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Dynamic cross-autocorrelation in stock returns☆

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ABSTRACT

I investigate whether the cross-autocorrelation pattern of US small- and large-firm returns changes with the variance of returns using an exponential vector autoregressive model with volatility. The model allows the testing of dynamic cross-autocorrelation effects, while controlling for own time-varying autoregressive coefficients. Using daily and weekly data from 1965 to 2015, a constant cross-autocorrelation pattern is rejected. Returns on a large-firm portfolio are found to lead returns on a small-firm portfolio. The lead-lag relation changes over time with the variance of the large-firm returns. Traditional vector autoregressions with constant cross-autoregressive coefficients appear to be overly restrictive when testing lead-lag relations in stock markets.

1. Introduction

A number of papers study time-varying autocorrelation in stock returns (e.g. Chen et al., 2008; Campbell et al., 1993). In contrasts, time-varying cross-autocorrelation among stock returns has received less attention. Rothman et al. (2001) and Camacho (2004) investigate dynamic lead-lag relations between macroeconomic variables such as money and output, but cross-autocorrelation effects in stock markets are commonly tested by vector autoregressions (VARs) with constant own- and cross-autoregressive coefficients (e.g. Boulatov et al., 2013; Hou, 2007; Chordia and Swaminathan, 2000).[1] This study explores whether the cross-autocorrelation pattern of US small- and large-firm returns changes with the conditional variance of returns.

Three explanations support time-varying cross-autocorrelation between stock returns. Of these explanations, two can explain a lead-lag relation between small- and large-firm returns. First, a model proposed by Chan (1993) explains cross-autocorrelations among stock returns in a context where market makers observe noisy signals about their stocks, but cannot immediately condition prices on the signals of other stocks, which contain market-wide information. The model implies that both own- and cross-autocorrelations can vary with the size of market movement. This view is supported by Chan's empirical results, which show that both own- and cross-autocorrelation coefficients of daily US stock returns are higher under large market movements than small ones. If the signal quality is better for large firms than for small firms, the model explains why large firm returns have a tendency to lead small firm returns.

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[1] Previous studies consider various explanations for autocorrelation and cross-autocorrelation in stock returns (see, for example, Anderson, 2011; Bernhardt and Mahani, 2007; Hou, 2007).

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Second, nonsynchronous trading can cause spurious autocorrelation and cross-autocorrelation in individual security and portfolio returns, implying that changes in trading probabilities may cause variation in the own- and cross-autocorrelation patterns over time. Lo and MacKinlay (1990) demonstrate that an asymmetry of cross-autocorrelations among securities can exist if trading probabilities among securities differ. Their empirical results imply that weekly returns of large firms lead small-firm returns. Although firm size acts as a proxy for relative market thinness, markets would have to be unrealistically thin to claim that nonsynchronous trading could be the only reason for the observed autocorrelation patterns (see Lo and MacKinlay, 1990; Chan, 1993).

Schwert (1989) highlights three theories that predict a positive relation between volatility and volume.[2] If volume is related to changes in cross-autocorrelations, the variance of returns may partly capture these changes. For example, Chordia and Swaminathan (2000) report that returns of high-volume portfolios lead returns of low-volume portfolios after controlling for firm size, and argue that nonsynchronous trading cannot solely explain these findings. They report that low-volume portfolios respond more slowly to information in market returns and that different speed of information adjustment is a significant source of cross-autocorrelation among short-horizon stock returns. The result that market-wide information affects the cross-autocorrelation pattern comports with the model of Chan (1993). Moreover, their finding that differences in adjustments to information are a source of cross-autocorrelation is in line with Chan's (1993) model, where differences in signal quality between stocks affect lead-lag patterns.

Third, a number of studies show that autocorrelations in stock returns change over time, making it unlikely that cross-autocorrelations would simultaneously remain time-invariant. Campbell et al. (1993) report that autocorrelation in stock market indexes and large individual stock returns declines with trading volume. McKenzie and Faff (2003) also document a negative relation between trading volume and the first-lag autocorrelation in stock returns. Sentana and Wadhwani (1992) report that autocorrelation in daily stock index returns changes with the variance of the index return. In their feedback-trading model (Shiller, 1984; Sentana and Wadhwani, 1992), the demand of the first investor group is based on risk-return considerations, while feedback traders base their demand on past returns. Koutmos (1997) and LeBaron (1992) also find that autocorrelation in stock index returns changes with the variance of returns.

This study extends LeBaron's (1992) exponential autoregressive (EAR) model with volatility to an exponential vector autoregressive (EVAR) model. The extended model allows current values of dependent variables to depend on their own lagged values and on lagged values of other variables with coefficients that change with the conditional variances of the variables. The model allows for testing time-varying cross-autocorrelation effects, while controlling for own time-varying autoregressive coefficients. The model nests LeBaron's original model and a VAR model with time-invariant coefficients and GARCH errors. To my best knowledge, the same modeling approach has not been previously used.

Dynamic cross-autocorrelation is previously studied using a logistic vector smooth transition autoregressive model (LVSTAR) in a macroeconomic context by Rothman et al. (2001) and Camacho (2004). The former investigates nonlinear Granger causality in the money-output relation, while the latter studies the nonlinear relation between the gross-domestic product of the US and the Conference Board composite index of leading indicators. One exception is Hiemstra and Jones (1994), who test linear and nonlinear lead-lag relation between stock returns and volume. In general, an EVAR model and a LVSTAR model both share the idea of two (or more) parameter regimes, while the former uses an exponential function as a transition function instead of a logistic function. Any lagged variable (e.g., lagged return, innovation or squared return or innovation) can act as a transition variable between regimes. He et al. (2009), for example, introduce a VAR parameter constancy test against a special case of the LVSTAR in which the model parameters change from one regime to another as a logistic function of time. The EVAR with volatility considers the conditional variance of the variables as the transition variables.

Using daily and weekly returns on small-firm and large-firm portfolios from 1965 to 2015, a traditional VAR framework is rejected in favor of the EVAR model with volatility. Traditional VARs with time-invariant coefficients are unable to detect dynamic cross-autocorrelations among stock returns. Returns on a large-firm portfolio lead returns on a small-firm portfolio. The lead-lag relation changes with the variance of the large-firm returns. Since the large-firm portfolio closely reflects market movements, this finding is in line with the Chan (1993) model and the empirical findings of Chordia and Swaminathan (2000), implying that market-wide information affects the cross-autocorrelation pattern in stock returns.

For a small-firm portfolio, the first-lag return autocorrelation changes with the variance of the small-firm returns. During low-variance periods, the autoregressive coefficient is significantly higher than during high-variance periods. Since volatility serves as a proxy for information flow, variations in the own- and cross-autoregressive coefficients can be related to the arrival of new information. During low-information periods, persistence in small-firm returns increases, while most of the persistence vanishes during high-information periods. The same applies for the observed lead-lag relation: changes in information flow for the large-firm portfolio affect the lead-lag relation between small and large firms. This may help to explain why a number of empirical studies suggest market efficiency varies over time (see Lim and Brooks, 2011).[3]

The first-lag autocorrelation in large firm returns is found to be time-invariant, implying that previously documented changes in stock market index return autocorrelations (e.g., Campbell et al., 1993) are mainly attributable to the dynamic own- and cross-autocorrelation in small firm returns. Kim et al. (2011) find a relation between changing market conditions and dynamic return

[2] For example, if investors hold heterogeneous beliefs, arrival of new information can cause both price movements and trading volume. Lamoureux and Lastrapes (1990) and Gallant et al. (1992) empirically document a positive relation between volatility and volume.

[3] While I do not attempt to relate my results to market efficiency, it is worth noting that return predictability may not be economically exploitable due to transaction costs.

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