D_illinois  |        |           |       |      |                      |
| _ce1 L1.    | .0138224  | .0227041  | 0.61  | 0.543 | -.0306768 .0583215 |
| _ce2 L1.    | .0567664  | .0137396  | 4.13  | 0.000 | .0298373 .0836955  |

LR test of identifying restrictions: chi2(1) = .3139  
Prob > chi2 = 0.575

All the coefficients are significant at the 5% level, except those on Indiana and Illinois in the first cointegrating equation. From an economic perspective, the issue is whether the unemployment rates in Indiana and Illinois adjust when the first cointegrating equation is out of equilibrium. We could impose restrictions on one or both of those parameters and refit the model, or we could just decide to use the current results.
Technical note

vec can be used to fit models in which the parameters in $\beta$ are not identified, in which case only the parameters in $\Pi$ and the moving-average impact matrix $C$ are identified. When the parameters in $\beta$ are not identified, the values of $\hat{\beta}$ and $\hat{\alpha}$ can vary depending on the starting values. However, the estimates of $\Pi$ and $C$ are identified and have known asymptotic distributions. This method is valid because these additional normalization restrictions impose no restriction on $\Pi$ or $C$.

Specification of constants and trends

As discussed in [TS] vec intro, allowing for a constant term and linear time trend allow us to write the VECM as

$$\Delta y_t = \alpha(\beta y_{t-1} + \mu + \rho t) + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + \gamma + \tau t + \epsilon_t$$

Five different trend specifications are available:

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>trend</td>
<td>none</td>
<td>$H(r)$</td>
</tr>
<tr>
<td>rtrend</td>
<td>$\tau = 0$</td>
<td>$H^*(r)$</td>
</tr>
<tr>
<td>constant</td>
<td>$\rho = 0$, and $\tau = 0$</td>
<td>$H_1(r)$</td>
</tr>
<tr>
<td>rconstant</td>
<td>$\rho = 0$, $\gamma = 0$ and $\tau = 0$</td>
<td>$H^*_1(r)$</td>
</tr>
<tr>
<td>none</td>
<td>$\mu = 0$, $\rho = 0$, $\gamma = 0$, and $\tau = 0$</td>
<td>$H_2(r)$</td>
</tr>
</tbody>
</table>

$\text{trend(trend)}$ allows for a linear trend in the cointegrating equations and a quadratic trend in the undifferenced data. A linear trend in the cointegrating equations implies that the cointegrating equations are assumed to be trend stationary.

$\text{trend(rtrend)}$ defines a restricted trend model that excludes linear trends in the differenced data but allows for linear trends in the cointegrating equations. As in the previous case, a linear trend in a cointegrating equation implies that the cointegrating equation is trend stationary.

$\text{trend(constant)}$ defines a model with an unrestricted constant. This allows for a linear trend in the undifferenced data and cointegrating equations that are stationary around a nonzero mean. This is the default.

$\text{trend(rconstant)}$ defines a model with a restricted constant in which there is no linear or quadratic trend in the undifferenced data. A nonzero $\mu$ allows for the cointegrating equations to be stationary around nonzero means, which provide the only intercepts for differenced data. Seasonal indicators are not allowed with this specification.

$\text{trend(none)}$ defines a model that does not include a trend or a constant. When there is no trend or constant, the cointegrating equations are restricted to being stationary with zero means. Also, after adjusting for the effects of lagged endogenous variables, the differenced data are modeled as having mean zero. Seasonal indicators are not allowed with this specification.
Technical note

(vec) uses a switching algorithm developed by Boswijk (1995) to maximize the log-likelihood function when constraints are placed on the parameters. The starting values affect both the ability of the algorithm to find a maximum and its speed in finding that maximum. By default, vec uses the parameter estimates that correspond to Johansen’s normalization. Sometimes, other starting values will cause the algorithm to find a maximum faster.

To specify starting values for the parameters in $\alpha$, we specify a $1 \times (K \times r)$ matrix in the `afrom()` option. Specifying starting values for the parameters in $\beta$ is slightly more complicated. As explained in Methods and formulas, specifying `trend(constant), trend(rtrend), or trend(trend)` causes some of the estimates of the trend parameters appearing in $\hat{\beta}$ to be “backed out”. The switching algorithm estimates only the parameters of the cointegrating equations whose estimates are stored in `e(betavec)`. For this reason, only the parameters stored in `e(betavec)` can have their initial values set via `bfrom()`.

The table below describes which trend parameters in the cointegrating equations are estimated by the switching algorithm for each of the five specifications.

<table>
<thead>
<tr>
<th>Trend specification</th>
<th>Trend parameters in cointegrating equations</th>
<th>Trend parameter estimated via switching algorithm</th>
</tr>
</thead>
<tbody>
<tr>
<td>none</td>
<td>none</td>
<td>none</td>
</tr>
<tr>
<td>rconstant</td>
<td>_cons</td>
<td>_cons</td>
</tr>
<tr>
<td>constant</td>
<td>_cons</td>
<td>none</td>
</tr>
<tr>
<td>rtrend</td>
<td>_cons, _trend</td>
<td>_trend</td>
</tr>
<tr>
<td>trend</td>
<td>_cons, _trend</td>
<td>none</td>
</tr>
</tbody>
</table>

Collinearity

As expected, collinearity among variables causes some parameters to be unidentified numerically. If vec encounters perfect collinearity among the dependent variables, it exits with an error.

In contrast, if vec encounters perfect collinearity that appears to be due to too many lags in the model, vec displays a warning message and reduces the maximum lag included in the model in an effort to find a model with fewer lags in which all the parameters are identified by the data. Specifying the `noreduce` option causes vec to skip over these additional checks and corrections for collinearity. Thus the `noreduce` option can be used to force the estimation to proceed when not all the parameters are identified by the data. When some parameters are not identified because of collinearity, the results cannot be interpreted but can be used to find the source of the collinearity.
vec stores the following in e():

Scalars
- `e(N)` number of observations
- `e(k_rank)` number of unconstrained parameters
- `e(k_eq)` number of equations in `e(b)`
- `e(k_dv)` number of dependent variables
- `e(k_ce)` number of cointegrating equations
- `e(n_lags)` number of lags
- `e(df_m)` model degrees of freedom
- `e(ll)` log likelihood
- `e(chi2_res)` value of test of overidentifying restrictions
- `e(df_lr)` degrees of freedom of the test of overidentifying restrictions
- `e(beta_iden)` 1 if the parameters in $\beta$ are identified and 0 otherwise
- `e(beta_icnt)` number of independent restrictions placed on $\beta$
- `e(k_#)` number of variables in equation #
- `e(df_m#)` model degrees of freedom in equation #
- `e(r2_#)` $R^2$ of equation #
- `e(chi2_#)` $\chi^2$ statistic for equation #
- `e(rmse_#)` RMSE of equation #
- `e(aic)` value of AIC
- `e(hqic)` value of HQIC
- `e(sbic)` value of SBIC
- `e(tmin)` minimum time
- `e(tmax)` maximum time
- `e(detsig_ml)` determinant of the estimated covariance matrix
- `e(rank)` rank of $e(V)$
- `e(converge)` 1 if the switching algorithm converged, 0 if it did not converge

Macros
- `e(cmd)` vec
- `e(cmdline)` command as typed
- `e(trend)` trend specified
- `e(tsfmt)` format of the time variable
- `e(tvar)` variable denoting time within groups
- `e(endog)` endogenous variables
- `e(covariates)` list of covariates
- `e(eqnames)` equation names
- `e(cenames)` names of cointegrating equations
- `e(reduce_opt)` `noreduce`, if `noreduce` is specified
- `e(reduce_lags)` list of maximum lags to which the model has been reduced
- `e(title)` title in estimation output
- `e(aconstraints)` constraints placed on $\alpha$
- `e(bconstraints)` constraints placed on $\beta$
- `e(sindicators)` seasonal indicator variables
- `e(properties)` b V
- `e(predict)` program used to implement `predict`
- `e(marginsok)` predictions allowed by `margins`
- `e(marginsnotok)` predictions disallowed by `margins`
- `e(marginsdefault)` default `predict()` specification for `margins`
**Methods and formulas**

Methods and formulas are presented under the following headings:

- General specification of the VECM
- The log-likelihood function
- Unrestricted trend
- Restricted trend
- Unrestricted constant
- Restricted constant
- No trend
- Estimation with Johansen identification
- Estimation with constraints: $\beta$ identified
- Estimation with constraints: $\beta$ not identified
- Formulas for the information criteria
- Formulas for predict

**General specification of the VECM**

vec estimates the parameters of a VECM that can be written as

\[
\Delta y_t = \alpha \beta' y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + v + \delta t + w_1 s_1 + \cdots + w_m s_m + \epsilon_t
\]  

(1)

where

- $y_t$ is a $K \times 1$ vector of endogenous variables,
- $\alpha$ is a $K \times r$ matrix of parameters,
- $\beta$ is a $K \times r$ matrix of parameters,
- $\Gamma_1, \ldots, \Gamma_{p-1}$ are $K \times K$ matrices of parameters,
- $v$ is a $K \times 1$ vector of parameters,
- $\delta$ is a $K \times 1$ vector of trend coefficients,
- $t$ is a linear time trend,
- $s_1, \ldots, s_m$ are orthogonalized seasonal indicators specified in the sindicators() option, and
- $w_1, \ldots, w_m$ are $K \times 1$ vectors of coefficients on the orthogonalized seasonal indicators.
There are two types of deterministic elements in (1): the trend, $v + \delta t$, and the orthogonalized seasonal terms, $w_{1}s_{1} + \cdots + w_{m}s_{m}$. Johansen (1995, chap. 11) shows that inference about the number of cointegrating equations is based on nonstandard distributions and that the addition of any term that generalizes the deterministic specification in (1) changes the asymptotic distributions of the statistics used for inference on the number of cointegrating equations and the asymptotic distribution of the ML estimator of the cointegrating equations. In fact, Johansen (1995, 84) notes that including event indicators causes the statistics used for inference on the number of cointegrating equations to have asymptotic distributions that must be computed case by case. For this reason, event indicators may not be specified in the present version of vec.

If seasonal indicators are included in the model, they cannot be collinear with a constant term. If they are collinear with a constant term, one of the indicator variables is omitted.

As discussed in Specification of constants and trends, we can reparameterize the model as

$$\Delta y_{t} = \alpha(\beta y_{t-1} + \mu + \rho t) + \sum_{i=1}^{p-1} \Gamma_{i}\Delta y_{t-i} + \gamma + \tau t + \epsilon_{t}$$

(2)

### The log-likelihood function

We can maximize the log-likelihood function much more easily by writing it in concentrated form. In fact, as discussed below, in the simple case with the Johansen normalization on $\beta$ and no constraints on $\alpha$, concentrating the log-likelihood function produces an analytical solution for the parameter estimates.

To concentrate the log likelihood, rewrite (2) as

$$Z_{0t} = \alpha\tilde{\beta}'Z_{1t} + \Psi Z_{2t} + \epsilon_{t}$$

(3)

where $Z_{0t}$ is a $K \times 1$ vector of variables $\Delta y_{t}$, $\alpha$ is the $K \times r$ matrix of adjustment coefficients, and $\epsilon_{t}$ is a $K \times 1$ vector of independent and identically distributed normal vectors with mean 0 and contemporaneous covariance matrix $\Omega$. $Z_{1t}, Z_{2t}, \tilde{\beta}$, and $\Psi$ depend on the trend specification and are defined below.

The log-likelihood function for the model in (3) is

$$L = -\frac{1}{2} \left\{ TK \ln(2\pi) + T \ln(|\Omega|) \\
+ \sum_{t=1}^{T} (Z_{0t} - \alpha\tilde{\beta}'Z_{1t} - \Psi Z_{2t})'\Omega^{-1}(Z_{0t} - \alpha\tilde{\beta}'Z_{1t} - \Psi Z_{2t}) \right\}$$

(4)

with the constraints that $\alpha$ and $\tilde{\beta}$ have rank $r$.

Johansen (1995, chap. 6), building on Anderson (1951), shows how the $\Psi$ parameters can be expressed as analytic functions of $\alpha, \tilde{\beta}$, and the data, yielding the concentrated log-likelihood function

$$L_{c} = -\frac{1}{2} \left\{ TK \ln(2\pi) + T \ln(|\Omega|) \\
+ \sum_{t=1}^{T} (R_{0t} - \alpha\tilde{\beta}'R_{1t})'\Omega^{-1}(R_{0t} - \alpha\tilde{\beta}'R_{1t}) \right\}$$

(5)
where
\[ M_{ij} = T^{-1} \sum_{t=1}^{T} Z_{it} Z_{jt}', \quad i, j \in \{0, 1, 2\}; \]
\[ R_{0t} = Z_{0t} - M_{02} M_{22}^{-1} Z_{2t}; \text{ and} \]
\[ R_{1t} = Z_{1t} - M_{12} M_{22}^{-1} Z_{2t}. \]

The definitions of \( Z_{1t}, Z_{2t}, \tilde{\beta} \), and \( \Psi \) change with the trend specifications, although some of their components stay the same.

**Unrestricted trend**

When the trend in the VECM is unrestricted, we can define the variables in (3) directly in terms of the variables in (1):

\[ Z_{1t} = y_{t-1} \text{ is } K \times 1 \]
\[ Z_{2t} = (\Delta y'_{t-1}, \ldots, \Delta y'_{t-p+1}, 1, t, s_1, \ldots, s_m)' \text{ is } \{K(p - 1) + 2 + m\} \times 1; \]
\[ \Psi = (\Gamma_1, \ldots, \Gamma_{p-1}, v, \delta, w_1, \ldots, w_m) \text{ is } K \times \{K(p - 1) + 2 + m\} \]
\[ \tilde{\beta} = \beta \text{ is the } (K + 1) \times r \text{ matrix composed of the } r \text{ cointegrating vectors.} \]

In the unrestricted trend specification, \( m_1 = K, m_2 = K(p - 1) + 2 + m \), and there are \( n_{\text{parms}} = Kr +Kr + K\{K(p - 1) + 2 + m\} \) parameters in (3).

**Restricted trend**

When there is a restricted trend in the VECM in (2), \( \tau = 0 \), but the intercept \( v = \alpha \mu + \gamma \) is unrestricted. The VECM with the restricted trend can be written as

\[ \Delta y_t = \alpha(\beta', \rho) \left( y_{t-1} \right) + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + v + w_1 s_1 + \cdots + w_m s_m + \epsilon_t \]

This equation can be written in the form of (3) by defining

\[ Z_{1t} = (y'_{t-1}, t)' \text{ is } (K + 1) \times 1 \]
\[ Z_{2t} = (\Delta y'_{t-1}, \ldots, \Delta y'_{t-p+1}, 1, s_1, \ldots, s_m)' \text{ is } \{K(p - 1) + 1 + m\} \times 1 \]
\[ \Psi = (\Gamma_1, \ldots, \Gamma_{p-1}, v, w_1, \ldots, w_m) \text{ is } K \times \{K(p - 1) + 1 + m\} \]
\[ \tilde{\beta} = (\beta', \rho)' \text{ is the } (K + 1) \times r \text{ matrix composed of the } r \text{ cointegrating vectors and the } r \text{ trend coefficients} \rho \]

In the restricted trend specification, \( m_1 = K + 1, m_2 = \{K(p - 1) + 1 + m\} \), and there are \( n_{\text{parms}} = Kr + (K + 1)r + K\{K(p - 1) + 1 + m\} \) parameters in (3).

**Unrestricted constant**

An unrestricted constant in the VECM in (2) is equivalent to setting \( \delta = 0 \) in (1), which can be written in the form of (3) by defining

\[ Z_{1t} = y_{t-1} \text{ is } (K \times 1) \]
\[ Z_{2t} = (\Delta y'_{t-1}, \ldots, \Delta y'_{t-p+1}, 1, s_1, \ldots, s_m)' \text{ is } \{K(p - 1) + 1 + m\} \times 1; \]
\[ \Psi = (\Gamma_1, \ldots, \Gamma_{p-1}, v, w_1, \ldots, w_m) \text{ is } K \times \{K(p - 1) + 1 + m\} \]
\[ \tilde{\beta} = \beta \text{ is the } K \times r \text{ matrix composed of the } r \text{ cointegrating vectors} \]
In the unrestricted constant specification, \( m_1 = K, m_2 = \{K(p - 1) + 1 + m\} \), and there are \( n_{\text{parms}} = Kr + Kr + K\{K(p - 1) + 1 + m\} \) parameters in (3).

**Restricted constant**

When there is a restricted constant in the VECM in (2), it can be written in the form of (3) by defining

\[
Z_{1t} = (y'_{t-1}, 1)' \quad \text{is} \quad (K + 1) \times 1
\]

\[
Z_{2t} = (\Delta y'_{t-1}, \ldots, \Delta y'_{t-p+1})' \quad \text{is} \quad K(p - 1) \times 1
\]

\[
\Psi = (\Gamma_1, \ldots, \Gamma_{p-1}) \quad \text{is} \quad K \times K(p - 1)
\]

\[
\tilde{\beta} = (\beta', \mu)' \quad \text{is} \quad (K + 1) \times r \quad \text{matrix composed of the} \quad r \quad \text{cointegrating vectors and the} \quad r \quad \text{constants in the cointegrating relations.}
\]

In the restricted trend specification, \( m_1 = K + 1, m_2 = K(p - 1) \), and there are \( n_{\text{parms}} = Kr + (K + 1)r + K\{K(p - 1)\} \) parameters in (3).

**No trend**

When there is no trend in the VECM in (2), it can be written in the form of (3) by defining

\[
Z_{1t} = y_{t-1} \quad \text{is} \quad K \times 1
\]

\[
Z_{2t} = (\Delta y'_{t-1}, \ldots, \Delta y'_{t-p+1})' \quad \text{is} \quad K(p - 1) + m \times 1
\]

\[
\Psi = (\Gamma_1, \ldots, \Gamma_{p-1}) \quad \text{is} \quad K \times K(p - 1)
\]

\[
\tilde{\beta} = \beta \quad \text{is} \quad K \times r \quad \text{matrix of} \quad r \quad \text{cointegrating vectors}
\]

In the no-trend specification, \( m_1 = K, m_2 = K(p - 1) \), and there are \( n_{\text{parms}} = Kr + K(p - 1) + K\{K(p - 1)\} \) parameters in (3).

**Estimation with Johansen identification**

Not all the parameters in \( \alpha \) and \( \tilde{\beta} \) are identified. Consider the simple case in which \( \tilde{\beta} \) is \( K \times r \) and let \( Q \) be a nonsingular \( r \times r \) matrix. Then

\[
\alpha\tilde{\beta}' = \alpha QQ^{-1}\tilde{\beta}' = \alpha Q(\tilde{\beta}Q^{-1})' = \alpha\hat{\beta}'
\]

Substituting \( \hat{\alpha}\hat{\beta}' \) into the log likelihood in (5) for \( \alpha\tilde{\beta}' \) would not change the value of the log likelihood, so some a priori identification restrictions must be found to identify \( \alpha \) and \( \tilde{\beta} \). As discussed in Johansen (1995, chap. 5 and 6) and Boswijk (1995), if the restrictions exactly identify or overidentify \( \tilde{\beta} \), the estimates of the unconstrained parameters in \( \tilde{\beta} \) will be superconsistent, meaning that the estimates of the free parameters in \( \tilde{\beta} \) will converge at a faster rate than estimates of the short-run parameters in \( \alpha \) and \( \Gamma_i \). This allows the distribution of the estimator of the short-run parameters to be derived conditional on the estimated \( \tilde{\beta} \).

Johansen (1995, chap. 6) has proposed a normalization method for use when theory does not provide sufficient a priori restrictions to identify the cointegrating vector. This method has become widely adopted by researchers. Johansen’s identification scheme is

\[
\tilde{\beta}' = (I_r, \hat{\beta}')
\]

where \( I_r \) is the \( r \times r \) identity matrix and \( \hat{\beta} \) is a \( (m_1 - r) \times r \) matrix of identified parameters.
Johansen’s identification method places $r^2$ linearly independent constraints on the parameters in $\tilde{\beta}$, thereby defining an exactly identified model. The total number of freely estimated parameters is $n_{\text{parms}} - r^2 = \{K + m_2 + (K + m_1 - r)r\}$, and the degrees of freedom $d$ is calculated as the integer part of $(n_{\text{parms}} - r^2)/K$.

When only the rank and the Johansen identification restrictions are placed on the model, we can further manipulate the log likelihood in (5) to obtain analytic formulas for the parameters in $\tilde{\beta}$, $\alpha$, and $\Omega$. For a given value of $\tilde{\beta}$, $\alpha$ and $\Omega$ can be found by regressing $R_{0t}$ on $\tilde{\beta}^{'}R_{1t}$. This allows a further simplification of the problem in which

$$\alpha(\tilde{\beta}) = S_{01}\tilde{\beta}(\tilde{\beta}^{'}S_{11}\tilde{\beta})^{-1}$$

$$\Omega(\tilde{\beta}) = S_{00} - S_{01}\tilde{\beta}(\tilde{\beta}^{'}S_{11}\tilde{\beta})^{-1}\tilde{\beta}^{'}S_{10}$$

$$S_{ij} = (1/T)\sum_{t=1}^{T} R_{it}R_{jt}^{'} \quad i, j \in \{0, 1\}$$

Johansen (1995) shows that by inserting these solutions into equation (5), $\hat{\beta}$ is given by the $r$ eigenvectors $v_1, \ldots, v_r$ corresponding to the $r$ largest eigenvalues $\lambda_1, \ldots, \lambda_r$ that solve the generalized eigenvalue problem

$$|\lambda_i S_{11} - S_{10}^{-1} S_{01}| = 0 \quad (7)$$

The eigenvectors corresponding to $\lambda_1, \ldots, \lambda_r$ that solve (7) are the unidentified parameter estimates. To impose the identification restrictions in (6), we normalize the eigenvectors such that

$$\lambda_i S_{11} v_i = S_{01} S_{00}^{-1} S_{01} v_i \quad (8)$$

and

$$v_i^{'} S_{11} v_j = \begin{cases} 1 & \text{if } i = j \\ 0 & \text{otherwise} \end{cases} \quad (9)$$

At the optimum the log-likelihood function with the Johansen identification restrictions can be expressed in terms of $T$, $K$, $\hat{S}_{00}$, and the $r$ largest eigenvalues

$$L_c = -\frac{1}{2}T \left\{ K \ln(2\pi) + K + \ln(|S_{00}|) + \sum_{i=1}^{r} \ln(1 - \hat{\lambda}_i) \right\}$$

where the $\hat{\lambda}_i$ are the eigenvalues that solve (7), (8), and (9).

Using the normalized $\hat{\beta}$, we can then obtain the estimates

$$\hat{\alpha} = S_{01} \hat{\beta}(\hat{\beta}^{'} S_{11} \hat{\beta})^{-1} \quad (10)$$

and

$$\hat{\Omega} = S_{00} - \hat{\alpha}^{'} \hat{\beta} S_{10}$$

Let $\hat{\beta}_y$ be a $K \times r$ matrix that contains the estimates of the parameters in $\beta$ in (1). $\hat{\beta}_y$ differs from $\hat{\beta}$ in that any trend parameter estimates are omitted from $\hat{\beta}$. We can then use $\hat{\beta}_y$ to obtain predicted values for the $r$ nondemeaned cointegrating equations

$$\hat{E}_t = \hat{\beta}_y^{'} y_t$$
The \( \hat{E} \) series in \( \hat{E}_t \) are called the predicted, nondemeaned cointegrating equations because they still contain the terms \( \mu \) and \( \rho \). We want to work with the predicted, demeaned cointegrating equations. Thus we need estimates of \( \mu \) and \( \rho \). In the \text{trend(rconstant)} specification, the algorithm directly produces the estimator \( \hat{\mu} \). Similarly, in the \text{trend(rtrend)} specification, the algorithm directly produces the estimator \( \hat{\rho} \). In the remaining cases, to back out estimates of \( \mu \) and \( \rho \), we need estimates of \( \nu \) and \( \delta \), which we can obtain by estimating the parameters of the following VAR:

\[
\Delta y_t = \alpha \hat{E}_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + v + \delta t + w_1 s_1 + \cdots + w_m s_m + \epsilon_t \tag{11}
\]

Depending on the trend specification, we use \( \hat{\alpha} \) to back out the estimates of

\[
\hat{\mu} = (\hat{\alpha}' \hat{\alpha})^{-1} \hat{\alpha}' \hat{v} \tag{12}
\]

\[
\hat{\rho} = (\hat{\alpha}' \hat{\alpha})^{-1} \hat{\alpha}' \hat{\delta} \tag{13}
\]

if they are not already in \( \hat{\beta} \) and are included in the trend specification.

We then augment \( \hat{\beta}_y \) to

\[
\hat{\beta}_f' = (\hat{\beta}_y', \hat{\mu}, \hat{\rho})
\]

where the estimates of \( \hat{\mu} \) and \( \hat{\rho} \) are either obtained from \( \hat{\beta} \) or backed out using (12) and (13). We next use \( \hat{\beta}_f \) to obtain the \( r \) predicted, demeaned cointegrating equations, \( \hat{E}_t \), via

\[
\hat{E}_t = \hat{\beta}_f' (y_t', 1, t)'
\]

We last obtain estimates of all the short-run parameters from the VAR:

\[
\Delta y_t = \alpha \hat{E}_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + \gamma + \tau t + w_1 s_1 + \cdots + w_m s_m + \epsilon_t \tag{14}
\]

Because the estimator \( \hat{\beta}_f \) converges in probability to its true value at a rate faster than \( T^{-\frac{1}{2}} \), we can take our estimated \( \hat{E}_{t-1} \) as given data in (14). This allows us to estimate the variance–covariance (VCE) matrix of the estimates of the parameters in (14) by using the standard VAR VCE estimator. Equation (11) can be used to obtain consistent estimates of all the parameters and of the VCE of all the parameters, except \( v \) and \( \delta \). The standard VAR VCE of \( \hat{\nu} \) and \( \hat{\delta} \) is incorrect because these estimates converge at a faster rate. This is why it is important to use the predicted, demeaned cointegrating equations, \( \hat{E}_{t-1} \), when estimating the short-run parameters and trend terms. In keeping with the cointegration literature, \textit{vec} makes a small-sample adjustment to the VCE estimator so that the divisor is \((T - d)\) instead of \( T \), where \( d \) represents the degrees of freedom of the model. \( d \) is calculated as the integer part of \( n_{\text{parms}}/K \), where \( n_{\text{parms}} \) is the total number of freely estimated parameters in the model.

In the \text{trend(rconstant)} specification, the estimation procedure directly estimates \( \mu \). For \text{trend(constant)}, \text{trend(rtrend)}, and \text{trend(trend)}, the estimates of \( \mu \) are backed out using (12). In the \text{trend(rtrend)} specification, the estimation procedure directly estimates \( \rho \). In the \text{trend(trend)} specification, the estimates of \( \rho \) are backed out using (13). Because the elements of the estimated VCE are readily available only when the estimates are obtained directly, when the trend parameter estimates are backed out, their elements in the VCE for \( \hat{\beta}_f \) are missing.
Under the Johansen identification restrictions, vec obtains \( \hat{\beta} \), the estimates of the parameters in the \( r \times m_1 \) matrix \( \tilde{\beta}' \) in (5). The VCE of vec(\( \hat{\beta} \)) is \( rm_1 \times rm_1 \). Per Johansen (1995), the asymptotic distribution of \( \hat{\beta} \) is mixed Gaussian, and its VCE is consistently estimated by

\[
\left( \frac{1}{T - d} \right) (I_r \otimes H_J) \{ (\hat{\alpha}' \Omega^{-1} \hat{\alpha}) \otimes (H'_J S_{11} H_J) \}^{-1} (I_r \otimes H_J)' \tag{15}
\]

where \( H_J \) is the \( m_1 \times (m_1 - r) \) matrix given by \( H_J = (0'_{r \times (m_1 - r)}, I_{m_1 - r})' \). The VCE reported in \( e(\text{V}_\beta) \) is the estimated VCE in (15) augmented with missing values to account for any backed-out estimates of \( \mu \) or \( \rho \).

The parameter estimates \( \hat{\alpha} \) can be found either as a function of \( \hat{\beta} \), using (10) or from the VAR in (14). The estimated VCE of \( \hat{\alpha} \) reported in \( e(\text{V}_{\text{alpha}}) \) is given by

\[
\frac{1}{T - d} \hat{\Omega} \otimes \hat{\Sigma}_B
\]

where \( \hat{\Sigma}_B = (\hat{\beta}' S_{11} \hat{\beta})^{-1} \).

As we would expect, the estimator of \( \Pi = \alpha \beta' \) is

\[ \hat{\Pi} = \hat{\alpha} \hat{\beta}' \]

and its estimated VCE is given by

\[
\frac{1}{T - d} \hat{\Omega} \otimes (\hat{\beta} \hat{\Sigma}_B \hat{\beta}')
\]

The moving-average impact matrix \( C \) is estimated by

\[
\hat{C} = \hat{\beta}_\perp (\hat{\alpha}_\perp \hat{\Gamma}_\perp \hat{\beta}_\perp)^{-1} \hat{\alpha}_\perp
\]

where \( \hat{\beta}_\perp \) is the orthogonal complement of \( \hat{\beta}_y \), \( \hat{\alpha}_\perp \) is the orthogonal complement of \( \hat{\alpha} \), and

\[ \hat{\Gamma} = I_K - \sum_{i=1}^{p-1} \Gamma_i. \]

The orthogonal complement of a \( K \times r \) matrix \( Q \) that has rank \( r \) is a matrix \( Q_\perp \) of rank \( K - r \), such that \( Q'Q_\perp = 0 \). Although this operation is not uniquely defined, the results used by vec do not depend on the method of obtaining the orthogonal complement. vec uses the following method: the orthogonal complement of \( Q \) is given by the \( r \) eigenvectors with the highest eigenvalues from the matrix \( Q'(Q'Q)^{-1}Q' \).

Per Johansen (1995, chap. 13) and Drukker (2004), the VCE of \( \hat{C} \) is estimated by

\[
\frac{T - d}{T} \hat{S}_q \hat{V}_\nu \hat{S}_q'
\]

where

\[ \hat{S}_q = \hat{C} \otimes \hat{\xi} \]

\[ \hat{\xi} = \begin{cases} (\hat{\xi}_1, \hat{\xi}_2) & \text{if } p > 1 \\ \hat{\xi}_1 & \text{if } p = 1 \end{cases} \]

\[ \hat{\xi}_1 = (\hat{C}' \hat{T}' - I_K) \hat{\alpha} \]

\[ \hat{\alpha} = \hat{\alpha} (\hat{\alpha}' \hat{\alpha})^{-1} \]

\[ \hat{\xi}_2 = \iota_{p-1} \otimes \hat{C} \]

\( \iota_{p-1} \) is a \( (p - 1) \times 1 \) vector of ones

\( \hat{V}_\nu \) is the estimated VCE of \( \hat{\nu} = (\hat{\alpha}, \hat{\Gamma}_1, \ldots \hat{\Gamma}_{p-1}) \).
Estimation with constraints: $\beta$ identified

vec can also fit models in which the adjustment parameters are subject to homogeneous linear constraints and the cointegrating vectors are subject to general linear restrictions. Mathematically, vec allows for constraints of the form

$$R_\alpha' \text{vec}(\alpha) = 0$$  \(17\)

where $R_\alpha$ is a known $K_r \times n_\alpha$ constraint matrix, and

$$R_\beta' \text{vec}(\tilde{\beta}) = b$$  \(18\)

where $R_\beta$ is a known $m_1 r \times n_\beta$ constraint matrix and $b$ is a known $n_\beta \times 1$ vector of constants.

Although (17) and (18) are intuitive, they can be rewritten in a form to facilitate computation. Specifically, (17) can be written as

$$\text{vec}(\alpha') = Ga$$  \(19\)

where $G$ is $K_r \times n_\alpha$ and $a$ is $n_\alpha \times 1$. Equation (18) can be rewritten as

$$\text{vec}(\tilde{\beta}) = Hb + h_0$$  \(20\)

where $H$ is a known $n_1 r \times n_\beta$ matrix, $b$ is an $n_\beta \times 1$ matrix of parameters, and $h_0$ is a known $n_1 r \times 1$ matrix. See [P] makecns for a discussion of the different ways of specifying the constraints.

When constraints are specified via the aconstraints() and bconstraints() options, the Boswijk (1995) rank method determines whether the parameters in $\tilde{\beta}$ are underidentified, exactly identified, or overidentified.

Boswijk (1995) uses the Rothenberg (1971) method to determine whether the parameters in $\tilde{\beta}$ are identified. Thus the parameters in $\tilde{\beta}$ are exactly identified if $\rho_\beta = r^2$, and the parameters in $\tilde{\beta}$ are overidentified if $\rho_\beta > r^2$, where

$$\rho_\beta = \text{rank} \left\{ R_\beta (I_r \otimes \tilde{\beta}) \right\}$$

and $\tilde{\beta}$ is a full-rank matrix with the same dimensions as $\tilde{\beta}$. The computed $\rho_\beta$ is stored in e(beta_icnt).

Similarly, the number of freely estimated parameters in $\alpha$ and $\tilde{\beta}$ is given by $\rho_{jacob}$, where

$$\rho_{jacob} = \text{rank} \left\{ (\tilde{\alpha} \otimes I_{m_1})H, (I_K \otimes \tilde{\beta})G \right\}$$

Using $\rho_{jacob}$, we can calculate several other parameter counts of interest. In particular, the degrees of freedom of the overidentifying test are given by $(K + m_1 - r)r - \rho_{jacob}$, and the number of freely estimated parameters in the model is $n_{\text{parms}} = Km_2 + \rho_{jacob}$.

Although the problem of maximizing the log-likelihood function in (4), subject to the constraints in (17) and (18), could be handled by the algorithms in [R] ml, the switching algorithm of Boswijk (1995) has proven to be more convergent. For this reason, vec uses the Boswijk (1995) switching algorithm to perform the optimization.
Given starting values \((\hat{b}_0, \hat{a}_0, \hat{\Omega}_0)\), the algorithm iteratively updates the estimates until convergence is achieved, as follows:

\[
\hat{\alpha}_j \text{ is constructed from (19) and } \hat{a}_j
\]

\[
\hat{\beta}_j \text{ is constructed from (20) and } \hat{b}_j
\]

\[
\hat{b}_{j+1} = \{H'(\hat{\alpha}_j^{-1} \hat{\Omega}_j^{-1} \hat{\alpha}_j \otimes S_{11})H\}^{-1}H'(\hat{\alpha}_j^{-1} \hat{\Omega}_j^{-1} \otimes S_{11})\{\text{vec}(\hat{P}) - (\hat{\alpha}_j \otimes I_{n_z_1})h_0\}
\]

\[
\hat{a}_{j+1} = \{G(\hat{\Omega}_j^{-1} \otimes \hat{\beta}_j S_{11} \hat{\beta}_j)G\}^{-1}G'(\hat{\Omega}_j^{-1} \otimes \hat{\beta}_j S_{11})\text{vec}(\hat{P})
\]

\[
\hat{\Omega}_{j+1} = S_{00} - S_{01} \hat{\beta}_j \hat{\alpha}_j' - \hat{\alpha}_j \hat{\beta}_j' S_{10} + \hat{\alpha}_j \hat{\beta}_j' S_{11} \hat{\beta}_j \hat{\alpha}_j'
\]

The estimated VCE of \(\hat{\beta}\) is given by

\[
\frac{1}{(T - d)}H\{H'(W \otimes S_{11})H\}^{-1}H'
\]

where \(W\) is \(\hat{\alpha}' \hat{\Omega}^{-1} \hat{\alpha}\). As in the case without constraints, the estimated VCE of \(\hat{\alpha}\) can be obtained either from the VCE of the short-run parameters, as described below, or via the formula

\[
\hat{V}_{\hat{\alpha}} = \frac{1}{(T - d)}G \left[ G' \left\{ \hat{\Omega}^{-1} \otimes (\hat{\beta}' S_{11} \hat{\beta})G \right\}^{-1} \right] G'
\]

Boswijk (1995) notes that, as long as the parameters of the cointegrating equations are exactly identified or overidentified, the constrained ML estimator produces superconsistent estimates of \(\hat{\beta}\). This implies that the method of estimating the short-run parameters described above applies in the presence of constraints, as well, albeit with a caveat: when there are constraints placed on \(\alpha\), the VARs must be estimated subject to these constraints.

With these estimates and the estimated VCE of the short-run parameter matrix \(\hat{V}_\hat{\nu}\), Drukker (2004) shows that the estimated VCE for \(\hat{\Pi}\) is given by

\[
(\hat{\beta} \otimes I_K)\hat{V}_{\hat{\nu}} (\hat{\beta} \otimes I_K)'
\]

Drukker (2004) also shows that the estimated VCE of \(\hat{C}\) can be obtained from (16) with the extension that \(\hat{V}_\hat{\nu}\) is the estimated VCE of \(\hat{\nu}\) that takes into account any constraints on \(\hat{\alpha}\).

**Estimation with constraints: \(\beta\) not identified**

When the parameters in \(\beta\) are not identified, only the parameters in \(\Pi = \alpha \beta\) and \(C\) are identified. The estimates of \(\Pi\) and \(C\) would not change if more identification restrictions were imposed to achieve exact identification. Thus the VCE matrices for \(\hat{\Pi}\) and \(\hat{C}\) can be derived as if the model exactly identified \(\beta\).
Formulas for the information criteria

The AIC, SBIC, and HQIC are calculated according to their standard definitions, which include the constant term from the log likelihood; that is,

\[
\text{AIC} = -2 \left( \frac{L}{T} \right) + \frac{2n_{\text{parms}}}{T} \\
\text{SBIC} = -2 \left( \frac{L}{T} \right) + \frac{\ln(T)}{T} n_{\text{parms}} \\
\text{HQIC} = -2 \left( \frac{L}{T} \right) + \frac{2\ln\{\ln(T)\}}{T} n_{\text{parms}}
\]

where \( n_{\text{parms}} \) is the total number of parameters in the model and \( L \) is the value of the log likelihood at the optimum.

Formulas for predict

\( \text{xb, residuals and stdp} \) are standard and are documented in \([\text{R}]\) \text{predict}. \text{ce} causes predict to compute \( \hat{E}_t = \hat{\beta}_f y_t \) for the requested cointegrating equation.

\text{levels} causes \text{predict} to compute the predictions for the levels of the data. Let \( \hat{y}_t^d \) be the predicted value of \( \Delta y_t \). Because the computations are performed for a given equation, \( y_t \) is a scalar. Using \( \hat{y}_t^d \), we can predict the level by \( \hat{y}_t = \hat{y}_t^d + y_{t-1} \).

Because the residuals from the VECM for the differences and the residuals from the corresponding VAR in levels are identical, there is no need for an option for predicting the residuals in levels.

References


Also see

- **vec postestimation** — Postestimation tools for vec
- **tsset** — Declare data to be time-series data
- **var** — Vector autoregressive models
- **var svar** — Structural vector autoregressive models
- **vec intro** — Introduction to vector error-correction models
- **20 Estimation and postestimation commands**