The Quarterly Review of Economics and Finance 53 (2013) 53–60

Contents lists available at SciVerse ScienceDirect

The Quarterly Review of Economics and Finance

journal homepage: www.elsevier.com/locate/qref

Simultaneous stochastic volatility transmission across American equity markets☆

Enzo Weber[a,b,*]

[a] Universität Regensburg, D-93040 Regensburg, Germany
[b] Institute for Employment Research (IAB), Germany

ARTICLE INFO

Article history:
Received 29 August 2011
Received in revised form
24 September 2012
Accepted 1 November 2012
Available online 9 November 2012

JEL classification:
C32
G15

Keywords:
Stochastic volatility
Identification
Variance transmission

ABSTRACT

Information flows across international financial markets typically occur within hours, making volatility spillovers appear contemporaneously in daily data. Such simultaneous transmission of variances is featured by the stochastic volatility model developed in this paper, in contrast to usually employed multivariate ARCH processes. The arising identification problem is solved by considering heteroscedasticity of the structural volatility innovations. Estimation takes place in an appropriately specified state space setup. In the empirical application, unidirectional volatility spillovers from the US stock market to three American countries are revealed. The impact is strongest for Canada, followed by Mexico and Brazil, which are subject to idiosyncratic crisis effects.

1. Introduction

For the last several decades, volatility in financial markets has attracted a considerable amount of econometric research. Therein, main strands can be identified as autoregressive conditional heteroscedasticity (ARCH) and stochastic volatility (SV). This sustained interest can be explained by the important role volatility plays in finance disciplines like risk management, portfolio allocation or asset pricing. In the same vein, the *transmission* of volatility between different financial segments attracted attention both from the theoretical and applied perspective. Ross (1989), amongst others, interprets spillovers in variance as information flows between different markets. This view is in line with connecting volatility to market activity variables like trade volume, news arrival or order flow. Furthermore, propagation of variability can be related to spreading uncertainty and transmission of crises, described by the term contagion in the economic literature.

In the vast multivariate ARCH literature, causality in the second moments is given by observed lead-lag-relations. The survey by Laurent, Bauwens, and Rombouts (2006) contains a large collection of ARCH-type models specifying volatility at time t depending on shocks from $t-1$ (and further lags); amongst many others, see the applications of Hassan and Malik (2007) or Koulakiotis, Dasilas, and Papasyriopoulos (2009). *Contemporaneous* interaction is naturally incompatible with the conditional and deterministic model character. However, given that efficient markets process and transmit information quite quickly, in standard daily data financial interaction appears to be instantaneous to a large degree.

The SV approach, reviewed by Chib, Omori, and Asai (2007), can incorporate such contemporaneous commonalities in the volatility processes. This is achieved either by allowing for correlation between the respective stochastic innovations at time t or by considering common factors. Furthermore, SV models are closely linked to theoretical finance and continuous time approaches. For example, Tauchen and Pitts (1983) and Andersen (1996) provide microstructure speculative trading arguments in favour of SV. However, the sources of the contemporaneous commonalities given by reduced-form correlation between the variance shocks are still left unidentified. Consequently, the origins of both information flows and market turbulences cannot be inferred from econometric investigation, at least not without relying on exogeneity assumptions. Nevertheless, such information is important for instance for risk management, monitoring of financial markets or regulative policy in designing sound market structures.

In response to the shortcomings in the ARCH and SV literature, this paper develops a SV model, which accounts for instantaneous variance spillovers across different financial variables. Importantly,

☆ I am grateful to two anonymous referees, Massimo Guidolin, Jürgen Wolters and Cordelia Thielitz for their comments. Of course, all remaining errors are my own.
* Correspondence address: Universität Regensburg, D-93040 Regensburg, Germany. Tel.: +49 941 943 1952; fax: +49 941 943 4917.
E-mail address: enzo.weber@wiwi.uni-regensburg.de

1062-9769/$ – see front matter
http://dx.doi.org/10.1016/j.qref.2012.11.001

causality is not assessed on the basis of conventional approaches relying on lead-lag relations of observed time sequences. Thus, the first contribution lies in formulating a structural-form SV process in contrast to the reduced-form versions proposed in the literature (e.g., Harvey, Ruiz, & Shephard, 1994). Naturally, such a specification creates the problem of identifying the model simultaneity. For this reason, as a second contribution, I take into account ARCH effects in the variances of the structural SV innovations. This time variation in volatility of volatility allows for identifying the contemporaneous structure through heteroscedasticity; see Rigobon (2002), Sentana and Fiorentini (2001) and Weber (2010a, 2010b) for related approaches in the domain of conditional mean models. In consequence, transmission within single days can be quantified without relying on intraday data, which are barely available for many variables and may be subject to serious microstructure problems (e.g., bid-ask bounce, stale quotes, intraday volatility seasonality). In short, the underlying paper combines several techniques that have been treated separately in the literature: SV, GARCH, structural vector autoregression and identification through heteroscedasticity. This approach is entirely new and solves the problem of quantifying simultaneous volatility spillovers.

Eventually, a state space framework is constructed that combines the unobserved SV and ARCH components and paves the way for Quasi Maximum Likelihood (QML) estimation. The model is applied to major stock markets in the US, Canada, Mexico and Brazil, which exhibit large or even perfect overlap in their trading hours. Therefore, addressing volatility spillovers in the conventional way as in Engle, Ito, and Lin (1990) or Melvin and Melvin (2003) is not feasible: these approaches focus on transmission of a single asset's volatility around the globe as different trading places open and close. In contrast, the underlying paper does not rely on such a predetermined time sequence. Namely, the methodology is able to identify unidirectional instantaneous information flows from the S&P 500 to the other American equity exchanges. In terms of variance contributions, it turns out that the US governs 8% of stock market variability in Brazil, 11% in Mexico and 60% in Canada. However, these numbers considerably rise when the turbulent crisis years in the 1990s are excluded.

The paper proceeds as follows: the next section introduces the SV model and discusses estimation by QML. The empirical application is put forth in Section 3, and the last section concludes.

2. Methodology

2.1. Model and identification

The current paper deals with modelling transmission effects in the volatility domain. For the conditional mean the following rather simple specification is chosen, see e.g., Harvey et al. (1994). In detail, assume that each of the k asset returns follows the process

$$y_{it} = \varepsilon_{it} e^{h_{it}/2} \quad i = 1, \ldots, k. \tag{1}$$

Here, h_{it} denotes the log conditional variance of y_{it}, and the ε_{it} are the shocks to the mean. For the vector $\varepsilon_t = (\varepsilon_{1t}, \ldots, \varepsilon_{kt})'$ assume multivariate normality as $\varepsilon_t \sim N(0, \Sigma)$, where the elements on the main diagonal of Σ are normalised to unity. Any interaction effects between the returns are taken into account by the correlations in Σ. In this, a standard specification was chosen in order to concentrate on the key issue of volatility spillovers, which is addressed in the following.

With $h_t = (h_{1t}, \ldots, h_{kt})'$, the data generating process of the log conditional variances is described by the first-order structural vector autoregressive (SVAR) model[1]

$$Ah_t = C + Bh_{t-1} + \eta_t, \tag{2}$$

where C is a k-dimensional vector of constants and η_t the innovations vector. A and B represent $k \times k$ coefficient matrices, so that the off-diagonal elements in A mirror the contemporaneous spillovers between the volatilities. Evidently, the structural volatility process (2) is fully simultaneous and therefore unavoidably subject to the generic identification problem in SVARs. Besides C and B, the set of unknowns consists of k^2 parameters from A, $k(k-1)/2$ covariances between the η_{it} and their k variances.

Normalising the diagonal elements of A to unity reduces the number of unknowns by k. Furthermore, due to the structural character of the model (as in SVARs), the innovations in η_t are assumed to be uncorrelated, eliminating the $k(k-1)/2$ covariances. There remain k^2 unknowns, which has to be compared to the information available from the reduced form

$$h_t = K + \Pi h_{t-1} + u_t, \tag{3}$$

with $K = A^{-1}C$ and $\Pi = A^{-1}B$. Eventually, the covariance matrix of the reduced-form residuals $u_t = A^{-1}\eta_t$ delivers $k(k+1)/2$ distinct determining equations. Altogether, there is still a lack of $k(k-1)/2$ pieces of information.

For solving this indeterminacy, I rely on the idea of utilising heteroscedasticity for identification purposes: basically, assume that the k variances of the SV shocks η_t are time varying. The same then holds for the k reduced-form variances and $k(k-1)/2$ such covariances of u_t, which result directly as linear combinations of the structural variances. Obviously, each shift in variance generates more information from a complete new reduced-form covariance matrix ($k(k+1)/2$) than it introduces additional unknowns (k variances) in the structural form. Thereby, full identification of the simultaneous system can be achieved.

In the conditional mean domain, the general principle of identifying structural heteroscedastic systems was discussed in Sentana and Fiorentini (2001). This subsumes the case of regime switches just as other forms of heteroscedasticity. In particular, instead of relying on single breaks points, ARCH models can be employed to describe a rather continuous volatility process. For financial data, this is likely to provide an appropriate representation of the heteroscedasticity. Further examples are given by Rigobon (2002) and Weber (2010a, 2010b). As an important modification, here I adapt the principle to identification of simultaneity in variance.

For explicit parameterisation, assume $\eta_t \sim N(0, \Omega_t)$, where Ω_t contains $\omega_{1t}, \ldots, \omega_{kt}$ on the main diagonal and zeros off-diagonal. Thus, the SV innovations are allowed to have time-dependent conditional variances ω_{it}. In line with a large literature on time variation in volatility, and specifically Corsi, Mittnik, Pigorsch, and Pigorsch (2008) regarding volatility of volatility, these variances are specified as GARCH(1,1) processes

$$\omega_{it} = (1 - d_i - g_i)\omega_i + d_i \eta_{it-1}^2 + g_i \omega_{it-1} \quad i = 1, \ldots, k, \tag{4}$$

where ω_i denotes the ith unconditional variance and d_i and g_i are the ARCH and GARCH parameters. Due to the conditional uncorrelatedness of the innovations, besides the variances no conditional covariances have to be considered.

Two major differences of this approach to standard GARCH models should be stressed: first, we specify GARCH variances of

[1] Lags of higher orders can be easily introduced in this framework casting the model in VAR(1) companion form.