CFR-Working Paper NO. 10-06

Tell-Tale Tails: A data driven approach to estimate unique market information shares

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A data driven approach to estimate unique market information shares

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March 26, 2010

Abstract

The trading of securities on multiple markets raises the question of each market's share in the discovery of the informationally efficient price. We exploit salient distributional features of multivariate financial price processes to uniquely determine these contributions. Thereby we resolve the main drawback of the widely used Hasbrouck (1995) methodology which merely delivers upper and lower bounds of a market's information share. When these bounds diverge, as is the case in many applications, informational leadership becomes blurred. We show how fat tails and tail dependence of price changes, which emerge as a result of differences in market design and liquidity, can be exploited to estimate unique information shares. The empirical application of the new methodology emphasizes the leading role of the credit derivatives market compared to the corporate bond market in pricing credit risk during the pre-crisis period.

JEL Classification codes: G10, G14, C32

Keywords: price discovery; information share; fat tails; tail dependence; liquidity; credit risk

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We thank L. Bauwens, R. Blanco, M. Biewen, W. Härdle, N. Hautsch, J. Hasbrouck, K. Kehrle, J. Krahnen, M. Lanne, B. Lehmann, H. Lütkepohl, A. Menkveld, M. Paolella, J. Russell, C. Schlag, C. Trenkler, R. Tschernig, and D. Veredas for helpful comments and support of our work. Earlier versions of this paper were presented at U Aarhus (CREATES), U Berlin, U Frankfurt, U London, and U Louvain (CORE). This research project is funded by the German Research Foundation (DFG) grant GR 2288. We retain responsibility for all remaining errors.

1 Introduction

One of the most frequently asked questions in empirical finance is "Where is the market?" Whether in the case of cross-listings of stocks or newly developed derivative markets, this question has stirred up an enormous amount of research. Booth et al. (2002), for instance, examine the role of upstairs and downstairs markets in the price discovery process at the Helsinki Stock Exchange, while Huang (2002) estimates the contributions of market makers and electronic crossing networks to the price formation of NASDAQ stocks. Hasbrouck (2003) analyzes the importance of different trading venues for the price discovery process of US equity indices. The share of the futures market in US treasury price discovery is the focus of a study by Mizrach and Neely (2008), and Blanco et al. (2005) estimate the share of the bond market and the market of credit default swaps in the process of pricing credit risk. While dealing with the same question in different trading environments, all these studies report Hasbrouck (1995) information shares which is the most prevalent approach to measure contributions to price discovery.

In this paper we resolve the main drawback of Hasbrouck's (1995) methodology which does not deliver a unique measure, but merely information share upper and lower bounds. These bounds can diverge considerably and hinder a clear detection of the market that leads price discovery. Our approach identifies unique information shares by exploiting distributional properties of financial data, namely fat tails and tail dependence. Thereby we deliver a more accurate measure which can be applied to study price discovery in various fields of financial research.

Within Hasbrouck's methodology, information shares are defined as each market's contribution to the variance of the efficient price innovations. However, within a vector equilibrium correction framework the efficient price variance can generally not be decomposed without further restrictions. For that purpose Hasbrouck (1995) uses the Cholesky factorization of the innovation covariance matrix which implies a hierarchical ordering in terms of the contemporaneous information flow. Permuting the ordering of markets results in upper and lower information share bounds. When these bounds diverge, they measure contributions to price discovery very inaccurately.

Our approach towards estimating unique information shares is related to the identification of structural shocks through heteroskedasticity (see Rigobon 2003) and non-normal innovations (see Lanne and Lütkepohl 2010). These papers show that structural innovations within a multiple time series framework can be identified if the data exhibit heteroskedasticity that can be described by a multi-regime process associated with different innovation variances. We connect this insight with two salient facts of financial price processes: fat tailed return distributions combined with tail dependence. We show how these features, which may result from differences in market liquidity, can be exploited to disentangle the contemporaneous correlations of the price innovations across markets. In particular, the occurrence of a large price movement in one market can either represent an informative event or a transitory liquidity shock. Contemporaneous price movements of the other markets reveal the informational content of the large price change, and thereby identify market idiosyncratic innovations. Those *tell-tale* tail observations are the key to deliver unique information shares.

Drawing on the approach put forth by Lanne and Lütkepohl (2010), we assume that market idiosyncratic price innovations come from mixture distributions, and that the observed (composite) price innovations emerge as a linear combination of these structural shocks. We show that the resulting multivariate mixture distribution can account for fat tails and tail dependence, which we exploit for the computation of unique information shares. The basic data requirement to achieve this goal is that the correlations of the market price innovations in the tails and in the center of their joint distribution are sufficiently different.

Since there are no identifying restrictions suggested by finance theory, the possibility to disentangle the contemporaneous correlation structure of price innovations based on distributional properties of financial data is quite appealing. However, we also show that in the absence of further restrictions it is only possible to determine the set of information shares, but not to allocate them uniquely to the markets. We offer a solution by proposing identifying restrictions which naturally arise from the *one security-multiple markets* framework. They require that the idiosyncratic price innovation originating in one market exerts a stronger contemporaneous impact on its own price than on all the other markets. These restrictions enable us to estimate unique market information shares.

We use the new methodology to measure the contribution of the credit default swap and the corporate bond market to the pricing of credit risk. The results emphasize the informational leadership of the more liquid credit derivatives market during the pre-crisis period. They also corroborate the conclusions of previous studies that identify relative market liquidity as the most important variable for explaining market information shares (see Yan and Zivot 2010). Liquidity, as a result of market design, attracts trading volume and promotes a market's leadership in price discovery. Our methodology systematically exploits the informational content of those market design effects to deliver a unique measure of a market's information share.

The remainder of the paper is organized as follows. Section two provides a short review of Hasbrouck's (1995) approach to measure contributions to price discovery. Section three motivates and explains our new methodology, addresses and resolves identification issues and describes the estimation strategy. In Section four we present and discuss the results of the empirical application. Section five concludes.

2 Hasbrouck information shares

The law of one price dictates that prices quoted on different trading venues which refer to the same asset cannot diverge in the long run, since traders who seize arbitrage opportunities will force them back together. Assume that in the case of n parallel markets trading the same asset the dynamics of the vector of market prices $\mathbf{p}_t = (p_{1,t}, \ldots, p_{n,t})'$ can be described by a vector autoregression of order q. Granger's representation theorem then implies a vector equilibrium correction model (VECM),

$$\Delta \mathbf{p}_t = \boldsymbol{\alpha}\boldsymbol{\beta}'\mathbf{p}_{t-1} + \boldsymbol{\Gamma}_1 \Delta \mathbf{p}_{t-1} + \ldots + \boldsymbol{\Gamma}_{q-1}\Delta \mathbf{p}_{t-q+1} + \mathbf{u}_t \quad , \tag{2.1}$$

where $\mathbf{u}_t = (u_{1,t}, \ldots, u_{n,1})'$ is vector white noise with zero mean and covariance matrix $\boldsymbol{\Sigma}_u$. The $(n \times n-1)$ matrix $\boldsymbol{\beta}$ collects the $n-1$ linearly independent cointegrating vectors. Hasbrouck (1995) proposes to normalize $\boldsymbol{\beta}$ using the first market price as a benchmark, i.e. $\boldsymbol{\beta}'{=}[\boldsymbol{\iota}_{n-1} \quad -\mathbf{I}_{n-1}]$, where $\boldsymbol{\iota}_{n-1}$ denotes an $n-1$ dimensional column unit vector and $\mathbf{I}_{n-1}$ the identity matrix of dimension $n-1$. Further, $\boldsymbol{\alpha}$ is an $(n \times n-1)$ matrix of adjustment coefficients, and $\boldsymbol{\Gamma}_1$ through $\boldsymbol{\Gamma}_{q-1}$ are $(n \times n)$ parameter matrices.

A cointegrating rank of $h = n-1$ implies that there exists one stochastic trend common to all n market prices, which is associated with the notion of the efficient price of the underlying asset. It is driven by the permanent impact of idiosyncratic innovations in each of the market's price series. *Idiosyncratic* innovations are contemporaneously and serially uncorrelated zero mean unit variance random variables, $\boldsymbol{\varepsilon}_t = (\varepsilon_{1,t}, .., \varepsilon_{n,t})' \sim (0, \mathbf{I}_n)$. They relate to the *composite* price innovations by $\mathbf{u}_t = \mathbf{B}\boldsymbol{\varepsilon}_t$, where $\mathbf{B}$ denotes a $(n \times n)$ parameter matrix. Johansen (1995) shows that in a VECM as in Equation (2.1) the long run impacts of idiosyncratic innovations on the system variables are given by $\boldsymbol{\Xi}\mathbf{B}\boldsymbol{\varepsilon}_t$, where

$$\boldsymbol{\Xi} = \boldsymbol{\beta}_\perp[\boldsymbol{\alpha}'_\perp(\mathbf{I}_n - \sum_{i=1}^{q-1}\boldsymbol{\Gamma}_i)\boldsymbol{\beta}_\perp]^{-1}\boldsymbol{\alpha}'_\perp \quad , \tag{2.2}$$

with $\boldsymbol{\beta}_\perp$ and $\boldsymbol{\alpha}_\perp$ the orthogonal complements of $\boldsymbol{\beta}$ and $\boldsymbol{\alpha}$. In general, $\boldsymbol{\Xi}$ is of rank $n-h$. Consequently, in the present application $\boldsymbol{\Xi}$ is of rank one and contains identical rows. Stock and Watson's (1988) common trends representation implies that the innovations to the efficient price are given by $v_t = \boldsymbol{\xi}'\mathbf{B}\boldsymbol{\varepsilon}_t$, where $\boldsymbol{\xi}'$ denotes the common row vector in $\boldsymbol{\Xi}$. The variance of the efficient price innovations

$$\mathrm{Var}(v_t) = \boldsymbol{\xi}'\boldsymbol{\Sigma}_u\boldsymbol{\xi} = \boldsymbol{\xi}'\mathbf{B}\mathbf{B}'\boldsymbol{\xi} \tag{2.3}$$

is a weighted sum of the idiosyncratic (unit) variances. The relative market weights define Hasbrouck's (1995) information share measure.

In order to identify $\mathbf{B}$, Hasbrouck (1995) uses the Cholesky factorization of $\boldsymbol{\Sigma}_u = \mathbf{C}\mathbf{C}'$, where $\mathbf{C}$ is the lower triangular Cholesky matrix, such that $\mathbf{B} = \mathbf{C}$. The $(1 \times n)$ vector of market information shares then results from

$$\mathbf{IS} = \frac{[\boldsymbol{\xi}'\mathbf{C}]^{(2)}}{\boldsymbol{\xi}'\mathbf{C}\mathbf{C}'\boldsymbol{\xi}} \quad , \tag{2.4}$$

where $^{(2)}$ denotes an element-wise squaring, such that the ith element of the vector $\mathbf{IS}$ gives the information share of market i.

Due to the arbitrary ordering of the markets in the Cholesky factorization, the information shares in (2.4) are not unique. Since idiosyncratic shocks in a market contemporaneously affect only those markets that have a lower rank in the ordering, the contribution of the market ordered first is maximized and that of the market ordered last is minimized. As there is generally no theoretical justification for such a hierarchy, the common procedure is to permutate the ordering, which results in information share upper and lower bounds. The main drawback of Hasbrouck's methodology is that these bounds can diverge considerably. Hupperets and Menkveld (2002), for instance, examine US listed Dutch blue chip stocks and estimate lower and upper bound information shares that differ by up to 50 percentage points. The information share bounds found by Booth et al. (2002) for the upstairs and downstairs markets at the Helsinki Stock Exchange diverge by about 80 percentage points.

3 Fat tails, tail dependence, and unique information shares

3.1 Motivation and econometric specification

The identification of variance shares and idiosyncratic innovations is a prevalent problem in various fields of economics. As an alternative to the Cholesky decomposition, macroeconomic VAR analyses exploit theoretically motivated restrictions on long run effects, by imposing constraints on $\mathbf{\Xi B}$, and/or short run effects, by imposing restrictions on $\mathbf{B}$ (see Lütkepohl 2008). However, finance theory does not suggest such restrictions concerning the one security-multiple markets framework. As a result, the indeterminacy of Hasbrouck's information share measure remained a caveat for 15 years.[1]

Our proposed solution exploits two stylized facts of financial price processes: fat tails and tail dependence. Fat tails mean that large negative or positive price changes occur more frequently than predicted by a normal distribution (see e.g. Haas et al. 2004). By tail dependence we refer to the phenomenon that the correlation of price changes in the tails of the distribution is different from that in the center (see e.g. Longin 2001). While these empirical facts are not at odds with finance theory, there are no first principles explanations

[1] An attempt to resolve the problem was put forth by Lien and Shrestha (2009) who propose an alternative decomposition of the innovation correlation matrix. However, the economic motivation behind their methodology is unclear.

for their existence.

Before we outline the mathematical details of our methodology, let us first illustrate how fat tails and tail dependence can help disentangle the contemporaneous correlation of the price innovations. For that purpose we follow Rigobon (2003) who uses scatter plots to visualize identification through heteroskedasticity. Our illustration focuses on the case of $n = 2$ markets.

Insert Figure 1 about here

The three panels in Figure 1 depict scatter plots of composite price innovations u_1 and u_2. The upward sloping regression lines indicate the positive contemporaneous correlation of the price innovations on the two markets. All three panels show price innovations clustering in the dense center of the bivariate distributions. In Panels I and II the correlations of the innovations in the center and in the tails of the bivariate distribution are distinctly different. Price innovations in the dense center of the Panel I distribution are positively correlated. However, tail observations in market two do not tend to be accompanied by particularly large absolute values of u_1. The Panel II data also exhibit tail dependence, but the correlation in the dense center is smaller than in the tails. Here the marginal distribution of u_1 is more leptokurtic, with price innovations that are mostly small in absolute value, but with occasional large positive or negative shocks. If, however, there is a large and positive (negative) innovation in market one, then the market two innovation tends to be large and positive (negative), too. The converse does not hold true: The horizontally flattened dense center of the Panel II scatter plot implies that extreme market two price innovations do not tend to be accompanied by u_1 observations that are large in absolute value.

An economic explanation for such observations is that the design of the trading process on market two may entail temporary shortages of liquidity, which cause large absolute price changes. These liquidity shocks on market two do not affect the common efficient price, and thus do not contemporaneously spill over to market one. As it turns out, such market imperfections are very useful for our quest. They reveal the contemporaneous dependence structure which is the key to identify unique information shares. In detail, given the factor structure

$$\begin{pmatrix} u_1 \\ u_2 \end{pmatrix} = \begin{pmatrix} b_{1,1} & b_{1,2} \\ b_{2,1} & b_{2,2} \end{pmatrix} \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \end{pmatrix} \quad , \tag{3.1}$$

the Panel I and II scatterplots suggest that the weight $b_{1,2}$, which transfers an idiosyncratic price shock occurring on market two into the price innovation of market one, is small, while $b_{2,1}$ is large.

Let us now set up a statistical model that accounts for fat tails and tail dependence. For that purpose, we draw on Lanne and Lütkepohl's (2010) idea to identify structural shocks in a VAR framework by assuming mixture distributions for the residuals. Such an assumption may not be obvious or sensible in a macroeconomic analysis involving variables like GDP, money supply, unemployment and interest rates. In the present application, however, it perfectly matches the stylized facts observed in financial data.

We retain the factor structure $\mathbf{u}_t = \mathbf{B}\boldsymbol{\varepsilon}_t = \mathbf{W}\mathbf{e}_t$, where $\mathbf{W}$ denotes a non-singular matrix, and $\mathbf{e}_t$ is an n-dimensional vector of contemporaneously and serially uncorrelated innovations. It results from a mixture of two serially independent Gaussian random vectors,

$$\mathbf{e}_t = \begin{cases} \mathbf{e}_{1,t} \sim \mathscr{N}(\mathbf{0}, \mathbf{I}_n) & \text{with probability } \gamma \\ \mathbf{e}_{2,t} \sim \mathscr{N}(\mathbf{0}, \mathbf{\Psi}) & \text{with probability } 1-\gamma \quad , \end{cases} \tag{3.2}$$

where $0 < \gamma < 1$ and $\mathbf{\Psi}$ is a diagonal matrix with positive elements $\psi_1, .., \psi_n$.

As shown by Rigobon (2003), the identification of structural shocks through heteroskedasticity relies on the existence of regimes with different innovation variances. Unlike Rigobon

(2003), who assumes exogenously defined variance regimes, Equation (3.2) specifies only a regime probability. This entails the necessity to deal with and deliver identifying restrictions. We will address this issue in the next section and for now assume that the set of mixture parameters $\theta_m = \{\gamma, \mathbf{\Psi}, \mathbf{W}\}$ can be uniquely identified.

It follows from (3.2) that the covariance matrix of the idiosyncratic innovations $\mathbf{e}_t$ is given by

$$\mathbf{\Sigma}_e = \gamma \mathbf{I}_n + (1-\gamma)\mathbf{\Psi} \quad , \tag{3.3}$$

such that

$$\mathbf{\Sigma}_u = \mathbf{B}\mathbf{B}' = \mathbf{W}\mathbf{\Sigma}_e\mathbf{W}' \quad , \tag{3.4}$$

which implies that $\mathbf{B} = \mathbf{W}\mathbf{\Sigma}_e^{0.5}$. Information shares which are independent of the ordering of markets, can then be computed replacing the Cholesky matrix $\mathbf{C}$ in Equation (2.4) by $\mathbf{W}\mathbf{\Sigma}_e^{0.5}$, viz

$$\mathbf{IS}_X(\theta_m, \theta_v) = \frac{\left[\xi'\mathbf{W}\mathbf{\Sigma}_e^{0.5}\right]^{(2)}}{\xi'\mathbf{W}\mathbf{\Sigma}_e\mathbf{W}'\xi} \quad , \tag{3.5}$$

where $\theta_v = \{\boldsymbol{\alpha}, \boldsymbol{\beta}, \mathbf{\Gamma}_1, \ldots, \mathbf{\Gamma}_q\}$ collects the VECM parameters. The X subscript indicates that the identification of information shares exploits the informational content of extreme (tail) observations.

Figure 2 illustrates how mixture of normal distributions can produce fat tails and tail dependence. The three Panels reveal that the innovations displayed in Figure 1 were drawn from bivariate normal mixtures with a low and a high variance regime.

Insert Figure 2 about here

Tail dependence prevails in Panels I and II, since here $\psi_1 \neq \psi_2$, while in Panel III $\psi_1 = \psi_2$. Identical regime variances imply that the correlation of the innovations is the same in the low and the high variance regime. In other words, the dependence of innovations in the tails of the distribution is not different from that in the center when $\psi_1 = \psi_2$. Figure 2 also reveals that the off-diagonal elements of the weight matrix $\mathbf{W}$ are as suspected by eyeballing the Panel I and II scatter plots in Figure 1. The parameter $w_{1,2}$ − the weight with which the idiosyncratic market two innovation e_2 contemporaneously affects the price on market one − is smaller than $w_{2,1}$, the weight with which the market one idiosyncratic innovation e_1 contemporaneously affects the price on market two.

Fat tails along with tail dependence represent the basic data features to successfully apply our methodology. Using mixtures of normal distributions, with regime variances that are different across markets, one can account for these features in a statistical model. However, as we will outline in the next section, additional restrictions are required to identify the vector of IS_X information shares according to Equation (3.5).

3.2 Identification

The identification of unique information shares involves two aspects, namely to determine the *set* of information shares and to allocate them to the n markets. As shown by Lanne and Lütkepohl (2010), the identification of the weighting matrix $\mathbf{W}$ requires that the diagonal elements of $\mathbf{\Psi}$ (the idiosyncratic innovation variances) are all different. This result corresponds to Rigobon's (2003) finding that in order to permit identification through heteroskedasticity the regime variances have to be different.

In particular, Lanne and Lütkepohl (2010) show that if $\mathbf{\Psi}$ contains different elements on its main diagonal, then the columns of $\mathbf{W}$ are identified up to a multiplication of one or many of its columns by -1. However, being able to identify the columns of $\mathbf{W}$ only up to a sign shift does not affect the information shares computed according to Equation (3.5). Furthermore, the sign indeterminacy can be easily resolved by restricting the main diagonal elements of $\mathbf{W}$ to be greater than zero. This is a sensible restriction in almost any application. In the context of the present paper it implies that an idiosyncratic price innovation on market i, $e_{i,t}$, contemporaneously impacts on the composite innovation $u_{i,t}$ with the same sign and a nonzero weight.

However, distinct main diagonal elements of $\mathbf{\Psi}$ ensure the identification of the *columns* of $\mathbf{W}$, but not their *ordering*. The consequences are severe, as it is only possible to identify the set of information shares, but not to assign them uniquely to the n markets. As we prove in Appendix A, there exist $n!$ possibilities to allocate information shares to the n markets. These information share vectors result from alternative parametrizations which are observationally equivalent to $\theta_m = \{\gamma, \mathbf{\Psi}, \mathbf{W}\}$. They imply the same joint density of the random vector $\mathbf{u}_t$ which, resulting from Equation (3.2) and $\mathbf{u}_t = \mathbf{W}\mathbf{e}_t$, is given by

$$\begin{aligned} f(\mathbf{u}_t;\theta_m) &= \gamma \times (2\pi)^{-n/2} \det(\mathbf{W})^{-1} \exp\left\{-\frac{\mathbf{u}_t'(\mathbf{W}\mathbf{W}')^{-1}\mathbf{u}_t)}{2}\right\} \\ &\quad + (1-\gamma) \times (2\pi)^{-n/2} \det(\mathbf{\Psi})^{-0.5} \det(\mathbf{W})^{-1} \exp\left\{-\frac{\mathbf{u}_t'(\mathbf{W}\mathbf{\Psi}\mathbf{W}')^{-1}\mathbf{u}_t}{2}\right\} \quad . \end{aligned} \tag{3.6}$$

We refer the reader to Appendix A for a formal proof. The key insight is that distinct diagonal elements of $\mathbf{\Psi}$ identify $\mathbf{W}$ uniquely only if the ordering of the columns of $\mathbf{W}$ cannot be altered. However, the re-parametrization $\theta_m^* = \{\gamma, \mathbf{\Psi^*}, \mathbf{W}^*\}$, where $\mathbf{W}^* = \mathbf{WP}$ and $\mathbf{\Psi}^* = \mathbf{P}'\mathbf{\Psi}\mathbf{P}$, with $\mathbf{P}$ a permutation matrix of order n, is observationally equivalent to the original parametrization $\theta_m = \{\gamma, \mathbf{\Psi}, \mathbf{W}\}$, such that $f(\mathbf{u}_t;\theta_m^*) = f(\mathbf{u}_t;\theta_m)$.[2] This implies that there exist $n! - 1$ sets of mixture parameters which are observationally equivalent to the original parametrization. Furthermore, there exist $n!$ additional parametrizations

[2] A permutation matrix $\mathbf{P}$ results from permuting the rows of an identity matrix. Every row and column therefore contains one element that equals one and the remaining elements are zero. Consequently, there exist $n!$ distinct permutation matrices of order n, one of which is the identity matrix. Post-(pre-) multiplication by a permutation matrix results in a matrix where the columns (rows) of a matrix are interchanged according to the permutation implied $\mathbf{P}$. The operation $\mathbf{WP}$ thus permutes the columns of $\mathbf{W}$. The operation $\mathbf{P}'\mathbf{\Psi}\mathbf{P}$ permutes the diagonal elements of $\mathbf{\Psi}$ accordingly.

$\tilde{\theta}_m = \{\tilde{\gamma}, \widetilde{\mathbf{\Psi}}, \widetilde{\mathbf{W}}\}$ where $\widetilde{\mathbf{W}} = \mathbf{W}\mathbf{\Psi}^{0.5}\mathbf{P}$, $\widetilde{\mathbf{\Psi}} = \mathbf{P}'\mathbf{\Psi}^{-1}\mathbf{P}$ and $\tilde{\gamma} = 1 - \gamma$. These parametrizations are also observationally equivalent to θ_m.

As we show in Appendix A, these alternative parametrizations permute the original information shares according to

$$\mathbf{IS}_X(\theta_m^*, \theta_v) = \mathbf{IS}_X(\tilde{\theta}_m, \theta_v) = \mathbf{IS}_X(\theta_m, \theta_v) \times \mathbf{P} \quad , \tag{3.7}$$

such that there exist $n!$ different, but observationally equivalent information share vectors. In other words, it is impossible to determine which information share belongs to a single market.

Equation (3.7) implies that in order to ensure identification we need additional restrictions that prevent the permutation of the columns of $\mathbf{W}$ and the diagonal elements of $\mathbf{\Psi}$. Fortunately, the one security-multiple markets application framework suggests the following constraints:

$$\begin{aligned} w_{i,i} &> 0 & \forall \quad i \\ w_{i,i} &> |w_{j,i}| & \forall \quad j \neq i \quad , \end{aligned} \tag{3.8}$$

where $w_{i,j}$ is the row i, column j element $\mathbf{W}$. The restriction that the diagonal elements of $\mathbf{W}$ are larger than the remaining elements in the same column is economically plausible, since we expect the weight with which the idiosyncratic shock originating in market i, $e_{i,t}$, contemporaneously affects the own market composite price innovation $u_{i,t}$ to be larger in absolute value than the weights with which it contemporaneously affects the composite price innovations of all other markets.

The restrictions in (3.8) leave $\mathbf{P} = \mathbf{I}_n$ as the only eligible permutation matrix. The two remaining parametrizations θ_m and $\overline{\theta}_m = \{1 - \gamma, \mathbf{\Psi}^{-1}, \mathbf{W}\mathbf{\Psi}^{0.5}\}$ imply the same allocation of information shares to the n markets. Restricting one of the regime variances to be greater than one leaves θ_m as the only eligible parametrization. Together with the restriction that all elements of $\mathbf{\Psi}$ are distinct, the constraints in (3.8) suffice to identify the set of information shares and allocate them uniquely.

3.3 Estimation

Maximum Likelihood presents the natural method to estimate the model parameters. Using $\mathbf{u}_t = A(L)\mathbf{p}_t$, where

$$A(L) = 1 - L - \boldsymbol{\alpha}\boldsymbol{\beta}'L - \mathbf{\Gamma}_1 \Delta L - \ldots - \mathbf{\Gamma}_{q-1}\Delta L^{q-1} \tag{3.9}$$

and Equation (3.6), the conditional log-likelihood function reads

$$\begin{aligned} \mathscr{L}(\theta_m,\theta_v) = \sum_{t=1}^{T} \ln \Bigg(& \gamma \times (2\pi)^{-n/2} \det(\mathbf{W})^{-1} \exp\left\{-\frac{\mathbf{u}_t'(\mathbf{W}\mathbf{W}')^{-1}\mathbf{u}_t}{2}\right\} \\ & + (1-\gamma) \times (2\pi)^{-n/2} \det(\mathbf{\Psi})^{-0.5} \det(\mathbf{W})^{-1} \exp\left\{-\frac{\mathbf{u}_t'(\mathbf{W}\mathbf{\Psi}\mathbf{W}')^{-1}\mathbf{u}_t}{2}\right\}\Bigg) \quad . \end{aligned} \tag{3.10}$$

Estimation of the VECM parameters θ_v and the mixture parameters θ_m in a single step is computationally burdensome. We therefore adopt the two-step estimation strategy outlined by Lütkepohl (2005) and Vlaar (2004). The first step either estimates the cointegrating vectors, or uses those suggested by theory (i.e. $\boldsymbol{\beta}'=[\boldsymbol{\iota}_{n-1} \quad -\mathbf{I}_{n-1}]$). Equation by equation OLS of (2.1) then delivers consistent estimates of θ_v which can be used to compute an estimate of the long run impacts vector $\boldsymbol{\xi}$ from Equation (2.2). The second estimation step maximizes the concentrated log-likelihood which results from replacing the VECM parameters in (3.10) by their first step estimates, i.e. $\mathbf{u}_t$ is replaced by

$$\widehat{\mathbf{u}}_t = (1 - L - \widehat{\boldsymbol{\alpha}}\widehat{\boldsymbol{\beta}}'L - \widehat{\mathbf{\Gamma}}_1\Delta L - \ldots - \widehat{\mathbf{\Gamma}}_{q-1}\Delta L^{q-1})\mathbf{p}_t \quad , \tag{3.11}$$

to obtain estimates of θ_m. Maximization of the concentrated log-likelihood imposes the identifying constraints (3.8). Plugging in the first step estimates $\hat{\theta}_v$ and the second step estimates $\hat{\theta}_m$ in (3.5) delivers IS_X information share estimates. Standard errors for the estimates resulting from this two-step procedure can be delivered by a parametric bootstrap along the lines of MacKinnon (2002). Details are provided in Appendix B.

4 Empirical application

4.1 Credit default swaps, credit spread, and the price of credit risk

To illustrate the benefit of our methodology we revisit a research question addressed by Blanco et al. (2005) who quantify the information share of the corporate bond market and the market for credit derivatives in pricing credit risk. Given the importance of credit securitization and the controversial role played by credit derivatives during the recent financial crisis, research on this topic is more relevant than ever.

Both corporate bonds and credit derivatives, of which credit default swaps (CDSs) are the most important instruments, are traded on over-the-counter markets. The corporate bond market determines credit spreads (p_{CS}), the difference between risky bond yields and the risk-free rate. A CDS is a contract between two counterparties trading credit risk. The protection buyer transfers default risk by paying a fee to the protection seller who is willing to assume the risk. In return, the buyer receives a payoff if the underlying financial instrument defaults. The economic effect of a CDS is thus similar to that of an insurance contract, but the buyer of credit protection via a CDS does not necessary have to hold the insured security. The annualized fee, expressed in basis points of the notional volume, is referred to as the CDS price (p_{CDS}). Since credit spread and CDS price are linked by an approximate arbitrage relation (see Duffie 1999, Hull and White 2000a, Hull and

White 2000b), Blanco et al. (2005) assume cointegration between the two $I(1)$ price series such that $p_{CDS,t} - p_{CS,t}$ is $I(0)$.[3]

Blanco et al.'s (2005) study is an exemplary application of Hasbrouck's (1995) methodology. They set up the VECM in Equation (2.1) with $p_{1,t} = p_{CDS,t}$ and $p_{2,t} = p_{CS,t}$. Here the common stochastic trend can be interpreted as the price of credit risk. This research question is especially interesting for the application of our methodology, since liquidity matters on markets for credit risk. Collin-Dufresne et al. (2001) point out that movements in liquidity premia explain a large proportion of the total variation in credit spreads. As outlined in Section 3, differences in market liquidity are the key to identify unique information shares.

4.2 Data

We make use of the data on CDS prices and credit spreads collected by Blanco et al. (2005).[4] The time series of CDS prices are midpoints of daily close- of-business indicative quotes supplied by the CDS broker CreditTrade and J.P. Morgan Securities. The CDS prices are for single-name standard ISDA benchmark contracts for physical settlement, a notional volume of $ ten million, and five years maturity, the most liquid maturity in the CDS market.[5] Risky bond yields are from Bloomberg. By linearly interpolating yields

[3] The arbitrage relation can be explained as follows. Suppose an investor buys a T-year par bond with yield to maturity of y issued by the reference entity. The investor also buys credit protection on that entity for T years at p_{CDS}. The net annual return is $y - p_{CDS}$ which, by arbitrage, and because default risk is eliminated, should be equal to the T-year risk-free rate denoted by x. If $y - p_{CDS} < x$, then shorting the risky bond, writing protection on the CDS market, and buying the risk free rate would present an arbitrage opportunity. If $y - p_{CDS} > x$, then buying the risky bond and protection, and shorting the risk-free bond becomes profitable. Accordingly, the price of the CDS should equal the credit spread, $p_{CDS} = p_{CS} = y - x$. However, with market imperfections such as liquidity premia, not exactly matching maturity dates, and cheapest to delivery options in case of default, the arbitrage relation is not perfect. Assuming cointegration accounts for the approximate nature of the arbitrage relation between CDS price and credit spread.

[4] We are grateful to R. Blanco for making these data available.

[5] The International Swaps and Derivatives Association (ISDA) contracts define default events and ways of settlement in case of default (cash or physical delivery, i.e. delivery of a reference asset).

between three and five years and yields with more than six and a half years to maturity at the start of the sample, a five-year yield to maturity is estimated to match the CDS maturity. Euro and Dollar five year swap rates, respectively, are used as proxies for the risk-free rate. The resulting time series of CDS prices and credit spreads for 33 reference entities (16 US and 17 European companies) run from January 2, 2001 to June 20, 2002 (383 trading days). In the following, we focus on those 26 reference entities for which the data support the existence of the hypothesized cointegrating relation (see Table III in Blanco et al. 2005). Descriptive statistics are reported in Table 1.

Insert Table 1 about here

4.3 Estimation results and discussion

Two-step estimation of IS_X information shares is performed as described in Section 3.3. Estimation results are reported in Tables 2 and 3. For the first step estimation, we assume the theoretical cointegrating vector $\beta = (1, -1)'$ and $q = 2$ in Equation (2.1). The first step estimates are used to compute upper and lower bounds of Hasbrouck information share estimates and alternative measures of contributions to price discovery. Table 2 reports the mixture parameter estimates and the Wald test results for the null hypothesis of identical regime variances, $\psi_1 = \psi_2$. For all reference entities the null is rejected at conventional significance levels. As outlined above, this is a necessary condition for the identification of unique information shares according to our methodology.

Insert Table 2 about here

Along with IS_X estimates, Table 3 contains lower and upper bounds of the Hasbrouck information share estimates of the CDS market. We further include the estimates of the long run impact coefficients $\boldsymbol{\xi} = (\xi_{CDS}, \xi_{CS})'$, and the ratio of adjustment coefficients

$\lambda_{CS} = \frac{|\alpha_{CS}|}{|\alpha_{CDS}|+|\alpha_{CS}|}$.[6] Standard errors for these estimates as well as for Hasbrouck information shares are obtained applying the non-parametric bootstrap procedure proposed by Grammig et al. (2005).

Insert Table 3 about here

Table 3 shows that the mean of $\hat{\lambda}_{CS}$, averaged across reference entities, amounts to 0.84. This indicates a strong (weak) adjustment of the credit spread (CDS price) to previous day price differences, suggesting that the corporate bond market follows the CDS market.[7] The Hasbrouck information share estimates also indicate a larger contribution of the CDS market to price discovery. While for some reference entities the bounds of the Hasbrouck information shares are narrow, they are quite wide for others. For instance, the lower bound of the CDS market Hasbrouck information share estimate for *Ford* amounts to 52.3 %, (s.e. = 20.3), the upper bound is 80.0 % (s.e. = 16.9).

The last column in Table 3 reports the estimates of the CDS market IS_X information shares. For the reference entity *Ford* the IS_X estimate amounts to 83.4 % (s.e. = 16.8), a value above the Hasbrouck information share upper bound estimate. Table 3 shows that the more pronounced leadership of the CDS market indicated by our unique information share measure is a general result. For those reference entities with wide bounds, the IS_X information shares tend to be close to the Hasbrouck information share upper bounds. The CDS market IS_X estimate averaged across entities amounts to 86.1 % which is close to the mean upper bound of the Hasbrouck share.

This result of a distinct informational leadership of the more liquid CDS market corrobo-

[6] Baillie et al. (2002) show that with $\beta = (1, -1)'$ it follows from Equation (2.2) that $\frac{|\alpha_{CS}|}{|\alpha_{CDS}|+|\alpha_{CS}|} = \frac{|\xi_{CDS}|}{|\xi_{CDS}|+|\xi_{CS}|}$.

[7] Adjustment coefficient ratios are frequently reported in price discovery studies which deal with the one security-two markets framework, often with a reference to Gonzalo and Granger (1995) factor weights (see e.g. Booth et al. 1999, Harris et al. 2002, Eun and Sabherwal 2003). However, their use as a measure of a market's contribution to price discovery has been criticized on methodological and theoretical grounds (see Hasbrouck 1995, Hasbrouck 2002, De Jong 2002, Lehmann 2002, Baillie et al. 2002).

rates the conclusions of Grammig et al. (2008) who study price discovery for internationally cross listed stocks and identify relative market liquidity as the most important variable for explaining the information shares of home and foreign market. Liquidity, as a result of market design, attracts trading volume and promotes a market's leadership price discovery (see also Yan and Zivot 2010). Our findings suggest that this conclusion also holds for markets trading credit risk.

Insert Figure 3 about here

The scatter plots of the VECM residuals depicted in Figure 3 match and illustrate the liquidity story. The four panels show horizontally flattened dense centers of the bivariate distributions, which imply that tail observations for the credit spread residuals do not tend to be accompanied by extreme CDS residuals. However, when the CDS residual is large and positive (negative), the credit spread residual tends to be large and positive (negative), too. This pattern complies with the notion of a corporate bond market where transitory price changes may occur only due to a lack of liquidity. Price innovations in the more liquid CDS market, on the other hand, tend to convey information with respect to the price of credit risk which spills over contemporaneously to the credit spreads.

The estimates of the weight matrix $\mathbf{W}$ reported in Table 2 are in line with these scatter plots. The estimate of $w_{2,1}$, the weight with which an idiosyncratic CDS innovation contemporaneously affects the credit spread, tends to be larger than the estimate of $w_{1,2}$, the weight with which an idiosyncratic credit spread innovation contemporaneously affects the CDS price. The estimate of $w_{1,2}$ is in most cases not significantly different from zero. The relative illiquidity of the corporate bond market thus helps to identify contemporaneous effects and facilitates the estimation of unique information shares.

For some of the reference entities, the bounds of the Hasbrouck information shares are narrow because the contemporaneous correlations of the credit spread and CDS price residuals are small. In these cases, the estimates of the off-diagonal elements of $\mathbf{W}$ are small and not significantly different from zero, and the IS_X estimates are close to the Hasbrouck information share midpoints. We take it as a sign of robustness that both the standard identification method and the one proposed in this paper deliver very similar results when no ambiguity in terms of wide bounds prevails. Furthermore, the estimation precision in terms of standard errors is comparable for Hasbrouck and IS_X information shares. Hence, the increase in precision offered by our methodology is unambiguous.

5 Conclusion

"Where does price discovery take place?" is one of the key questions in empirical finance. It is raised when studying the competition for order flow between traditional and alternative trading platforms, national and international exchanges, and parallel markets for traditional and innovative financial instruments.

Hasbrouck's (1995) methodology is the standard approach to address this research question empirically. He proposes to estimate the information share for each of the parallel markets on which financial instruments linked by the law of one price are traded. Information shares result from a variance decomposition of the innovations of the markets prices' common stochastic trend which is associated with the notion of the efficient price of the underlying security.

The competitive edge of Hasbrouck's information shares over alternative methodologies to measure contributions to price discovery is widely accepted (see the synopsis by Lehmann 2002). However, most applications suffer from a lack of identification since the contemporaneous dependence structure of price innovations across markets cannot be disentangled without further restrictions. As a solution, Hasbrouck (1995) performs a Cholesky decomposition of the covariance matrix of the price innovations. Thereby a hierarchical ordering of markets is assumed that is hardly ever justifyable. In empirical work researchers often resort to permuting the ordering of the markets, which yields upper and lower bounds of information shares rather than a unique measure. These bounds can become so wide that it is impossible to determine even the leading market.

The present paper resolves the problem of indetermined information shares by exploiting the informational content of distributional properties of financial prices. We show that different dependencies of contemporaneous price innovations in the tails and in the center of the distributions deliver the necessary information to determine unique information shares. Such tail dependence can be caused by the design of the trading process which may induce market specific liquidity effects. Since in most applications of the Hasbrouck methodology the market structures are clearly different - this is why alternative trading platforms emerge in the first place - our methodology presents an appealing solution. Regarding the pricing of credit risk, it is the relatively higher liquidity of the CDS market compared to the corporate bond market which sharpens the finding of the informational leadership of the credit derivatives market during the pre-crisis period.

The relation between market liquidity and contributions to price discovery has recently been emphasized by Yan and Zivot (2010). Our methodology systematically exploits the informational content of those market design effects and thereby delivers a unique measure for a market's information share. Researchers concerned with quantifying contributions to price discovery have a new tool to sharpen their conclusions.

Appendix

A Identification: propositions and proofs

Proposition 1. *Denote by* $\theta_m = \{\gamma, \mathbf{\Psi}, \mathbf{W}\}$ *the set of mixture parameters that yields the density of* $f(\mathbf{u}_t;\theta_m)$ *given in Equation (3.6), and by* $\theta_v = \{\boldsymbol{\alpha}, \boldsymbol{\beta}, \mathbf{\Gamma}_1, \ldots, \mathbf{\Gamma}_q\}$ *a set of VECM parameters. Suppose the main diagonal elements of* $\mathbf{W}$ *are all greater than zero, and that the elements of the diagonal matrix* $\mathbf{\Psi}$ *are distinct. Furthermore, let* $\mathbf{IS}_X(\theta_m, \theta_v)$ *denote the vector of information shares given by Equation (3.5). Then, holding the mixture probability* γ *fixed, there exist* $n! - 1$ *further sets of mixture parameters* $\theta_m^* = \{\gamma, \mathbf{\Psi}^*, \mathbf{W}^*\}$ *given by* $n! - 1$ *distinct permutations of the columns in* $\mathbf{W}$ *and the corresponding elements in* $\mathbf{\Psi}$*,*

$$\mathbf{\Psi}^* = \mathbf{P}'\mathbf{\Psi}\mathbf{P} \tag{A.1}$$

$$\mathbf{W}^* = \mathbf{W}\mathbf{P} \tag{A.2}$$

where $\mathbf{P}$ *is a permutation matrix of order* n*. The parametrizations* θ_m^* *are observationally equivalent to* θ_m *in that*

$$f(\mathbf{u}_t;\theta_m) = f(\mathbf{u}_t;\theta_m^*) \quad . \tag{A.3}$$

and permute the original vector of information shares according to

$$\mathbf{IS}_X(\theta_m^*, \theta_v) = \mathbf{IS}_X(\theta_m, \theta_v) \times \mathbf{P} \quad . \tag{A.4}$$

Proof: To prove the first part of Proposition 1 note that the observational equivalence of two mixture parametrizations $\theta_m = \{\gamma, \mathbf{\Psi}, \mathbf{W}\}$ and $\theta_m^* = \{\gamma, \mathbf{\Psi}^*, \mathbf{W}^*\}$ entails identity of the variance covariance matrices $Var(\mathbf{u}_t) = \gamma\mathbf{W}\mathbf{W}' + (1-\gamma)\mathbf{W}\mathbf{\Psi}\mathbf{W}' = \gamma\mathbf{W}^*\mathbf{W}^{*\prime} + (1 -$

$\gamma)\mathbf{W}^*\mathbf{\Psi}^*\mathbf{W}^{*\prime}$. Hence, let $\mathbf{Q}$ be a matrix, such that $\mathbf{W}^* = \mathbf{WQ}$, and $\mathbf{\Psi}^*$ be a diagonal matrix with distinct positive elements. Then $f(\mathbf{u}_t;\theta_m) = f(\mathbf{u}_t;\theta_m^*)$ implies

$$\mathbf{W}[\gamma\mathbf{I}_n + (1-\gamma)\mathbf{\Psi}]\mathbf{W}' = \mathbf{WQ}[\gamma\mathbf{I}_n + (1-\gamma)\mathbf{\Psi}^*]\mathbf{Q}'\mathbf{W}' \quad . \tag{A.5}$$

Multiplication of A.5 from the left with $\mathbf{W}^{-1}$ and from the right with its transpose and rearranging terms yields

$$\gamma(\mathbf{I}_n - \mathbf{QQ}') = (1-\gamma)(\mathbf{Q\Psi}^*\mathbf{Q}' - \mathbf{\Psi}) \quad . \tag{A.6}$$

This holds for $0 < \gamma < 1$ only if both sides of Equation (A.6) are zero which implies that

$$\mathbf{\Psi} = \mathbf{Q\Psi}^*\mathbf{Q}' \tag{A.7}$$

and

$$\mathbf{QQ}' = \mathbf{I}_n \quad . \tag{A.8}$$

It follows from Equation (A.8) that $\mathbf{Q}$ has to be orthogonal, i.e. $\mathbf{Q}' = \mathbf{Q}^{-\mathbf{1}}$. Hence Equation (A.7) can be regarded as a spectral decomposition of $\mathbf{\Psi}$, where $\mathbf{\Psi}^*$ contains the eigenvalues of $\mathbf{\Psi}$ on its diagonal, and the columns of $\mathbf{Q}$ are the corresponding eigenvectors. As all elements of $\mathbf{\Psi}$ are assumed to be distinct, the columns of $\mathbf{Q}$ are linearly independent, unit length vectors. Consequently, all possible solutions for $\mathbf{Q}$ are given by $\mathbf{Q} = \mathbf{PS}$, where $\mathbf{P}$ is an n-dimensional permutation matrix and $\mathbf{S}$ an n-dimensional diagonal matrix, whose diagonal elements are either 1 or -1. Therefore $\mathbf{W}^* = \mathbf{WPS}$, which implies that the columns of $\mathbf{W}$ are identified up to multiplication by -1. However, as the main diagonal elements of $\mathbf{W}$ are restricted to be greater than zero, only $\mathbf{S} = \mathbf{I}_n$ is eligible which yields (A.2). This implies that there exit $n!$ permutations of the columns in $\mathbf{W}$ of which $n! - 1$

yield a matrix $\mathbf{W}^*$ which is distinct from $\mathbf{W}$. The only permutation matrix that leaves the ordering of the columns in $\mathbf{W}$ unchanged is $\mathbf{P} = \mathbf{I}_n$. Regarding Equation (A.7) it follows that

$$\boldsymbol{\Psi} = \mathbf{P}\mathbf{S}\boldsymbol{\Psi}^*\mathbf{S}'\mathbf{P}' = \mathbf{P}\boldsymbol{\Psi}^*\mathbf{P}' \quad . \tag{A.9}$$

Solving for $\boldsymbol{\Psi}^*$ yields (A.1). $\boldsymbol{\Psi}^* = \mathbf{P}'\boldsymbol{\Psi}\mathbf{P}$ is a diagonal matrix, which results from a permutation of the diagonal elements of $\boldsymbol{\Psi}$. This proves the first part of Proposition 1.

To prove (A.4), start from Equation (3.5), which written in detail reads

$$\mathbf{IS}_X(\theta_m, \theta_v) = \frac{\left[\boldsymbol{\xi}'\mathbf{W}(\gamma\mathbf{I}_n + (1-\gamma)\boldsymbol{\Psi})^{0.5}\right]^{(2)}}{\boldsymbol{\xi}'\mathbf{W}(\gamma\mathbf{I}_n + (1-\gamma)\boldsymbol{\Psi})\mathbf{W}'\boldsymbol{\xi}} \quad . \tag{A.10}$$

Since (A.5) holds, θ_m and θ_m^* imply the same covariance matrix of $\mathbf{u}_t$, the denominator in Equation (A.10) is not affected by the permutation of elements in $\mathbf{W}$ and $\boldsymbol{\Psi}$ according to Equations (A.1) and (A.2). Therefore $\mathbf{IS}_X(\theta_m^*, \theta_v)$ can differ from $\mathbf{IS}_X(\theta_m, \theta_v)$ only by their numerators, which relate to each other by

$$\begin{aligned}
[\boldsymbol{\xi}'\mathbf{W}^*(\gamma\mathbf{I}_n + (1-\gamma)\boldsymbol{\Psi}^*)^{0.5}]^{(2)} &= [\boldsymbol{\xi}'\mathbf{W}\mathbf{P}(\gamma\mathbf{I}_n + (1-\gamma)\mathbf{P}'\boldsymbol{\Psi}\mathbf{P})^{0.5}]^{(2)} \\
&= [\boldsymbol{\xi}'\mathbf{W}\mathbf{P}\mathbf{P}'\boldsymbol{\Sigma}_e^{0.5}\mathbf{P}]^{(2)} \\
&= [\boldsymbol{\xi}'\mathbf{W}'\boldsymbol{\Sigma}_e^{0.5}]^{(2)}\mathbf{P} \quad .
\end{aligned}$$

Thus, $\mathbf{IS}_X(\theta_m^*, \theta_v)$=$\mathbf{IS}_X(\theta_m, \theta_v)\mathbf{P}$, such that $\mathbf{IS}_X(\theta_m^*, \theta_v) \neq \mathbf{IS}_X(\theta_m, \theta_v)\ \forall\ \mathbf{P} \neq \mathbf{I}_n$. This leaves $n! - 1$ distinct permutation matrices $\mathbf{P}$ associated with $n! - 1$ different sets of mixture parameters which are observationally equivalent, but imply different information share vectors. Thereby the proposition is proven. $\square$

Proposition 2. *Denote by* $\theta_m = \{\gamma, \boldsymbol{\Psi}, \mathbf{W}\}$ *the set of mixture parameters that yields the density of* $f(\mathbf{u}_t; \theta_m)$ *given in Equation (3.6), and by* $\theta_v = \{\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\Gamma}_1, \ldots, \boldsymbol{\Gamma}_q\}$ *a set of VECM parameters. Suppose that the elements of the diagonal matrix* $\boldsymbol{\Psi}$ *are distinct. Furthermore, let* $\mathbf{IS}_X(\theta_m, \theta_v)$ *denote the vector of information shares given by Equation (3.5). If it holds for the elements of* $\mathbf{W}$ *that*

$$\begin{aligned} w_{i,i} &> 0 & \forall \quad i \\ w_{i,i} &> |w_{j,i}| & \forall \quad j \neq i \end{aligned} \tag{A.11}$$

then there exists only one set of mixture parameters $\overline{\theta} = \{\overline{\gamma}, \overline{\boldsymbol{\Psi}}, \overline{\mathbf{W}}\}$*, given by*

$$\begin{aligned} \overline{\gamma} &= 1 - \gamma \\ \overline{\boldsymbol{\Psi}} &= \boldsymbol{\Psi}^{-1} \\ \overline{\mathbf{W}} &= \mathbf{W}\boldsymbol{\Psi}^{0.5} \quad , \end{aligned} \tag{A.12}$$

that is observationally equivalent to θ_m *in that* $f(\mathbf{u}_t; \theta_m) = f(\mathbf{u}_t; \overline{\theta}_m)$*. Furthermore, the parametrization* $\overline{\theta}_m$ *implies*

$$\mathbf{IS}_X(\overline{\theta}_m, \theta_v) = \mathbf{IS}_X(\theta_m, \theta_v) \quad . \tag{A.13}$$

Proof: Let $\mathbf{Q}$ be a matrix, such that $\overline{\mathbf{W}} = \mathbf{WQ}$, then it has to hold that

$$\mathbf{W}[\gamma \mathbf{I}_n + (1-\gamma)\boldsymbol{\Psi}]\mathbf{W}' = \mathbf{WQ}[(1-\gamma)\mathbf{I}_n + \gamma\overline{\boldsymbol{\Psi}}]\mathbf{Q}'\mathbf{W}' \quad . \tag{A.14}$$

By multiplying (A.14) from the left with $\mathbf{W}^{-1}$ and from the right with its transpose and rearranging terms yields

$$\gamma(\mathbf{I}_n - \mathbf{Q}\overline{\boldsymbol{\Psi}}\mathbf{Q}') = (1-\gamma)(\mathbf{QQ}' - \boldsymbol{\Psi}) \quad . \tag{A.15}$$

This holds only if both sides of Equation (A.15) are zero, which implies that $\mathbf{Q}\overline{\mathbf{\Psi}}\mathbf{Q}' = \mathbf{I}_n$ and that $\mathbf{Q}\mathbf{Q}' = \mathbf{\Psi}$. The latter equation gives $\mathbf{Q} = \mathbf{\Psi}^{0.5}$, and using this result for the first yields $\overline{\mathbf{\Psi}} = \mathbf{\Psi}^{-1}$ and $\overline{\mathbf{W}} = \mathbf{W}\mathbf{\Psi}^{0.5}$, which shows Equation (A.12). The restrictions in (A.11) rule out permuting the columns of $\overline{\mathbf{W}}$ and the diagonal elements of $\overline{\mathbf{\Psi}}$. Without these restrictions $\widetilde{\mathbf{W}} = \overline{\mathbf{W}}\mathbf{P}$ and $\widetilde{\mathbf{\Psi}} = \mathbf{P}\overline{\mathbf{\Psi}}\mathbf{P}'$ with $\mathbf{P} \neq \mathbf{I}_n$ would yield $n!-1$ observationally equivalent parametrizations. Thereby the first part of Proposition 2 is proven.

Since (A.14) holds, the vector $\mathbf{IS}_X(\overline{\theta}_m)$ can only differ from $\mathbf{IS}_X(\theta_m)$ by the vectors in the numerators, but

$$\begin{aligned}
[\boldsymbol{\xi}'\overline{\mathbf{W}}(\overline{\gamma}\mathbf{I}_n + (1-\overline{\gamma})\overline{\mathbf{\Psi}})^{0.5}]^{(2)} &= [\boldsymbol{\xi}'\mathbf{W}\mathbf{\Psi}^{0.5}((1-\gamma)\mathbf{I}_n + \gamma\mathbf{\Psi}^{-1})^{0.5}]^{(2)} \\
&= [\boldsymbol{\xi}'\mathbf{W}((1-\gamma)\mathbf{\Psi}\mathbf{I}_n + \gamma\mathbf{\Psi}\mathbf{\Psi}^{-1})^{0.5}]^{(2)} \qquad \text{(A.16)} \\
&= [\boldsymbol{\xi}'\mathbf{W}(\gamma\mathbf{I}_n + (1-\gamma)\mathbf{\Psi})^{0.5}]^{(2)} \quad .
\end{aligned}$$

As the right hand side of (A.16) is the numerator of $\mathbf{IS}_X(\theta_m)$ it follows that $\mathbf{IS}_X(\overline{\theta}_m) = \mathbf{IS}_X(\theta_m)$ which proves the second part of Proposition 2. $\square$

B Bootstrap

We conduct a parametric bootstrap to provide standard errors and confidence intervals for parameter and information share estimates resulting from the two-step estimation procedure outlined in Section 3.3. The procedure works as follows. We first draw an iid sequence of random variables from a normal mixture distribution. This distribution is generated using the mixture parameters which are estimated in the second (Maximum Likelihood) step of the estimation procedure. Next, we generate simulated price series according to Equation (2.1) using observations from the original price series as starting values, the estimated or pre-specified cointegrating vectors, the first step OLS estimates of the VECM parameters, and the simulated mixture residuals. The length of the simulated series equals the number of observations in the original data set plus 100. We discard the first 100 data points in order to reduce the dependence on the starting values. The two-step estimation procedure described in Section 3.3 is then applied to the simulated data. We store the resulting parameter estimates and compute estimates of $\boldsymbol{\xi}$ using (2.2), upper and lower bounds of Hasbrouck information shares according to (2.4), and IS_X information shares according to (3.5). This procedure is repeated $B = 399$ times, as suggested by Davidson and MacKinnon (2000). They recommend choosing the number of bootstrap replications B such that $\alpha(B + 1)$ is an integer. $B = 399$ implies that the 20th largest bootstrap estimate is the critical value at $\alpha = 0.05$. Standard errors for parameter and information share estimates are computed from the empirical distribution of the bootstrap estimates.

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Figures and Tables

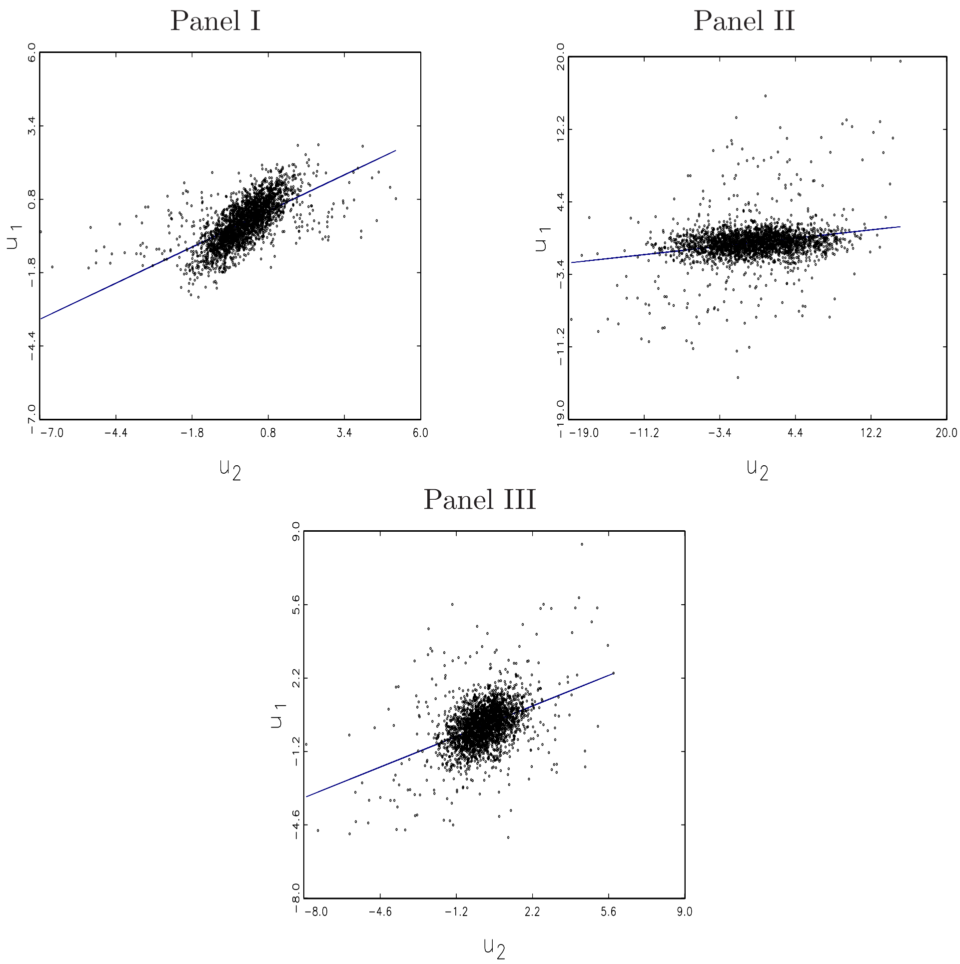
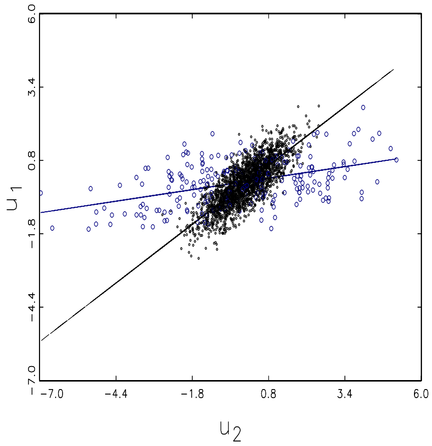


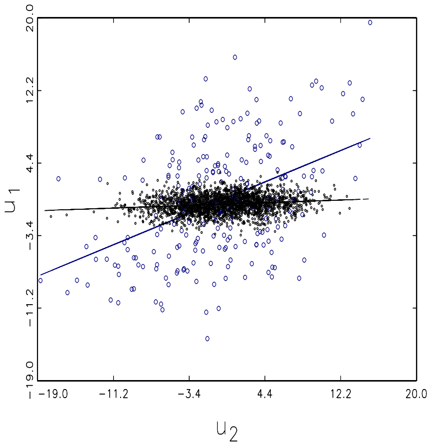
Figure 1: Scatter plots of composite price innovations. The lines result from a regression of u_1 on u_2.

Panel I



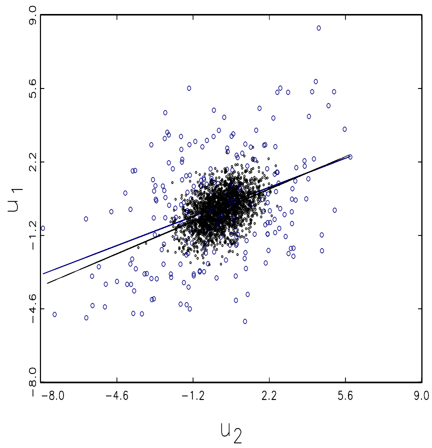
$$\mathbf{W} = \begin{pmatrix} 0.8 & 0.05 \\ 0.6 & 0.5 \end{pmatrix},\ \psi_1 = 1,\ \psi_2 = 20,\ \gamma = 0.9$$

Panel II



$$\mathbf{W} = \begin{pmatrix} 1 & 0.05 \\ 0.5 & 4 \end{pmatrix},\ \psi_1 = 40,\ \psi_2 = 2,\ \gamma = 0.9$$

Panel III



$$\mathbf{W} = \begin{pmatrix} 0.8 & 0.2 \\ 0.2 & 0.8 \end{pmatrix},\ \psi_1 = 10,\ \psi_2 = 10,\ \gamma = 0.9$$

Figure 2: Scatter plots of composite price innovations with DGPs revealed. Data are generated by bivariate mixture distributions. The small dots represent observations from regime 1, the circles represent observations from regime 2. The lines result from regressions of u_1 on u_2 using data from the respective regimes.

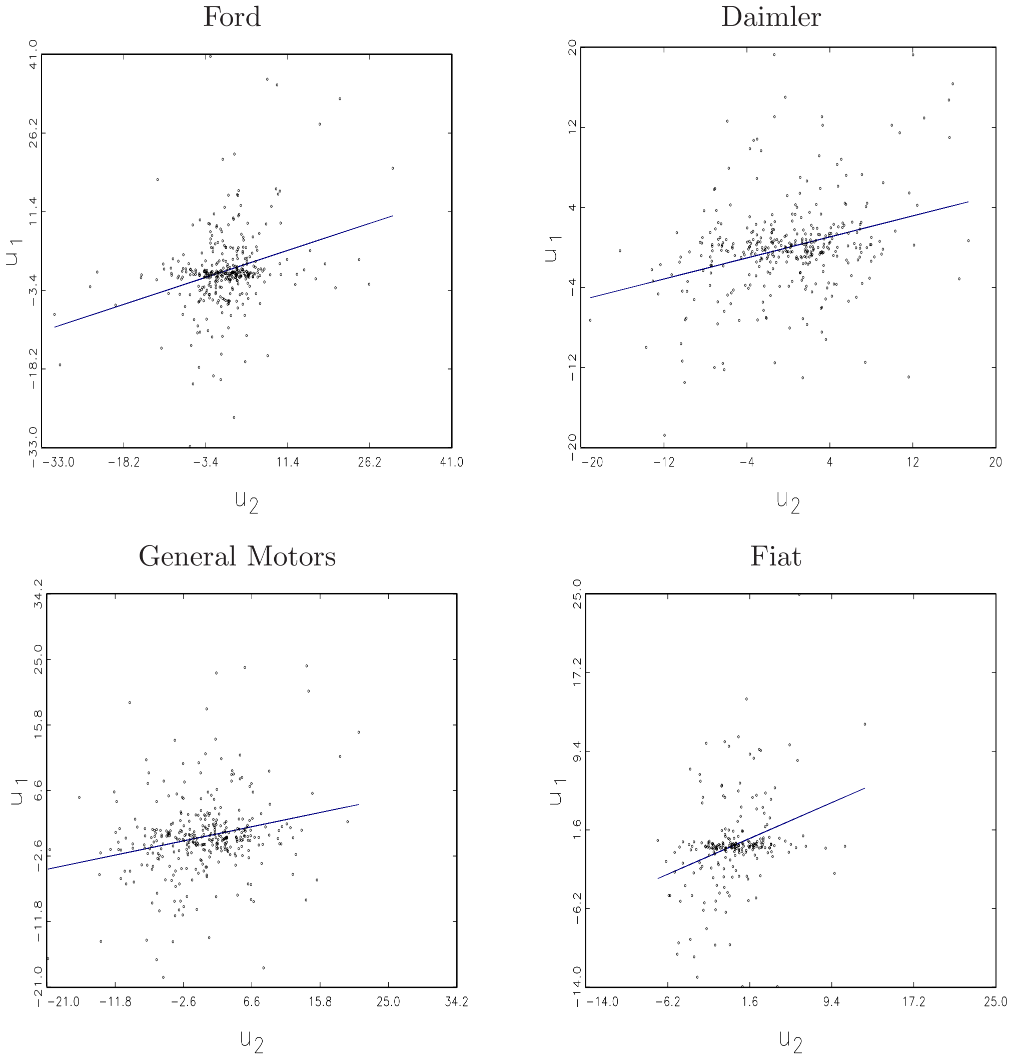


Figure 3: Scatterplots of VECM residuals. The four panels show scatterplots of residuals from the first step VECM estimation for four reference entities. u_1 are CDS residuals, u_2 credit spread residuals. The lines result from a regression of u_1 on u_2.

	Country	Sector	Rating	Mean		Std. Dev.		Kurtosis		
				p_{CDS}	p_{CS}	Δp_{CDS}	Δp_{CS}	Δp_{CDS}	Δp_{CS}	Corr
AOL	United States	Internet	BBB	93.20	80.17	5.48	7.46	17.04	14.54	0.02
Bank of Am.	United States	Banking	A	36.14	39.69	2.58	4.41	12.24	4.73	0.07
Bank One	United States	Banking	A	45.17	50.78	2.71	5.90	5.79	0.51	-0.02
Bear Stearns	United States	Banking	A	71.40	80.93	3.84	6.76	9.83	1.66	0.02
Citigroup	United States	Banking	AA	32.17	26.43	2.72	4.94	9.88	0.70	-0.02
Fleet Boston	United States	Banking	A	49.32	44.08	2.05	4.99	12.31	17.77	0.19
Ford	United States	Automobile/finance	BBB	143.47	140.89	7.57	6.70	7.31	6.57	0.26
GE Capital	United States	Finance	AAA	30.40	7.18	2.27	5.56	71.63	0.63	0.07
General Mot.	United States	Automobile/finance	BBB	119.04	108.39	5.72	6.6	4.22	0.915	0.15
Goldman Sachs	United States	Banking	A	51.91	55.72	2.98	5.40	7.62	0.80	-0.01
JPMorgan	United States	Banking	AA	44.52	42.02	2.67	3.8	7.82	2.648	-0.10
Morgan St.	United States	Banking	AA	47.67	47.98	3.21	4.97	18.69	4.82	0.03
Lehman Bros.	United States	Banking	A	69.86	77.61	3.82	7.28	6.80	1.80	-0.03
Merrill Lynch	United States	Banking	AA	50.24	43.56	2.98	5.58	18.08	0.67	-0.02
Wal Mart	United States	Retail	AA	19.77	-0.85	0.99	4.59	43.99	9.30	0.04
Wells Fargo	United States	Banking	A	26.32	30.17	2.38	5.37	15.60	3.78	-0.07
British Tel.	United Kingdom	Telecom.	A	103.02	113.04	4.12	4.69	2.67	0.60	0.27
Commerzbank	Germany	Banking	A	27.31	14.70	1.11	3.64	32.73	0.44	-0.07
Daimler	Germany	Automobile	BBB	128.50	120.65	4.92	6.01	3.65	1.15	0.28
Deutsche Tel.	Germany	Telecom.	BBB	144.64	121.46	7.70	4.67	5.34	4.36	0.47
Fiat	Italy	Automobi	A	106.30	100.52	4.48	3.27	5.95	3.60	0.31
Iberdrola	Spain	Utilities	A	32.54	49.25	1.01	3.00	40.57	17.80	0.04
Metro	Germany	Retail	BBB	62.94	80.29	1.99	3.55	42.29	6.70	0.06
Siemens	Germany	Telecom.	AA	44.69	33.68	2.04	3.47	9.43	33.48	0.12
Telefonica	Spain	Telecom.	A	85.65	73.31	4.06	2.75	10.13	0.77	0.22
Volvo	Sweden	Automobile	A	72.50	79.83	3.95	2.86	19.19	4.18	0.13

Table 1: Data descriptives. The table lists the reference entities and basic descriptives of CDS prices and corporate bond spreads. We report the mean of the CDS price and credit spreads (in basis points) as well as the standard deviation, kurtosis and correlation of their first differences. The sampling period is January 2, 2001 to June 20, 2002 (383 trading days).

Reference Entity	ψ_1	ψ_2	γ	w_{11}	w_{12}	w_{21}	w_{22}	Wald test
AOL	14954.11	4.85	0.675	0.086	-0.020	0.004	4.711	892
	(1279.24)	(0.81)	(0.038)	(0.197)	(0.029)	(0.048)	(0.207)	< 0.01
Bank of Am.	363.19	1.42	0.640	0.203	0.014	0.032	3.865	375
	(73.77)	(0.26)	(0.030)	(0.061)	(0.022)	(0.032)	(0.211)	< 0.01
Bank One	32.86	1.37	0.655	0.737	-0.053	0.102	4.971	119
	(5.94)	(0.28)	(0.039)	(0.064)	(0.065)	(0.099)	(0.262)	< 0.01
Bear Stearns	119.04	1.90	0.660	0.587	0.000	0.014	5.122	184
	(21.41)	(0.35)	(0.031)	(0.076)	(0.054)	(0.074)	(0.265)	< 0.01
Citigroup	66.63	0.84	0.657	0.535	0.010	0.045	4.652	290
	(11.59)	(0.15)	(0.034)	(0.049)	(0.044)	(0.054)	(0.212)	< 0.01
FleetBoston	71.81	1.72	0.634	0.110	-0.008	0.061	3.834	329
	(132.47)	(0.36)	(0.035)	(0.057)	(0.018)	(0.044)	(0.257)	< 0.01
Ford	22.85	6.44	0.664	2.654	-0.199	0.765	3.655	12
	(4.19)	(1.17)	(0.037)	(0.194)	(0.401)	(0.324)	(0.284)	< 0.01
GE Capital	1588.61	1.63	0.704	0.155	0.002	0.036	4.734	438
	(383.33)	(0.35)	(0.023)	(0.058)	(0.011)	(0.036)	(0.208)	< 0.01
General Mot.	28.99	2.10	0.634	1.523	0.132	0.342	4.883	65
	(5.50)	(0.43)	(0.045)	(0.151)	(0.182)	(0.137)	(0.357)	< 0.01
Goldman Sachs	123.07	1.15	0.656	0.428	-0.056	0.015	4.693	325
	(21.72)	(0.22)	(0.031)	(0.055)	(0.037)	(0.047)	(0.247)	< 0.01
JPMorgan	1229.12	4.52	0.618	0.105	-0.023	-0.011	2.171	367
	(208.01)	(0.85)	(0.033)	(0.081)	(0.031)	(0.029)	(0.169)	< 0.01
Morgan St.	345.38	2.22	0.664	0.293	-0.021	0.025	4.029	269
	(40.36)	(0.48)	(0.029)	(0.076)	(0.042)	(0.030)	(0.109)	< 0.01
Lehman Bros.	82.70	1.07	0.636	0.612	-0.007	-0.027	6.210	208
	(65.20)	(0.40)	(0.028)	(0.068)	(0.027)	(0.040)	(0.210)	< 0.01
Merrill Lynch	861.94	0.92	0.660	0.172	-0.014	-0.008	4.995	882
	(14.51)	(0.20)	(0.034)	(0.076)	(0.060)	(0.072)	(0.344)	< 0.01
Wal Mart	408.64	2.16	0.707	0.138	-0.007	0.054	4.087	213
	(164.31)	(0.15)	(0.031)	(0.080)	(0.018)	(0.027)	(0.231)	< 0.01
Wells Fargo	82.85	1.42	0.679	0.496	0.000	-0.022	4.529	110
	(84.48)	(0.53)	(0.020)	(0.018)	(0.009)	(0.055)	(0.174)	< 0.01
British Tel.	725.77	1.17	0.607	0.201	0.031	0.059	4.157	505
	(14.65)	(0.31)	(0.030)	(0.044)	(0.038)	(0.073)	(0.223)	< 0.01
Commerzbank	488.85	0.66	0.709	0.151	-0.003	-0.038	3.229	233
	(149.08)	(0.24)	(0.035)	(0.119)	(0.037)	(0.042)	(0.277)	< 0.01
Daimler	39.52	2.14	0.621	1.04	0.013	0.388	4.277	83
	(112.52)	(0.24)	(0.023)	(0.032)	(0.011)	(0.033)	(0.153)	< 0.01
Deutsche Tel.	173.24	3.66	0.591	0.730	-0.064	0.227	2.298	115
	(8.17)	(0.44)	(0.043)	(0.123)	(0.139)	(0.101)	(0.334)	< 0.01
Fiat	310.05	1.19	0.623	0.352	-0.001	0.074	2.713	126
	(38.51)	(0.72)	(0.033)	(0.206)	(0.137)	(0.073)	(0.210)	< 0.01
Iberdrola	632.95	5.58	0.708	0.117	-0.007	0.020	2.138	188
	(64.74)	(0.30)	(0.043)	(0.149)	(0.062)	(0.039)	(0.209)	< 0.01
Metro	485.80	8.20	0.691	0.199	-0.043	0.022	2.115	166
	(139.85)	(1.28)	(0.020)	(0.019)	(0.008)	(0.040)	(0.088)	< 0.01
Siemens	1393.36	4.14	0.667	0.098	-0.010	0.022	2.223	395
	(103.40)	(1.82)	(0.028)	(0.046)	(0.023)	(0.056)	(0.112)	< 0.01
Telefonica	567.30	1.46	0.651	0.275	0.004	0.044	2.291	600
	(250.22)	(0.82)	(0.036)	(0.075)	(0.021)	(0.039)	(0.130)	< 0.01
Volvo	225.96	2.79	0.666	0.460	0.075	0.052	2.124	261
	(117.30)	(0.25)	(0.030)	(0.105)	(0.031)	(0.023)	(0.118)	< 0.01

Table 2: Mixture model estimation results. The table shows second step ML estimates of the mixture parameters using the first step VECM residuals as input. The CDS price is the first series, the bond spread the second. In parentheses we report standard errors from a parametric bootstrap (see Appendix B). The last column gives the values of the Wald statistic for a test of $\psi_1 = \psi_2$ along with the corresponding p-values.

Reference Entity	λ_{CS}	ξ_{CDS}	ξ_{CS}	Hasbrouck IS(CDS) low	up	mid	IS_X(CDS)
Ford	0.58	0.31	0.22	52.3	80.0	66.2	83.4
	(0.21)	(0.09)	(0.08)	(20.3)	(16.9)	(18.3)	(16.8)
Daimler	0.81	0.48	0.12	71.3	94.1	82.7	93.9
	(0.23)	(0.12)	(0.11)	(21.8)	(14.2)	(17.6)	(23.0)
Telefonica	0.59	0.29	0.20	65.9	87.0	76.4	86.9
	(0.25)	(0.12)	(0.10)	(23.3)	(20.0)	(21.4)	(13.3)
Fiat	0.79	0.45	0.11	79.4	97.6	88.5	97.6
	(0.20)	(0.16)	(0.14)	(20.2)	(12.5)	(15.8)	(8.9)
General Mot.	0.75	0.40	0.14	72.1	90.1	81.1	88.3
	(0.23)	(0.07)	(0.06)	(16.0)	(11.0)	(13.1)	(11.0)
Volvo	0.52	0.26	0.24	59.0	76.5	67.8	74.5
	(0.22)	(0.08)	(0.07)	(20.4)	(17.8)	(18.8)	(18.0)
British Tel.	0.87	0.50	0.07	82.9	97.8	90.3	97.5
	(0.14)	(0.15)	(0.12)	(20.9)	(13.5)	(16.7)	(15.6)
FleetBoston	0.93	0.48	0.04	84.2	97.1	90.7	97.3
	(0.05)	(0.07)	(0.05)	(19.4)	(10.7)	(14.3)	(9.6)
Commerzbank	0.82	0.42	0.09	69.0	76.9	72.9	69.2
	(0.24)	(0.07)	(0.04)	(20.9)	(22.7)	(21.6)	(13.1)
Wal Mart	0.85	0.41	0.07	58.1	65.8	62.0	66.5
	(0.03)	(0.08)	(0.03)	(21.2)	(20.5)	(20.7)	(9.7)
Siemens	0.88	0.45	0.06	88.7	95.8	92.2	96.1
	(0.23)	(0.10)	(0.08)	(18.0)	(14.0)	(15.8)	(12.4)
Deutsche Tel.	0.72	0.83	-0.33	89.6	95.2	92.4	94.6
	(0.16)	(0.99)	(0.89)	(23.7)	(9.5)	(14.5)	(13.8)
Iberdrola	0.77	0.40	0.12	58.9	64.5	61.7	65.3
	(0.23)	(0.07)	(0.05)	(22.2)	(21.8)	(21.9)	(9.1)
Citigroup	0.72	0.33	0.13	65.8	70.7	68.3	70.4
	(0.15)	(0.04)	(0.03)	(14.9)	(13.7)	(14.0)	(13.6)
Bank One	0.69	0.30	0.14	51.5	56.0	53.8	58.2
	(0.17)	(0.03)	(0.03)	(16.7)	(16.2)	(16.2)	(14.8)
Bank of Am.	0.93	0.43	0.03	95.5	98.7	97.1	98.5
	(0.06)	(0.09)	(0.09)	(17.0)	(13.5)	(15.0)	(11.5)
Morgan St.	0.83	0.42	0.09	88.4	91.3	89.8	91.7
	(0.17)	(0.06)	(0.06)	(16.1)	(14.2)	(15.0)	(18.0)
Wells Fargo	0.75	0.33	0.11	67.1	68.1	68.1	67.1
	(0.11)	(0.04)	(0.04)	(18.4)	(17.2)	(17.2)	(19.6)
Lehman Bros.	0.80	0.39	0.10	84.0	86.0	85.0	84.2
	(0.11)	(0.04)	(0.03)	(10.9)	(11.1)	(10.9)	(12.8)
GECapital	0.98	0.53	0.01	97.8	99.8	98.8	99.8
	(0.16)	(0.08)	(0.05)	(10.1)	(7.5)	(8.6)	(7.9)
Metro	0.88	0.43	0.06	94.0	95.4	94.7	96.8
	(0.19)	(0.07)	(0.06)	(15.0)	(13.8)	(14.2)	(20.5)
Bear Stearns	0.78	0.36	0.10	82.5	83.7	83.1	83.7
	(0.16)	(0.04)	(0.04)	(14.1)	(13.1)	(13.4)	(12.1)
Merrill Lynch	0.90	0.43	0.05	96.5	97.7	97.1	96.7
	(0.26)	(0.05)	(0.04)	(8.7)	(9.3)	(8.9)	(10.1)
JPMorgan	0.94	0.47	0.03	99.2	100.0	99.6	99.4
	(0.12)	(0.09)	(0.08)	(11.6)	(13.7)	(12.4)	(10.5)
AOL	0.97	0.48	0.01	99.6	99.9	99.7	99.9
	(0.23)	(0.08)	(0.07)	(6.4)	(5.2)	(5.7)	(6.9)
Goldman Sachs	0.80	0.37	0.10	84.1	84.1	84.1	85.6
	(0.21)	(0.04)	(0.04)	(12.9)	(12.6)	(12.5)	(11.5)
Mean	0.81	0.42	0.08	78.4	86.6	82.5	86.3
Std. Dev.	0.11	0.10	0.10	15.2	12.9	13.5	13.0

Table 3: Alternative measures for contributions to price discovery. The table reports the adjustment coefficient ratio ($\lambda_{CS} = \frac{|\alpha_{CS}|}{|\alpha_{CS}|+|\alpha_{CDS}|}$), long run impact coefficients (ξ_{CDS} and ξ_{CS}), Hasbrouck information shares for the CDS price (lower bound, upper bound, midpoint) and modified information shares for the CDS price (IS_X(CDS)). The values in parentheses are bootstrap standard errors.

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