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Structural Constant Conditional Correlation

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Abstract

A small strand of recent literature is occupied with identifying simultaneity in multiple equation systems through autoregressive conditional heteroscedasticity. Since this approach assumes that the structural innovations are uncorrelated, any contemporaneous connection of the endogenous variables needs to be exclusively explained by mutual spillover effects. In contrast, this paper allows for instantaneous covariances, which become identifiable by imposing the constraint of structural constant conditional correlation (SCCC). In this, common driving forces can be modelled in addition to simultaneous transmission effects. The new methodology is applied to the Dow Jones and Nasdaq Composite indexes in a small empirical example, illuminating scope and functioning of the SCCC model.

Keywords: Simultaneity, Identification, EGARCH, CCC
JEL classification: C32, G10

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1 Introduction

Identifying structural models that feature simultaneous effects between several variables is one of the key tasks of econometrics. In this, the conventional method solving identification problems in multivariate time series analysis works through parametric (zero) constraints, which allow recovering the structural model from its estimated reduced form. In several research areas, such as monetary economics, considerable progress has been made in theoretically deriving distinct identification schemes. Nonetheless, many economic setups are not compatible with using *a priori* parameter restrictions, since these inherently decide about directions of causality for reasons other than empirical exploration. An example is given in the present paper, which asks provocatively, whether large cap (Dow Jones Industrial Average) or high-tech (Nasdaq Composite) equities predominate the stock segment interdependence, as defined by mutual instantaneous transmission effects. Such a question can evidently not be tackled for instance by imposing a recursive structure on the model.

For heteroscedastic series, some authors in a small recent literature introduced methods that exploit non-constant variances for identifying simultaneous models "through heteroscedasticity" (see Rigobon 2003). A shift in the structural volatility, which yields more additional determining equations from the reduced-form covariance-matrix than unknown coefficients, describes the basic idea. Building on this logic, further research for example in Sentana and Fiorentini (2001), Rigobon (2002) and Weber (2007a) proposed estimating ARCH-type processes as to coherently describe the necessary volatility movements.

Even though these existing approaches support the identification of unconstrained contemporaneous interactions, they still assume the structural innovations are uncorrelated. Necessarily, such an assumption explains any correlation of the included variables exclusively by causal transmission effects. It follows that in presence of neglected exogenous shocks, the estimation is bound to overstate the bilateral causality. In the Dow-Nasdaq example, the fact that both these segments are subject to common news and influences is economically trivial, though econometrically rather intricate. While the problem might in principle be treated by augmenting the model by further essential variables, much relevant information will be unobservable or can hardly be covered in its entirety by necessarily low-dimensional time series systems. In consequence, this discussion stresses the importance of allowing for contemporaneous interaction in the structural innovations.

As a matter of fact, the assumption of uncorrelated structural residuals serves to assure that the additional information obtained from time-varying volatility is not simply exhausted by extra covariance parameters for each regime. That is, introducing unrestricted time-varying covariances would simply undo the identifiability created by heteroscedasticity. Weber (2007b) deals with this problem by specifying a common factor that parsimoniously models the contemporaneous covariance structure. Now, the contribution of the present paper lies in rendering instantaneous residual linkage identifiable by extending the idea of constant conditional correlation (CCC) from Bollerslev (1990) to *structural* disturbances, which is mirrored in the name SCCC for the new model. Put differently, time-varying covariances become assessable by restricting them to be governed by the conditional variance dynamics.

This methodological approach is discussed at length in the following section. Concerning the empirical US stock example, section 3 reveals a moderate preponderance of the Dow Jones compared to the Nasdaq Composite. The sensitivity of the estimation outcome to sample and model changes is discussed. The last section summarises the key results of the present analysis and proposes further econometric refinements.

2 Methodology

A simplified model for contemporaneous transmission effects between n endogenous variables y_{it} is specified as

$$Ay_t = \varepsilon_t \; . \tag{1}$$

Here, the coefficients representing instantaneous impacts are included in the matrix A, in which the diagonal elements are normalised to one. ε_t is an n-dimensional vector of structural innovations with unrestricted correlation matrix. Of course, this model can easily be adapted to cover vector autoregressive lags or deterministic terms, as considered in the empirical example in section 3.

For the moment, assume that the ε_{it} were uncorrelated. It is well known that even then, (1) as it stands is not identified and therefore cannot be consistently estimated. The derivation of the reduced-form model simply results in

$$y_t = A^{-1}\varepsilon_t \; . \tag{2}$$

Herein, it naturally proves impossible to recover the structural parameters from the reduced form without further constraints: In the matrix A with normalised diagonal, $n(n-1)$ simultaneous impacts have to be estimated. In (2), this contemporaneous interaction is reflected by cross-correlation of the reduced-form residuals. However, the information contained in the according covariance-matrix is not sufficient for identification, because due to its symmetry, it delivers only $n(n-1)/2$ equations for simultaneous covariances. The n variances are generally needed to balance the same number of their structural counterparts. In the above-mentioned bivariate Dow-Nasdaq example, this leads for instance to a lack of $2(2-1) - 2(2-1)/2 = 1$ equation. Since simply imposing zero constraints in order to reduce the number of parameters shall be excluded as a reasonable strategy, any acceptable solution logically has to augment the number of available determining equations.

The idea of considering such hitherto neglected information motivates the recent literature of so-called "identification through heteroscedasticity" (e.g. Rigobon 2003): For example, assume that it is possible to identify two separate time regimes with differing variances of the structural residuals ε_t, which shall still be uncorrelated. The variance shift between the regimes would deliver two distinct reduced-form covariance-matrices, so that $n(n-1)/2$ additional covariance equations and n additional variance equations could be obtained from the second matrix. Since the number of free parameters only rises by n, the number of structural variances, full identification can be achieved. While time-varying volatility has become a common feature throughout the empirical financial literature, determining a valid date for imposing a single shift in variance is naturally problematic. Therefore, in this point I will follow the econometric procedure in Weber (2007a), who specifies multivariate EGARCH processes for the structural residuals. This basically keeps up the intuition of identification through volatility regimes. Any ARCH-type model however practically defines a distinct variance state for every single observation. This can be thought of as modelling a quasi continuum of regimes, which is reflected in the estimated conditional variances.

Now, recall that the preceding paragraphs have assumed uncorrelated innovations "for the moment". As explained in the introduction, the absence of any common grounds in factor dependence is economically unrealistic; unfortunately however, unrestricted time-varying covariances would lead to the unfavourable situation that each shift in variance introduces as many structural parameters (variances and covariances) as additional equations from the reduced-form covariance-matrices, so that nothing would be gained from heteroscedasticity. In this respect, the current paper makes the contribution of allowing for contemporaneous interaction in the structural disturbances without compromising identifiability. This obvious dilemma is solved by restricting the covariance dynamics of the structural disturbances to result in constant conditional correlations, leading to the name structural CCC (SCCC) with reference to Bollerslev (1990). The idea is that once the constant correlation coefficient is taken into account, shifts in volatility introduce no additional unknown covariance parameters. Qualitatively comparable considerations underlie the structural factor model in Weber (2007b), which is applicable to systems of at least three endogenous variables.

In the following, the model setup shall be formalised. First, denote the conditional variances of the elements in ε_t by

$$\mathrm{Var}(\varepsilon_{jt}|\Omega_{t-1}) = h_{jt} \qquad j = 1, \ldots, n \; , \tag{3}$$

where Ω_{t-1} stands for the whole set of available information at time $t-1$.

Then, stack the conditional variances in the vector $H_t = \begin{pmatrix} h_{1t} & \ldots & h_{nt} \end{pmatrix}'$.

At last, denote the standardised white noise residuals by

$$\tilde{\varepsilon}_{jt} = \varepsilon_{jt}/\sqrt{h_{jt}} \qquad j = 1, \ldots, n \; . \tag{4}$$

Then, the multivariate EGARCH(1,1)-process, as suggested by Weber (2007a), is given by

$$\log H_t = C + G \log H_{t-1} + D(|\tilde{\varepsilon}_{t-1}| - \iota\sqrt{2/\pi}) + F\tilde{\varepsilon}_{t-1} \; , \tag{5}$$

where C is a n-dimensional vector of constants, G, D and F are $n \times n$ coefficient matrices, and ι denotes a column vector of n ones. The absolute value operation is to be applied element by element and provides the pure magnitude of shocks; the second term in parentheses simply expresses the according expected value. In addition, the signed $\tilde{\varepsilon}_t$ introduce asymmetric volatility effects. In (5), only the conditional variances are modelled. The covariances can be recovered by the constant conditional correlation assumption as

$$\mathrm{Cov}(\varepsilon_{it}, \varepsilon_{jt}|\Omega_{t-1}) = h_{ijt} = \rho_{ij}\sqrt{h_{it}h_{jt}} \qquad i \neq j \; , \tag{6}$$

where ρ_{ij} denotes the correlation between the ith and jth residual. Let ρ stack all ρ_{ij}.

While the last step completes the structural-form model, the conditional covariance-matrix of the reduced-form residuals $A^{-1}\varepsilon_t$ can be sketched as

$$\Sigma_t = A^{-1} \begin{pmatrix} h_{1t} & \leftarrow & h_{ijt} \\ & \ddots & \downarrow \\ \cdot & & h_{nt} \end{pmatrix} (A^{-1})' \; . \tag{7}$$

Since logarithmic modelling prevents the variances to become negative and (7) is in quadratic form, the covariance-matrix is assured to be positive definite accounting for the discussion in Bollerslev (1990). Cross-correlations, as represented by non-zero off-diagonal elements, can arise from spillovers according to the coefficients in A^{-1} or from structural covariances h_{ijt}. In this context, note as well that the constant correlation restriction only applies to the *structural* innovations; the realised variables y_{it} may well feature time-varying correlation depending on the variance developments and the spillovers in A.

Building on the preceding elaboration, identifiability can now be discussed concretely for the given model. For illustrational purposes and without loss of generality, I focus on the bivariate case, which is directly applicable to the Dow-Nasdaq example. The structural variance process (5) contains two parameters in C and four each in G, D and F. Together with the two parameters from the structural matrix A and one from ρ, the sum adds up to 17 coefficients. This has to be compared to the number arising from the reduced-form process for $vech(\Sigma_t)$, where the *vech* operator stacks the lower triangular portion of a matrix into a column vector. For the given example, this vector includes two variances and one covariance. Thus, in a general MGARCH, the equivalent of C has dimension 3×1 and those of G, D and F are 3×3. Consequently, the number of parameters arrives at a total of $3 + 3\,(3 \cdot 3) = 30$, which exceeds 17 and hence satisfies the necessary summing-up constraint. In addition, a sufficient condition is given by linear independence of the conditional variances, which is normally met by ARCH-type processes. Note that an unrestricted MGARCH for the structural residuals would be of the same shape as the one for $vech(\Sigma_t)$, so that no additional information would be obtained to recover the coefficients in A. In the parlance of volatility regimes, this corresponds to using up all additional determining equations for unconstrained covariance parameters.

The estimation can be done by Maximum Likelihood. For this purpose, the log-likelihood under the assumption of conditional normality is constructed as

$$L(A, \rho, C, G, D, F) = -\frac{1}{2} \sum_{t=1}^{T} (n \log 2\pi + \log |\Sigma_t| + y_t' \Sigma_t^{-1} y_t) \ . \tag{8}$$

Maximisation of (8) yields estimates of both the EGARCH parameters and the structural coefficients in A and ρ. As the assumption of conditional normality is often problematic for financial markets data, the estimation relies on Quasi-Maximum-Likelihood (QML, see Bollerslev and Wooldridge 1992). Numerical likelihood optimisation is performed using the BHHH algorithm (Berndt et al. 1974).

3 Blue Chip vs. High Tech

Several times, the preceding discussion has already recurred to the exemplary experiment of analysing mutual and common influences between the Dow Jones Industrial Average and the Nasdaq Composite. Here, the sample of daily returns begins on 2/5/1971, where Nasdaq had started, and ends on 10/31/2007; data source is Reuters. Figure 1 presents the return series and the well-known picture of the index development. Most eye-catching are the Black Monday in 1987 and the extremely volatile period around 2000, where stock prices fell due to the "new economy" bubble burst and the general recession.

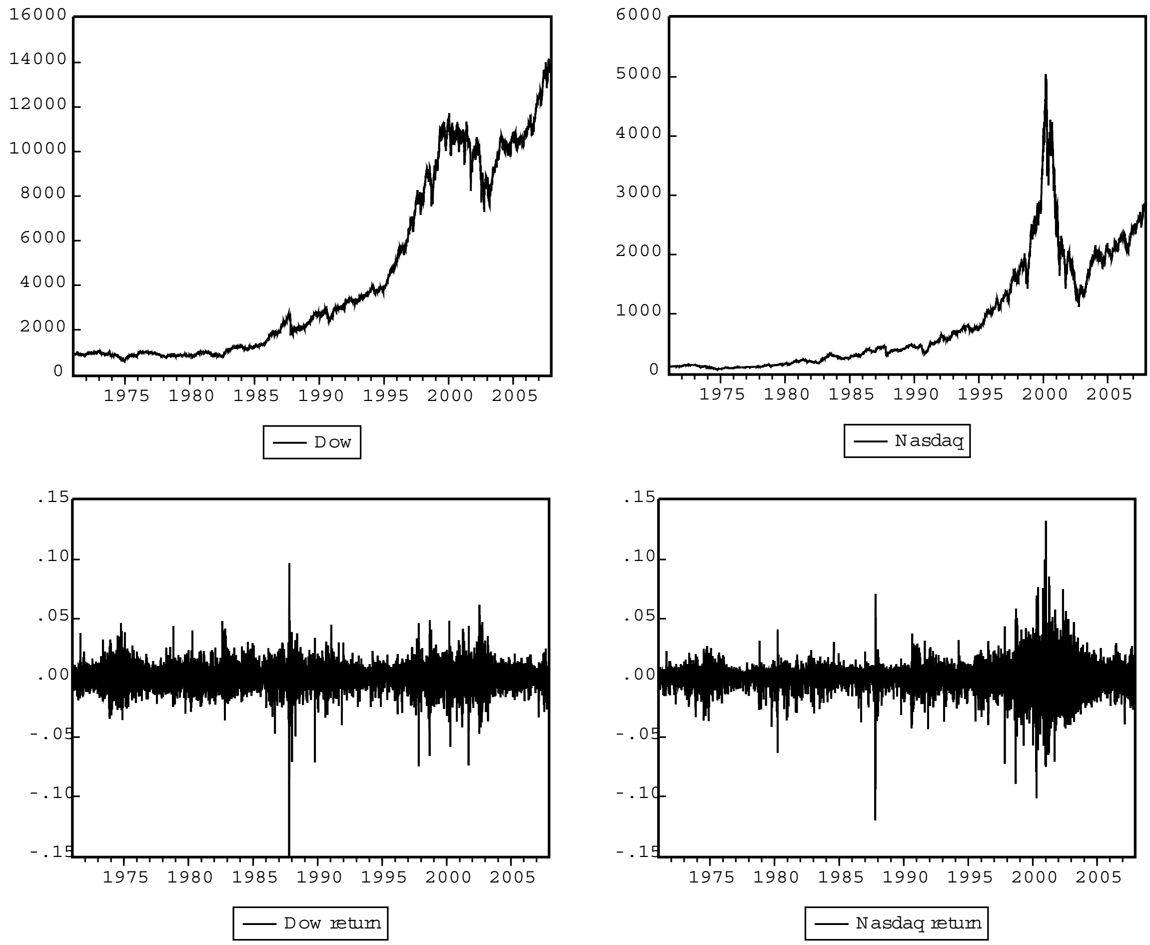

Figure 1: Dow Jones and Nasdaq Composite indexes and returns

The first step of the empirical procedure obtains residuals from regressing the returns on a constant and four day-of-the-week dummies. Based on the suggestion of the Bayesian information criterion, autoregressive lags were not included. Starting values for the optimisation of the likelihood (8) were obtained as follows: The EGARCH parameters were estimated in univariate models, whereas the off-diagonal elements were set to zero. The variance processes were started at the sample moments. A was initialised as the identity matrix, so that ρ equalled the unconditional return correlation; putting more weight on A and less on ρ had no relevant impact on the outcome of the QML procedure. The estimations were carried out in a Gauss programme employing the CML module.

Equations (9) and (10) display the results for the mean and variance models. The variable names denote close-to-close returns at time t and QML standard errors are in parentheses.

$$\begin{aligned} \mathrm{DJIA}_t &= \underset{(0.035)}{0.309}\ \mathrm{NQC}_t + \hat{\varepsilon}_{1t} \\ \mathrm{NQC}_t &= \underset{(0.024)}{0.402}\ \mathrm{DJIA}_t + \hat{\varepsilon}_{2t} \\ \hat{\rho} &= \underset{(0.068)}{0.196} \end{aligned} \tag{9}$$

$$\begin{pmatrix} \log h_{1t} \\ \log h_{2t} \end{pmatrix} = \begin{pmatrix} \underset{(0.003)}{-0.012} \\ \underset{(0.004)}{-0.016} \end{pmatrix} + \begin{pmatrix} \underset{(0.005)}{0.984} & \underset{(0.002)}{-0.007} \\ \underset{(0.006)}{-0.021} & \underset{(0.003)}{0.989} \end{pmatrix} \begin{pmatrix} \log h_{1t-1} \\ \log h_{2t-1} \end{pmatrix} + \begin{pmatrix} \underset{(0.023)}{0.130} & \underset{(0.017)}{0.067} \\ \underset{(0.019)}{0.125} & \underset{(0.018)}{0.171} \end{pmatrix} \begin{pmatrix} |\tilde{\varepsilon}_{1t-1}| \\ |\tilde{\varepsilon}_{2t-1}| \end{pmatrix} + \begin{pmatrix} \underset{(0.011)}{-0.041} & \underset{(0.006)}{-0.029} \\ \underset{(0.010)}{-0.051} & \underset{(0.007)}{-0.035} \end{pmatrix} \begin{pmatrix} \tilde{\varepsilon}_{1t-1} \\ \tilde{\varepsilon}_{2t-1} \end{pmatrix} \tag{10}$$

First of all, the mean equations deliver highly significant spillover effects in both directions. These confirm *a priori* expectations in a sense that the blue chip index Dow Jones dominates the mutual transmission, even if only moderately. Reasons for such spillovers might be found in stock price signalling, wealth and liquidity effects, cross-market hedging, herding behaviour or market microstructure. Furthermore, the benefit gained from the new SCCC model is verified by the estimate for ρ, which is highly significant when related to its standard error as well as in a system likelihood ratio test with $H_0 : \rho = 0$.

The variance model (10) is in line with (9) in that the more sizeable spillovers originate in the Dow Jones. In the volatility domain, transmission effects can economically be ascribed the role of a proxy for information flows between markets (Ross 1989). The negative parameters of the signed shocks represent the well-known asymmetric volatility effects. The negative off-diagonal coefficients in the autoregressive matrix indicate a certain dampening influence, which is however economically small. Being smaller than one, both eigenvalues of this matrix meet the stability criterion, even though the usual substantial persistence in variance can be found.

As a test for appropriate model specification, the autocorrelations of the squared standardised disturbances $\tilde{e}^2_{jt}$ were checked. The approximate 95% confidence bands are never exceeded but by the Nasdaq first-order autocorrelation, which does however not reach significance at the 1% level. In general, this confirms the common results in the literature, which state that GARCH-type models of orders $1, 1$ are fairly appropriate for financial markets data. The standardised residuals have excess kurtosis 4.4 and 1.5, respectively.

On the one hand, this substantiates the decision of using QML standard errors, but on the other hand, more heavy tailed distributions may be applied. As a robustness check, I re-estimated the model under a Student-t-likelihood. Deviations from (9) and (10) were numerically negligible.

However, the most important robustness checks naturally address the appropriateness of the SCCC assumption. A fundamental correlation of $\hat{\rho} = 20\%$ might appear to low for two leading US-based stock segments, especially given the overall unconditional correlation of 69%. As shown by Figure 1, at least the picture of the Nasdaq returns is largely dominated by the volatility generated by bubble and subsequent breakdown in the technology market. Therefore, the estimation procedure is re-run with a sample cut at the end of 1996.[2] The results are as follows:

$$\begin{aligned} \mathrm{DJIA}_t &= \underset{(0.069)}{0.154}\,\mathrm{NQC}_t + \hat{\varepsilon}_{1t} \\ \mathrm{NQC}_t &= \underset{(0.033)}{0.325}\,\mathrm{DJIA}_t + \hat{\varepsilon}_{2t} \\ \hat{\rho} &= \underset{(0.078)}{0.423} \end{aligned} \tag{11}$$

$$\begin{pmatrix} \log h_{1t} \\ \log h_{2t} \end{pmatrix} = \begin{pmatrix} \underset{(0.010)}{-0.039} \\ \underset{(0.015)}{-0.064} \end{pmatrix} + \begin{pmatrix} \underset{(0.009)}{0.975} & \underset{(0.008)}{-0.025} \\ \underset{(0.011)}{-0.040} & \underset{(0.009)}{0.959} \end{pmatrix} \begin{pmatrix} \log h_{1t-1} \\ \log h_{2t-1} \end{pmatrix} + \begin{pmatrix} \underset{(0.028)}{0.119} & \underset{(0.030)}{0.092} \\ \underset{(0.026)}{0.128} & \underset{(0.026)}{0.214} \end{pmatrix} \begin{pmatrix} |\tilde{\varepsilon}_{1t-1}| \\ |\tilde{\varepsilon}_{2t-1}| \end{pmatrix} + \begin{pmatrix} \underset{(0.013)}{-0.028} & \underset{(0.009)}{-0.029} \\ \underset{(0.015)}{-0.055} & \underset{(0.011)}{-0.041} \end{pmatrix} \begin{pmatrix} \tilde{\varepsilon}_{1t-1} \\ \tilde{\varepsilon}_{2t-1} \end{pmatrix} \tag{12}$$

In comparison to model (9), the correlation coefficient has more than doubled to 42%, which is clearly more in line with *a priori* expectations. This considerable change due to the sample shortening suggests that the extremely volatile period around 2000 is obviously not compatible with time-invariant correlation of the fundamental innovations. In particular, the widely celebrated shift from the "old" to the "new" economy sectors as well as the sudden reversal interfered the afore prevailing stable pattern. Nonetheless, the key feature of the first estimation carries over to the outcome in the smaller sample: The Dow still dominates the mutual transmission effects, uniformly in the mean and variance domain.

As a second noteworthy point, let us address the role of volatility spillovers in the given mean-variance multiple equation setup. Therein, similarity in the conditional variances can in principle be taken into account by interaction between the variances themselves or by correlation of the underlying driving shocks. That is, one should expect the CCC coefficient to rise substantially, when the off-diagonal elements in G, D and F are restricted

[2] Cutting the sample in the earlier 1990s does not produce qualitative differences.

to zero. Doing so, the according *full-sample* estimation results in

$$\begin{aligned} \mathrm{DJIA}_t &= \underset{(0.030)}{0.183}\,\mathrm{NQC}_t + \hat{\varepsilon}_{1t} \\ \mathrm{NQC}_t &= \underset{(0.029)}{0.290}\,\mathrm{DJIA}_t + \hat{\varepsilon}_{2t} \\ \hat{\rho} &= \underset{(0.052)}{0.456} \end{aligned} \tag{13}$$

$$\begin{pmatrix} \log h_{1t} \\ \log h_{2t} \end{pmatrix} = \begin{pmatrix} \underset{(0.002)}{-0.002} \\ \underset{(0.002)}{-0.003} \end{pmatrix} + \begin{pmatrix} \underset{(0.004)}{0.986} & 0 \\ 0 & \underset{(0.002)}{0.986} \end{pmatrix} \begin{pmatrix} \log h_{1t-1} \\ \log h_{2t-1} \end{pmatrix} + \begin{pmatrix} \underset{(0.026)}{0.134} & 0 \\ 0 & \underset{(0.020)}{0.213} \end{pmatrix} \begin{pmatrix} |\tilde{\varepsilon}_{1t-1}| \\ |\tilde{\varepsilon}_{2t-1}| \end{pmatrix} + \begin{pmatrix} \underset{(0.014)}{-0.043} & 0 \\ 0 & \underset{(0.007)}{-0.040} \end{pmatrix} \begin{pmatrix} \tilde{\varepsilon}_{1t-1} \\ \tilde{\varepsilon}_{2t-1} \end{pmatrix} . \tag{14}$$

Equations (13) and (14) exactly confirm the above presumption. The same holds for corresponding results in the shorter sample, which are available upon request. Logically, it can be argued that recurring to simple univariate ARCH processes in identifying simultaneous systems may lead to questionable parameter estimates. In particular, imposing parametric zero restrictions on the variance model in order to shift the identification problem from the mean to the volatility domain cannot be regarded as a virtually innocent strategy. Nevertheless, note that the predominance of the Dow is still preserved in the constrained system. In conclusion, the SCCC model yields solid and well-interpretable results, even if caution is advised in applying the SCCC assumption and in adopting adequate conditional volatility specifications.

In principle, the new methodology could be explicitly qualified by Monte Carlo experiments. I abstain from elaborating comprehensive results, simply because sufficiently iterated QML procedures would accumulate a prohibitive computation time. However, small-scale simulations were quite encouraging in that the CCC and spillover parameters showed usual deviations of no more than a few percent. Refining the practical estimation algorithm may bring the potential of further inspection to the fore.

4 Concluding Summary

Finding evidence for causal relations and distinguishing them from comovement based on third-party influences is a recurrent theme throughout many empirical economic analyses. Omnipresent identification problems often restrain the possibilities of estimating models featuring distinct structural interpretation. Recent progress came through literature contributions that exploit (autoregressive conditional) heteroscedasticity in the data in order to obtain the additional information needed for identifying simultaneous systems.

As a shortcoming, these existing approaches rely on assuming that the structural shocks are instantaneously uncorrelated. Consequently, the observed correlation between the included variables is to its full extent explained by mutual causal transmission effects. Obviously, this neglects any model-exogenous factors, which drive all the endogenous variables alike. Since the presence of such driving forces is economically straightforward, the estimation is bound to overstate the bilateral spillovers. Unfortunately, allowing for unrestricted covariance dynamics violates the conditions for identification.

This paper proposed a method of introducing contemporaneous residual interaction, whilst upholding identifiability. In detail, the dilemma is solved by allowing for covariances that develop in accordance with the new concept of structural constant conditional correlation (SCCC). This approach neither imposes zero or constant covariances nor does it imply constant correlation of the observed reduced-form disturbances. The usefulness of the methodology was demonstrated in an example including returns of the Dow Jones and Nasdaq Composite indexes. As might have been expected, the Nasdaq was subject to higher cross-market impacts than the Dow. Furthermore, substantial instantaneous correlation of the structural innovations has been established. In this context, the study was complemented by an insightful discussion of the important role of causality-in-variance effects and the scope of the SCCC assumption. As a result, further progress could be made for instance by constructing structural models allowing for appropriate time-varying correlation behaviour.

References

[1] Berndt, E., B. Hall, R. Hall, J. Hausman (1974): Estimation and Inference in Nonlinear Structural Models. Annals of Social Measurement, 3, 653-665.

[2] Bollerslev, T. (1990): Modeling the coherence in short-run nominal exchange rates: A multivariate generalized ARCH model. Review of Economics and Statistics, 72, 498-505.

[3] Bollerslev, T., J.M. Wooldridge (1992): Quasi-Maximum Likelihood Estimation and Inference in Dynamic Models with Time Varying Covariances. Econometric Reviews, 11, 143-172.

[4] Rigobon, R. (2002): The Curse of Non-Investment Grade Countries. Journal of Development Economics, 69, 423-449.

[5] Rigobon, R. (2003): Identification through heteroscedasticity. Review of Economics and Statistics, 85, 777-792.

[6] Ross, S.A. (1989): Information and volatility: the no-arbitrage martingale approach to timing and resolution irrelevancy. Journal of Finance, 44, 1-17.

[7] Sentana, E., G. Fiorentini (2001): Identification, estimation and testing of conditionally heteroskedastic factor models. Journal of Econometrics, 102, 143–164.

[8] Weber, E. (2007a): Volatility and Causality in Asia Pacific Financial Markets. CRC 649 Discussion Paper 2007-004, Humboldt-Universität zu Berlin.

[9] Weber, E. (2007b): Correlation vs. Causality in Stock Market Comovement. CRC 649 Discussion Paper 2007-064, Humboldt-Universität zu Berlin.

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