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The Variance Matrix of Sample Second-order Moments in Multivariate Linear Relations

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Abstract

We derive an expression for the variance matrix of the vector of (uncentered) sample second-order moments under multivariate linear relations and an independence assumption. An application of the result is presented

Key words: Moment structures, stochastic independence, non-normality, asymptotic distribution, non-central chi-square, goodness-of-fit statistic.



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1 Introduction

In a wide class of models for multivariate analysis, it is assumed that a vector of observable variables satisfies the following multivariate linear relation (e.g., Anderson, 1987):

(1)
$$z = \sum_{i=1}^{L} B_i \delta_i,$$

where z is a p-dimensional vector of observable variables, the δ_i 's are random vectors and the B_i 's are parameter matrices. The moment matrices $\Phi_{ii} := E\delta_i\delta_i$ ', i=1,2,...,L, where "E" denotes mathematical expectation, are assumed to be finite.

An example of (1) is the following linear latent variable model:

(2a)
$$\begin{cases} z = \Lambda \eta + \varepsilon \\ \eta = B \eta + \xi \end{cases}$$

where η is an m-dimensional vector of (possibly) latent variables, ϵ is an p-dimensional centered random vector of measurement errors, and ξ is an m-dimensional random vector (usually composed of disturbance terms of structural equations and exogenous variables). Without loss of generality, we assume that (I - B) is invertible and that the last component of ξ , η and z is a constant equal to 1 (with this we encompass models that restrict the means of observable variables, and not only the variances and covariances). Typically, Λ , B, Ψ := E $\epsilon\epsilon$ ' and Z := $E\xi\xi$ ' will be matrix-valued functions of a q-dimensional parameter vector θ .

Model (2a) is, in effect, a specific case of (1), since we can write

(2b)
$$z = \Lambda(I - B)^{-1}\xi + \varepsilon = \sum_{i=1}^{k} \Lambda(I - B)^{-1}J_{i}\xi_{i} + \sum_{i=1}^{k^{*}} T_{i}\varepsilon_{i},$$

where the ξ_i 's and ϵ_i 's are k and k* subvectors of ξ and ϵ , respectively, and the J_i 's and T_i 's are 0-1 matrices such that

$$\xi = \sum_{i=1}^{k} J_i \xi_i \text{ and } \epsilon = \sum_{i=1}^{k^*} T_i \epsilon_i.$$

It should be mentioned that model (2a) encompasses a variety of structural equation models like Factor Analysis and the so called LISREL models (Jöreskog and Sörbom, 1989). The gradient vector and Hessian matrix associated with model (2a), for different type of fitting functions, can be found in Neudecker and Satorra (1991).

A matrix that plays a fundamental role in assessing the asymptotic distribution of estimators and test statistics, is the following variance matrix of the vector of cross-product moments of z:

(3)
$$\Gamma := \text{var} (v \text{ zz'}),$$

which, throughout the paper, is assumed to be finite. Here "var" denotes variance matrix, and "v" is the operator that stacks the non-redundant elements of a symmetric matrix in a column vector. Note that $vzz' = D^+ vec zz'$, where "vec" stacks the rows of a matrix as

a column vector, $D^+ = (D'D)^{-1}D$ and D is the 0-1 "duplication" matrix for which vec zz' = D v zz' (for further details on the matrices D and D⁺, see Magnus and Neudecker, 1988). Note that Γ is a p* × p* matrix with p* := p(p+1)/2.

In this paper we derive the expression for Γ in terms of the matrices B_i 's and moment matrices of the δ_i 's, under the assumption that the δ_i 's of (1) are mutually independent. We do this in Section 2 of the paper. The expression to be obtained does not follow from known results on variances of quadratic forms, as (for example) the results of Browne and Neudecker (1988), Neudecker and Wansbeek (1987) and Rao and Kleffe (1988, Section 2.6), which do not consider a linear relation (1) with the δ_i 's possibly non-normally distributed.

The expression obtained for Γ is used in Section 3 to simplify the derivation of results on asymptotic robustness in moment structure analysis.

2 The expression for Γ under multivariate linear relations

In relation with (1), consider

(4)
$$E \delta_i = 0$$
, for $i=1,..., L-1$,

(5)
$$\delta_L = 1$$
 (i.e., δ_L is scalar constant to 1)

and the following independence assumption (IA):

(6) IA: The δ_i 's are mutually independent.

Under the current setting, the following lemma applies (The proof of the lemma is sketched in the Appendix).

Lemma 1

When (4) to (6) hold, the variance matrix Γ of (3) can be written as

(7)
$$\Gamma = \Omega - 2 D^{+}(\mu \mu' \otimes \mu \mu') D^{+}' +$$

$$\sum_{i=1}^{L-1} \{ 2D^{+}(B_{i} \otimes \mu) \{ E \delta_{i}(v \delta_{i} \delta_{i}')' \} D'(B_{i} \otimes B_{i})' D^{+}' +$$

$$2D^{+}(B_{i} \otimes B_{i}) D \{ E (v \delta_{i} \delta_{i}') \delta_{i}' \} (B_{i} \otimes \mu)' D^{+}' +$$

 $D^+(B_i\otimes B_i^-)D\{(var\,v(\delta_i\delta_i')-2D^+E(\delta_i\delta_i')\otimes E\;(\delta_i\delta_i')D^{+'}\}D^{'}(B_i\otimes B_i^-)'D^{+'}],$

where

(8)
$$\Omega := 2 D^{+} Ezz' \otimes Ezz' D^{+}$$

and $\mu := Ez$.

Remarks

1. When z is normally distributed, (7) simplifies to what we will call the normal (N) expression of Γ :

(9)
$$\Gamma_{\mathbf{N}} := 2 D^{+} [\operatorname{Ezz'} \otimes \operatorname{Ezz'} - \mu \mu' \otimes \mu \mu'] D^{+},$$

since for centered and normally distributed δ_i 's it holds that (e.g., Neudecker and Wansbeek, 1987)

(10a)
$$E \delta_{\mathbf{i}}(\mathbf{v} \delta_{\mathbf{i}} \delta_{\mathbf{i}}')' = 0$$

and

(10b)
$$\operatorname{var} v(\delta_i \delta_i') = 2D^+ E(\delta_i \delta_i') \otimes E(\delta_i \delta_i') D^{+'}.$$

2. Given any random vector z, applying the Lemma to the following (trivial) two-terms multivariate linear relation $z = (z-\mu) + \mu$, we obtain

(11)
$$\Gamma = 2 D^{+}(Ezz' \otimes Ezz' - \mu\mu' \otimes \mu\mu')D^{+'} +$$

$$2D^{+} (I \otimes \mu)(E(z-\mu)(v(z-\mu)(z-\mu)')') +$$

$$2 (E (v (z-\mu)(z-\mu)')(z-\mu)') (I \otimes \mu)' D^{+'} +$$

$$((var v(z-\mu)(z-\mu)') - 2 D^{+}E((z-\mu)(z-\mu)') \otimes E((z-\mu)(z-\mu)')D^{+'}),$$

where I is an identity matrix of appropriate dimensions. This is in accordance with an equivalent result of Rao and Kleffe (1988, Section 2.6).

Result (7) will now be used to show that, under certain conditions, Ω of (8) can substitute Γ in the formulae for asymptotic standard errors and test statistics in moment structure analysis. Since the matrix Ω involves only the second-order moments of the data, which are easier to estimate than higher-order moments, this substitution is of high practical relevance.

3 Asymptotic robustness in moment structure analysis

Consider the multivariate linear relation (1) under assumptions (4) to (6), and assume additionally that the B_i 's are continuously differentiable functions of a t-dimensional parameter vector τ and the Φ_{ii} 's are unrestricted symmetric matrices. Denote $\Sigma = Ezz'$, then we obtain a moment structure $\Sigma = \Sigma(\theta)$ where

(12)
$$\theta := [\tau', (v \Phi_{11})', ..., (v \Phi_{ii})', ..., (v \Phi_{LL})']'$$

is an (unrestricted) q-dimensional parameter vector $(q \ge t)$. This set up arises, for example, in (2b) when Λ and B are matrix-valued functions of τ and the ξ_i 's and ε_i 's are mutually independent random variables with unrestricted moment matrices (a specific model of this type is the factor analysis model). Since (1) implies that

(13)
$$E \ v \ (zz') \ = \ \sum_{i=1}^{L} \ D^{+}(B_{i} \otimes B_{i}) D \ v(\Phi_{ii}),$$

the partition (12) of θ implies that the $(p^* \times q)$ derivative matrix $\Delta := (\partial/\partial \theta') \sigma(\theta)$ can be written as

(14)
$$\Delta = [\Delta_{\tau}, D^{+}(B_{1} \otimes B_{1})D, ..., D^{+}(B_{i} \otimes B_{j})D, ..., D^{+}(B_{L} \otimes B_{L})D],$$

where $\Delta_{\tau} := (\partial/\partial \tau')\sigma(\theta)$ is a p* × t matrix and $\sigma(\theta) := v \Sigma(\theta)$.

Consider now a sample $z_1, z_2, ..., z_n$ of n independent observations of z, and let s := v(S) be the reduced vector of sample moments, where

(15)
$$S := \sum_{\alpha=1}^{n} (z_{\alpha} z_{\alpha'}) / n$$

is the (uncentered) sample (second-order) moment matrix of z. Straightforward application of the Central Limit theorem shows that

(16)
$$n^{1/2}(s - \sigma^0) \longrightarrow L N(0, \Gamma),$$

where "--->L" indicates convergence in distribution, σ^0 is the asymptotic limit of s and Γ is the p* × p* matrix defined in (3) above. Consider an estimate $\hat{\theta}$ of θ with the property of being $n^{1/2}$ -consistent (i.e., $n^{1/2}(\hat{\theta} - \theta)$ is bounded in distribution). Typically, $\hat{\theta}$ will be the minimizer of

(17)
$$F = (s - \sigma(\theta))' \hat{W} (s - \sigma(\theta)).$$

where \hat{W} is a weight matrix converging in probability to a positive definite matrix, say W. It can also be the minimizer of the (pseudo) maximum likelihood function

(18)
$$F_{ML} = \ln |\Sigma(\theta)| + \operatorname{tr} \{ S \Sigma(\theta)^{-1} \} - \ln |S| - p.$$

Instrumental variable estimators are also $n^{1/2}$ -consistent estimators of θ (e.g., Jennrich, 1987). Computer programs that produce such estimators for the class of models described in (2) are, for example, LISREL (Jöreskog and Sörbom, 1989), EQS (Bentler, 1989), LISCOMP (Muthén, 1987) and LINCS (Schoenberg, 1989).

Let us denote by $\overset{\wedge}{\tau}$ the (t \times 1) subvector of $\overset{\wedge}{\theta}$ corresponging to τ . By standard asymptotic theory, the asymptotic variance matrix of $\overset{\wedge}{\tau}$ is

(19)
$$\operatorname{avar}(\hat{\tau}) = \operatorname{n}^{-1}\Theta_{\tau}\Gamma\Theta_{\tau}',$$

where Θ_{τ} is the t × p leading sub-matrix of $(\Delta'W\Delta)^{-1}\Delta'W$, say $[(\Delta'W\Delta)^{-1}\Delta'W]_{t\times p}*$ (e.g., Satorra, 1989). Note that in the case of (pseudo) maximum likelihood estimation, then $W = \partial^2 F_{ML}(\sigma,\sigma)/\partial\sigma\partial\sigma'$ and equals Ω of (8) (e.g., Neudecker and Satorra, 1991).

Once the estimate $\hat{\theta}$ is known, the vector $\hat{\sigma} := \sigma(\hat{\theta})$ of fitted moments can be computed. To test the adequacy of the model, an asymptotic chi-square goodness-of-fit test statistic can be defined as

(20)
$$G = n(s - \overset{\wedge}{\sigma}) \hat{A} (s - \overset{\wedge}{\sigma}),$$

where \hat{A} is a consistent estimate of $\Delta_{\perp} (\Delta_{\perp}' \Gamma \Delta_{\perp})^{-} \Delta_{\perp}$ and "-" denotes a g-inverse. Under a sequence of local alternatives (Neyman, 1937; see McManus, 1991), namely

(21)
$$\sigma^0 := \sigma^0_n \quad \text{with} \quad \sqrt{n} (\sigma^0_n - \sigma) = \delta,$$

where δ is a finite p*-dimensional vector, standard results of Moore (1977) show that ¹

(22)
$$G \longrightarrow_L \chi^2_{\mathbf{r}}(\lambda),$$

where $\chi^2_{\mathbf{r}}(\lambda)$ is a non-central chi-square distribution with $\mathbf{r} = \operatorname{rank}(\Delta_{\perp}, \Gamma\Delta_{\perp})$ degrees of freedom and non-centrality parameter $\lambda = \delta' \Delta_{\perp}' (\Delta_{\perp}' \Gamma \Delta_{\perp})^{-} \Delta_{\perp} \delta$. Here Δ_{\perp} means an orthogonal complement of the derivative matrix Δ . The asymptotic distribution of G will, of course, be central chi-square when the drift parameter δ of (21) equals zero (i.e., when the model is "exactly true"). In the particular case of covariance structure analysis (where z is assumed to be of zero mean), the above goodness-of-fit statistic G was introduced by Browne (1984).

Since $\Theta_t \Delta$ and $\Delta_{\perp} \Delta$ equal zero, the partition (14) of Δ implies

(23)
$$\Theta_t D^+(B_i \otimes B_i)D = 0, i = 1,...,L,$$

and

(24)
$$\Delta_{\perp} 'D^{+}(B_{i} \otimes B_{i})D = 0, i = 1,...,L,$$

which, combined with the expression for Γ obtained in Lemma 1 (see (7)), yield the following fundamental results:

(25)
$$\Theta_{\tau} \Gamma \Theta_{\tau'} = \Theta_{\tau} \Omega \Theta_{\tau'}$$

and

(26)
$$\Delta_{\perp} ' \Gamma \Delta_{\perp} = \Delta_{\perp} ' \Omega \Delta_{\perp}.$$

¹In fact, noting that

$$\sqrt{n(s-\hat{\sigma})} = \sqrt{n(s-\sigma^0)} + \sqrt{n(\sigma^0-\sigma_0)} + \sqrt{n(\sigma_0-\hat{\sigma})} =$$

$$\sqrt{n(s-\sigma^0)} + \sqrt{n(\sigma^0-\sigma_0)} - \sqrt{n\Delta(\hat{\theta}-\theta)}$$

 $\sqrt{n(s - \sigma^O)} + \sqrt{n(\sigma^O - \sigma_O)} - \sqrt{n\Delta(\hat{\theta} - \theta)},$ under the sequence of local alternatives (17), we can write

$$\sqrt{n} \Delta_{\perp} (s - \stackrel{\wedge}{\sigma}) = \sqrt{n} \Delta_{\perp} (s - \sigma^{O}) + \sqrt{n} \Delta_{\perp} (\sigma^{O} - \sigma_{O}) --->_{L} N(\Delta_{\perp} \delta, \Delta_{\perp} \Gamma \Delta_{\perp}').$$

Result (25) and (26) have very interesting practical implications. In effect, (25) allows us to estimate the variance matrix of $\overset{\wedge}{\tau}$ as

$$avar(\hat{\tau}) = n^{-1}\Theta_{t} \hat{\Omega} \Theta_{t}' =$$

$$= [(\hat{\Delta}' \hat{W} \hat{\Delta})^{-1} \hat{\Delta}' \hat{W} \hat{\Omega} \hat{W} \hat{\Delta} (\hat{\Delta}' \hat{W} \hat{\Delta})^{-1}]_{t \bowtie t},$$

where $[\]_{t \times t}$ denotes the leading $t \times t$ submatrix of the matrix enclosed. Further, (26) allow us to construct an asymptotic chi-square goodness-of-fit statistic G^* as

(28)
$$G^* = n(s - \stackrel{\wedge}{\sigma})' \stackrel{\wedge}{\Delta}_{1} (\stackrel{\wedge}{\Delta}_{\perp}' \stackrel{\wedge}{\Omega} \stackrel{\wedge}{\Delta}_{1})^{-} \stackrel{\wedge}{\Delta}_{1}' (s - \stackrel{\wedge}{\sigma}).$$

Here "here" means evaluated at $\hat{\theta}$ or simply a consistent estimate. It should be noted that a consistent estimate of Ω is easily obtained by replacing S for Ezz' in (7b).

Limited to the context of covariance structure analysis, the asymptotic chi-squaredness of G* of (28), as well as the validity of the result (27), under the current assumptions was proven in Satorra and Bentler (1990, 1991). It should be noted that when FML is used,

then G* of (28) and the statistic nF_{ML}(S, Σ ($\hat{\theta}$)) have the same asymptotic distribution and, hence, both will be asymptotically chi-square under the current assumptions. Results (25) and (26) encompass asymptotic robustness results of Amemiya and Anderson (1990), Anderson (1987), Satorra and Bentler (1990), Browne and Shapiro (1988) and Satorra (1991). The present approach for proving results of asymptotic robustness has also been exploited in Satorra (1991).

Clearly, the possibility of using a consistent estimate of Ω instead of Γ simplifies computations considerably. In fact, when computing the variance matrix (27) of estimates of τ , as well as to computing G^* of (28), only the second-order moments of the data are involved. In contrast, under nonnormality of z, usual consistent estimates of Γ involve higher-order moments of the data.

Slight modifications of the arguments above will also show the validity of (25) and (26) when some of the matrices Φ_{ii} 's are restricted to be continuously differentiable functions of τ , provided that condition (10) is verified for the δ_i 's with restricted Φ_{ii} 's (as is the case when δ_i is normally distributed).

Appendix

This appendix sketches the proof of the Lemma

Results such as $K(A \otimes B)K = (B \otimes A)$, $K(A \otimes b) = b \otimes A$, and vec b b' = b \otimes b, where A is a matrix, b is a vector and K is the commutation matrix of appropriate dimension, and other standard results of matrix calculus (e.g., Magnus & Neudecker, 1988), will be used extensively in the proof of the lemma.

First note that under (1):

$$\begin{array}{ll} E & zz' = E \; (\; \sum\limits_{j} \;\; B_{j} \delta_{j} \;) \; (\;\; \sum\limits_{i} \;\; B_{i} \delta_{i} \;)' = & \;\; \sum\limits_{i} \;\; B_{i} \, E(\; \delta_{i} \delta_{i} ') \; B_{i} ' \end{array}$$

since E $\delta_i \delta_j = 0$ when $i \neq j$. Hence,

(A1)
$$(I+K)$$
 Ezz' \otimes Ezz' =

$$\sum_{i} \quad (\text{I+K}) \ (\text{B}_{i} \otimes \text{B}_{i} \) (\ \text{E} \ (\delta_{i} \delta_{i} ') \otimes \ \ \text{E} \ (\delta_{i} \delta_{i} ')) \ (\text{B}_{i} \otimes \text{B}_{i} \) ' \ +$$

$$\underset{i\neq j}{\sum}\quad (I+K)\,(B_i\otimes B_j\,)\,(E\,(\delta_i\delta_i')\otimes\,E\,(\delta_j\delta_j')\,)\,(B_i\otimes B_j\,)'.$$

and

$$\sum_i \ \sum_j \ \sum_k \ \sum_t \ (\mathrm{B}_j \otimes \mathrm{B}_i \) [\mathrm{E}(\delta_j \otimes \delta_i) (\delta_t \otimes \delta_k)' - \mathrm{E} \ (\delta_j \otimes \delta_i) \ \mathrm{E}(\delta_t \otimes \delta_k)'] \ (\mathrm{B}_t \otimes \mathrm{B}_k \)' = \mathrm{E}(\delta_j \otimes \delta_i) [\mathrm{E}(\delta_j \otimes \delta_i) (\delta_t \otimes \delta_k)' - \mathrm{E}(\delta_j \otimes \delta_i)] \ (\mathrm{E}(\delta_j \otimes \delta_i) (\delta_j \otimes \delta_i) (\delta_j \otimes \delta_i)] \ (\mathrm{E}(\delta_j \otimes \delta_i) (\delta_j \otimes \delta_i) (\delta_j \otimes \delta_i)] \ (\mathrm{E}(\delta_j \otimes \delta_i) (\delta_j \otimes \delta_i) (\delta_j \otimes \delta_i)] \ (\mathrm{E}(\delta_j \otimes \delta_i) (\delta_j \otimes \delta_i) (\delta_j \otimes \delta_i)] \ (\mathrm{E}(\delta_j \otimes \delta_i) (\delta_j \otimes \delta_i) (\delta_j \otimes \delta_i)] \ (\mathrm{E}(\delta_j \otimes \delta_i) (\delta_j \otimes \delta_i) (\delta_j \otimes \delta_i)] \ (\mathrm{E}(\delta_j \otimes \delta_i) (\delta_j \otimes \delta_i) (\delta_j \otimes \delta_i)] \ (\mathrm{E}(\delta_j \otimes \delta_i) (\delta_j \otimes \delta_i) (\delta_j \otimes \delta_i)] \ (\mathrm{E}(\delta_j \otimes \delta_i) (\delta_j \otimes \delta_i) (\delta_j \otimes \delta_i)] \ (\mathrm{E}(\delta_j \otimes \delta_i) (\delta_j \otimes \delta_i) (\delta_j \otimes \delta_i)] \ (\mathrm{E}(\delta_j \otimes \delta_i) (\delta_j \otimes \delta_i) (\delta_j \otimes \delta_i)] \ (\mathrm{E}(\delta_j \otimes \delta_i) (\delta_j \otimes \delta_i) (\delta_j \otimes \delta_i)] \ (\mathrm{E}(\delta_j \otimes \delta_i) (\delta_j \otimes \delta_i) (\delta_j \otimes \delta_i)] \ (\mathrm{E}(\delta_j \otimes \delta_i) (\delta_j \otimes \delta_i) (\delta_j \otimes \delta_i)] \ (\mathrm{E}(\delta_j \otimes \delta_i) (\delta_j \otimes \delta_i) (\delta_j \otimes \delta_i)] \ (\mathrm{E}(\delta_j \otimes \delta_i) (\delta_j \otimes \delta_i) (\delta_j \otimes \delta_i)] \ (\mathrm{E}(\delta_j \otimes \delta_i) (\delta_j \otimes \delta_i) (\delta_j \otimes \delta_i)] \ (\mathrm{E}(\delta_j \otimes \delta_i) (\delta_j \otimes \delta_i) (\delta_j \otimes \delta_i)] \ (\mathrm{E}(\delta_j \otimes \delta_i) (\delta_j \otimes \delta_i) (\delta_j \otimes \delta_i)] \ (\mathrm{E}(\delta_j \otimes \delta_i) (\delta_j \otimes \delta_i) (\delta_j \otimes \delta_i) (\delta_j \otimes \delta_i)] \ (\mathrm{E}(\delta_j \otimes \delta_i) (\delta_j \otimes \delta_i) (\delta_j$$

$$\begin{array}{cccc} \sum_{i} & \sum_{i} & \sum_{k} & \sum_{t} & (B_{j} \otimes B_{i} \) \ X_{ijkt} \ (B_{t} \otimes B_{k} \)' \ , \end{array}$$

where

$$X_{ijkt} \; := \; \; \mathsf{E} \; (\delta_j \otimes \delta_i) (\delta_t \otimes \delta_k)' \; - \; \mathsf{E} \; (\delta_j \otimes \delta_i) \; \mathsf{E} (\delta_t \otimes \delta_k)' \; .$$

Now, computing Xijkt under different combinations of subscripts, we deduce

(A2)
$$Var(vec zz') =$$

$$\sum_{i\neq j} \quad (B_j \otimes B_i \) \ [\ E(\delta_j \delta_j') \otimes E(\delta_i \delta_i') \] \ (B_j \otimes B_i \)' \ (I \ + K \) \ .$$

$$\sum\limits_{i\neq L}\;(l+K)\;(B_i\otimes B_L\;)\;[\;E(\delta_i\otimes \delta_L)(\delta_i\otimes \delta_i)'\;]\;(B_i\otimes B_i\;)'\;+$$

$$\textstyle\sum_{i\neq L} \; (B_i \otimes B_i \;) [E(\delta_i \otimes \delta_i) (\delta_L \otimes \delta_i)' \;\;] \; (B_i \otimes B_L \;)' \; (I+K) \; + \;\;$$

$$\sum_i \ (B_i \otimes B_i) \ [\ \text{var vec} \ \delta_i \delta_i'] \ (B_i \otimes B_i)' \ .$$

Consequently, we can write

and

$$\begin{array}{ll} (A4) & D^{+} \ Var \ (\ vec \ zz' \) \ D^{+'} = \\ & \sum_{i\neq j} \quad 2D^{+} \ (B_{j}\otimes B_{i} \) \ [E(\delta_{j}\delta_{j}')\otimes E(\delta_{i}\delta_{i}') \] \ \ (B_{j}\otimes B_{i} \)' \ D^{+'} \ . \\ & \sum_{i\neq L} \quad 2D^{+} \ (B_{i}\otimes B_{L} \) [E(\delta_{i}\otimes \delta_{L})(\delta_{i}\otimes \delta_{i})' \] \ (B_{i}\otimes B_{i} \)' \ D^{+'} \ + \\ & \sum_{i\neq L} \quad 2D^{+} \ (B_{i}\otimes B_{i} \) [E(\delta_{i}\otimes \delta_{i})(\delta_{L}\otimes \delta_{i})' \] \ \ (B_{i}\otimes B_{L} \)' \ D^{+'} \ + \\ & \sum_{i} \quad D^{+} \ (B_{i}\otimes B_{i} \) \ [\ var \ vec \ \delta_{i}\delta_{i}'] \ \ (B_{i}\otimes B_{i} \)' D^{+'} \ . \end{array}$$

The proof concludes by combining results (A3) and (A4). Q.E.D.

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