



# Time varying price discovery



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## HIGHLIGHTS

- We show how GARCH models can generate time-varying price discovery measures.
- We find evidence of substantial variation in the price discovery of credit spreads.
- A time-varying information share improves credit spread predictions.

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## ABSTRACT

We show how multivariate GARCH models can be used to generate a time-varying “information share” (Hasbrouck, 1995) to represent the changing patterns of price discovery in closely related securities. We find that time-varying information shares can improve credit spread predictions.

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## 1. Introduction

In this paper we contribute to the existing literature on price discovery, which looks at the incorporation of new information in closely linked securities trading in different markets, by proposing a time varying version of a standard price discovery measure. Specifically, we look at the time varying price discovery of credit spreads obtained from the CDS, bond, equity and option markets. Previous studies in this area show that changes in the price discovery mechanism are rather common. Blanco et al. (2005) find that the CDS market leads the bond market. Bai and Collin-Dufresne (2011) show that, during the financial crisis of 2008, the

price discovery occurring in the CDS market reduces significantly while it increases for the bond market. By looking at stock implied spreads (or returns) alongside CDS and bond spreads, Longstaff et al. (2003), Norden and Weber (2009) and Forte and Peña (2009) find that equities and CDSs lead the bond market. In the latter study as well as in Avino et al. (2013), who further extend the analysis to include option implied credit spreads, such time variations are also explicitly documented.

All the above studies employ either a VAR or VECM as the basis to quantify the price discovery that takes place in each market. With a VECM the percentage of price discovery which occurs in each market for a specific estimation period can be estimated with the “information share” (IS) of Hasbrouck (1995). One limitation of this approach is that the price discovery obtained for each market is fixed during the period under study. As a result, the approach taken so far to highlight time dependence is to estimate and compare price discovery measures in sub-periods of the original sample. We argue that this practice has limited applicability as the sub-periods need to be sufficiently long as to ensure robust estimates. This constrains the frequency with which time variations can be reliably measured.

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## 2. Data

We use daily observations of CDS mid-quotes, bond yields, equity prices and option implied volatilities for Marks & Spencer Plc from January 2006 until July 2009. CDS bid and ask quotes are obtained from GFI. We select senior unsecured CDS contracts with 5-year maturity. Following Blanco et al. (2005), we construct synthetic 5-year credit spreads using yields for two bonds and choose the 5-year swap rates as a proxy for the risk free rate.

We employ the CreditGrades structural model, as detailed in the Technical Document published by RiskMetrics (2002) and Cao et al. (2010), to estimate both the 5-year equity and option implied spreads, respectively. As an estimate of the equity volatility  $\sigma_S$ , we employ a 40-day moving average of past equity stock returns to be consistent with the 2-month maturity used to compute put option implied volatilities for the estimation of the 5-year option implied spreads. All inputs for the implied spreads are taken from Bloomberg.

## 3. Model

The four series of spreads are  $I(1)$  and cointegrated. Hence, we use the following VECM to describe changes in credit spreads in the four markets:

$$\Delta Y_t = \alpha + \Lambda CE_{t-1} + \sum_{k=1}^p \beta_k \Delta Y_{t-k} + \varepsilon_t \quad (1)$$

where

$$Y_t = (CDS_t, BCS_t, EIS_t, OIS_t)',$$

$$\alpha = (\alpha_1, \alpha_2, \alpha_3, \alpha_4)', \quad CE_t = (CE_{1,t}, CE_{2,t}, CE_{3,t})',$$

$$\Lambda = (\lambda_{ij})_{i=1,\dots,4,j=1,\dots,3},$$

$$\beta_k = (\beta_{k,ij})_{i=1,\dots,4,j=1,\dots,4}, \quad k = 1, \dots, p,$$

$$\varepsilon_t = (\varepsilon_{1,t}, \varepsilon_{2,t}, \varepsilon_{3,t}, \varepsilon_{4,t})'$$

$CDS, BCS, EIS$  and  $OIS$  indicate CDS mid-quotes, bond credit spreads, equity implied spreads and option implied spreads, respectively. The cointegrating equations are defined as:

$$CE_{1,t} = CDS_t - \phi_{11} - \phi_{21}OIS_t \quad (2)$$

$$CE_{2,t} = BCS_t - \phi_{12} - \phi_{22}OIS_t \quad (3)$$

$$CE_{3,t} = EIS_t - \phi_{13} - \phi_{23}OIS_t. \quad (4)$$

We then apply a 4-variate GARCH model to the VECM innovations as follows:

$$\varepsilon_t | \Omega_{t-1} \sim N(0, H_t) \quad (5)$$

where  $\Omega_{t-1}$  is the information set at time  $t - 1$ . Our analysis is based on the BEKK specification of the GARCH model of Engle and Kroner (1995):

$$H_t = C'C + A'(\varepsilon_{t-1}\varepsilon'_{t-1})A + B'H_{t-1}B \quad (6)$$

$$\text{where } H_t = \begin{pmatrix} h_{11,t} & \cdots & h_{14,t} \\ \vdots & \ddots & \vdots \\ h_{41,t} & \cdots & h_{44,t} \end{pmatrix}, \quad C = \begin{pmatrix} c_{11} & \cdots & c_{14} \\ \vdots & \ddots & \vdots \\ 0 & \cdots & c_{44} \end{pmatrix},$$

$$A = \begin{pmatrix} a_{11} & \cdots & a_{14} \\ \vdots & \ddots & \vdots \\ a_{41} & \cdots & a_{44} \end{pmatrix}, \quad B = \begin{pmatrix} b_{11} & \cdots & b_{14} \\ \vdots & \ddots & \vdots \\ b_{41} & \cdots & b_{44} \end{pmatrix}.$$

The above model lends itself well to a derivation of a time varying price discovery measure. The original version of Hasbrouck (1995)'s measure, the "information share" is static. The measure consists of an upper and a lower bound. These are derived by first estimating the Cholesky factorization of the covariance matrix ( $C$ )

of the VECM residuals in our system of  $n = 4$  variables in order to eliminate contemporaneous correlation:

$$C = MM' \quad (7)$$

where  $M$  is a lower triangular matrix with elements

$M = (m_{ij})_{i,j=1,\dots,n}$ . The upper and lower bounds of the IS measure for each market  $k$ , with  $1 \leq k \leq n$  are given in Eqs. (8) and (9):

$$IS(UB)_k = \frac{\left[ \sum_{i=1}^n \lambda_i^\perp m_{i1} \right]^2}{\left[ \sum_{i=1}^n \lambda_i^\perp m_{i1} \right]^2 + \left[ \sum_{i=2}^n \lambda_i^\perp m_{i2} \right]^2 + \cdots + \left[ \lambda_n^\perp m_{nn} \right]^2} \quad (8)$$

$$IS(LB)_k = \frac{\left[ \lambda_n^\perp m_{nn} \right]^2}{\left[ \sum_{i=1}^n \lambda_i^\perp m_{i1} \right]^2 + \left[ \sum_{i=2}^n \lambda_i^\perp m_{i2} \right]^2 + \cdots + \left[ \lambda_n^\perp m_{nn} \right]^2} \quad (9)$$

with  $(\lambda_i^\perp)$  the orthogonal vector to the error correction coefficient matrix  $\Lambda$  in the VECM. We follow Baillie et al. (2002) and use the mid-point of the bounds as an estimate of price discovery. We can produce a time dependent (daily) IS by replacing the time-invariant covariance matrix  $C$  used for the calculation of IS measures with its conditional counterpart obtained with (6), under the assumption that the  $\lambda_i^\perp$ 's are stable over the estimation period.

We apply the above IS measure in a simple forecasting exercise. We compare the forecasting power of a VAR of the four series with another VAR which replaces the explanatory variables (the past changes in the spreads) with cross-products of the changes in credit spreads and the IS measures of the corresponding markets, namely:  $IS_{CDS,t-1} \cdot \Delta CDS_{t-1}$ ,  $IS_{BCS,t-1} \cdot \Delta BCS_{t-1}$ ,  $IS_{EIS,t-1} \cdot \Delta EIS_{t-1}$  and  $IS_{OIS,t-1} \cdot \Delta OIS_{t-1}$ . We use a rolling window of length 200 days. The rationale behind this approach is that if a market reveals a large amount of information at any point in time then it should have stronger forecasting power at that time.

## 4. Results

We split our sample into a pre-crisis sub-sample and a crisis sub-sample. We set August 1st, 2007 as the starting time of the crisis period as the cost of insurance against default for several companies doubled in that month.

Descriptive statistics of the four series of credit spreads are shown in Table 1 (Panel A). Average spread changes across the four markets and their volatilities are higher during the subprime crisis. The kurtosis and skewness measures indicate that the distributions of CDS changes for the four markets are not normal regardless of the sub-period considered. The four series of spread changes are autocorrelated and show strong ARCH effects in each sub-period.

Panel B of Table 1 reports the (unconditional) IS measure for each market during each sub-period. The results show that in the pre-crisis period the credit risk price discovery for Marks & Spencer Plc is dominated by the equity implied spreads which account for 86% of the total price discovery, whereas during the subprime crisis the option implied spreads lead with 48% of price discovery, followed by the other markets.

Using the method described above, we compute the daily time-varying IS measure for each of the markets based on the BEKK GARCH specification for the error terms in our VECM, and present these in Fig. 1. The results highlight the variability of the price discovery measure as it allows us to capture a greater variety of patterns than an analysis based on the static IS measure shown in Table 1. Indeed, the period preceding the crisis is mainly characterized by the dominant role of the equity market. Then, in

**Table 1**

Descriptive statistics, cointegration and price discovery for Marks & Spencer Plc. This table reports descriptive statistics (Panel A) for the time series of Marks & Spencer's daily credit spread changes for the CDS, bond, equity and option markets during the period January 2006–December 2012. Panel B reports the midpoint of the unconditional information share (Hasbrouck, 1995) for each market. Statistics are shown for the whole sample, the pre-crisis period (January 2006–July 2007) and the subprime crisis (August 2007–July 2009). Panel C reports the mean squared error for individual forecasts of the credit spreads of each market using a VAR system of equations and a VAR system where the explanatory variables are cross-products of each market's information share and spread changes. The optimal number of lags is chosen according to the Akaike criterion.

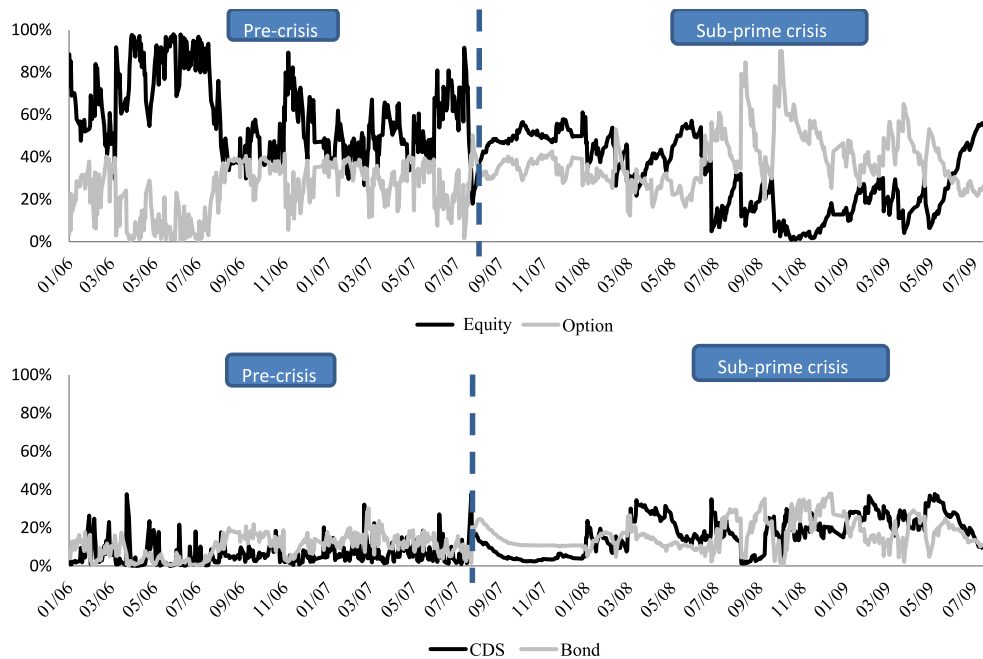
|   | CDS        |                 |              | Bond       |                 |              | Equity     |                 |              | Option     |                 |              |
|---|------------|-----------------|--------------|------------|-----------------|--------------|------------|-----------------|--------------|------------|-----------------|--------------|
|   | Pre-crisis | Subprime crisis | Whole sample | Pre-crisis | Subprime crisis | Whole sample | Pre-crisis | Subprime crisis | Whole sample | Pre-crisis | Subprime crisis | Whole sample |
| <b>A. Summary statistics</b>                    |            |                 |              |            |                 |              |            |                 |              |            |                 |              |
| Mean  | 0.05       | 0.07            | 0.07         | −0.05      | 0.32            | 0.16         | 0.00       | 0.02            | 0.01         | 0.00       | 0.05            | 0.03         |
| Std. Deviation                                  | 1.86       | 14.48           | 10.95        | 1.25       | 9.10            | 6.88         | 0.05       | 63.94           | 48.0         | 0.28       | 63.69           | 48.0         |
| Skewness  | 3.02       | −0.14           | −0.17        | 0.20       | 3.53            | 4.66         | −0.84      | 0.47            | 0.63         | −0.30      | 0.19            | 0.25         |
| Kurtosis  | 38.53      | 5.90            | 10.19        | 4.94       | 42.85           | 74.1         | 39.10      | 130.3           | 231.1        | 48.46      | 22.44           | 39.79        |
| Q(16)   | 15.32      | 38.38***        | 65.81***     | 31.50**    | 59.25***        | 102.5***     | 55.20***   | 4.04            | 7.09         | 86.38***   | 77.85***        | 137.1***     |
| ARCH(16) LM Test                                | 234.2***   | 72.31***        | 183.5***     | 47.74***   | 35.90***        | 69.93***     | 39.33***   | 0.32            | 0.11         | 9.65       | 259.6***        | 475.0***     |
| <b>B. Information share of Hasbrouck (1995)</b> |            |                 |              |            |                 |              |            |                 |              |            |                 |              |
| IS  | 0.02       | 0.16            | 0.14         | 0.04       | 0.18            | 0.18         | 0.86       | 0.19            | 0.20         | 0.08       | 0.48            | 0.49         |
| <b>C. Mean squared error of forecasts</b>       |            |                 |              |            |                 |              |            |                 |              |            |                 |              |
| VAR   | 376.363    |                 |              | 213.60     |                 |              | 8140.14    |                 |              | 5676.25    |                 |              |
| VAR with cross-products                         | 366.13     |                 |              | 153.78     |                 |              | 4794.88    |                 |              | 4754.22    |                 |              |

\* Indicates significance at the 10% level.

\*\* Indicates significance at the 5% level.

\*\*\* Indicates significance at the 1% level.

The Figure shows the daily midpoint of the conditional information share (IS) for the equity and option markets (upper panel) and the CDS and bond markets (lower panel) for Marks & Spencer Plc.



**Fig. 1.** Time-varying price discovery measure for Marks & Spencer Plc.

the heat of the crisis, immediately before and also after the default of Lehman Brothers, the option market takes a clear lead. From the second quarter of 2009, when the crisis subsides and stock markets start to recover, the equity market bounces back to its pre-crisis dominant role.

Panel C of Table 1 reports the mean squared errors for both the VAR model estimated for the four credit spreads and its augmented version (using cross-products as described in Section 3). Our results show that accounting for time variation in price discovery increases the forecasting power of the VAR model as the mean

squared error values of the augmented regressions are always lower than those of the standard VAR.

## 5. Conclusions

In this paper we derive a dynamic price discovery measure that offers the opportunity to represent, in a clear and intuitive way, the time varying behavior of the information flow among markets. In particular, we look at the price formation mechanism in the credit spreads obtained from the CDS, bond, stock and option markets. We show, with a case study, how multivariate GARCH models can

be used to compute a time-varying version of Hasbrouck (1995)'s price discovery indicator. Our results highlight the variability of the information flow across markets and confirm its high sensitivity to changing market conditions. We also show how this time-varying measure can be used to improve the forecasting power of a standard econometric model.

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