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Publication date:
2002

Link to publication in Tilburg University Research Portal

Citation for published version (APA):
Spierdijk, L., Nijman, T. E., & van Soest, A. H. O. (2002). *Modeling Comovements in Trading Intensities to Distinguish Sector and Stock Specific News*. (CentER Discussion Paper; Vol. 2002-69). Econometrics.

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No. 2002-69

MODELING COMOVEMENTS IN TRADING INTENSITIES TO DISTINGUISH SECTOR AND STOCK SPECIFIC NEWS

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July 2002

ISSN 0924-7815

Discussion paper

Modeling Comovements in Trading Intensities to Distinguish Sector and Stock Specific News

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July 23, 2002

Abstract

In this paper we propose a bivariate model for the trading intensities of stocks in a particular industry. The model consists of a univariate duration model for trades in either of the stocks and a probit-specification for which of the two stocks is traded. We apply the model to the trading intensities of stocks of US department store operators listed on the NYSE, using high frequency transaction data during the period August 1 until October 31, 1999. We establish significant comovements in the trading intensities of US department stocks, which we explain by distinguishing sector and stock specific news contained in the trading intensities. We provide estimates of the amounts of sector and stock specific news contained in the trading intensities and show that all stocks under consideration convey both sector and stock specific news.

Keywords: multivariate duration models, high frequency data, ACD-models, market microstructure

JEL classification: C41, G14

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I Introduction

There exists a large literature predicting that trading conveys information on the underlying value of the asset. The key ingredient of asymmetric information models is the presence of informed traders. Informed traders possess private information, which is the very reason why they trade. Uninformed traders, however, have not taken notice of certain information events and trade from liquidity perspectives. Due to the presence of informed traders, trading itself potentially reveals information on future returns. This suggests that the trading intensity or, equivalently, the durations between consecutive trades, may contain information on the underlying value of the asset. Admati and Pfleiderer (1988) and Easley and O'Hara (1992) predict that frequent trading indicates the presence of news, while Diamond and Verrecchia (1987) predict that slow trading refers to bad news.

It is likely that some information events will refer to sector specific news, while others will be stock specific. Suppose that trader A, who owns a specific stock, observes trader B trading a related stock. Trader A knows that there are several possibilities. Trader B is either informed or uninformed. When he is informed, trader B wants to take advantage of private news, that is either sector specific or stock specific news. Since the probability that trader B possesses private sector specific news is positive, his trade reveals information to trader A. Thus, if investors in one stock observe changes in the trade characteristics of related stocks, they know that this may indicate the existence of relevant information. Therefore, they will adapt their own trading behavior in reaction to this.

Comovements in the trading intensities of stocks are relevant from several points of view. The direction of the comovements in trading intensities provides information on lead-lag relationships; i.e. on 'driving' and 'following' stocks. Moreover, the relation between trading intensities provides insight in information dissemination and the dynamics of this process.

Engle and Lunde (1999) and Russell (1999) propose a model that captures the relation between the intensities of the trade and the quote process. Russell (1999) and Davis et al. (2001) jointly model the intensities of several types of events such as market and limit orders. In this paper we propose a more parsimonious reformulation of Russell (1999), consisting of a duration model for trades in the same industry and a probit-model for the type of stock in the industry that is traded. We establish significant comovements in the trading intensities of US department stocks, which we explain by distinguishing sector and stock specific news. We provide estimates of the amounts of sector and stock specific news contained in the trading intensities and show that all stocks under consideration convey both sector and stock specific news.

The setup of this paper is as follows. Section 2 briefly discusses the data. Section 3 provides a review of the literature on multivariate duration models. Section 4 introduces a new model for the joint modeling of several trading intensities. This model is applied to transaction data on stocks of US department store operators in the same section. Section 5 is devoted to distinguishing stock and sector specific news in the trading intensities of stocks of US department stores. In Section 6 the economic effect of the comovements is investigated using a simulation. In Section 7 the model of Section 4 is extended with explanatory variables. Finally, Section 8 concludes.

II The data

This paper uses high frequency data taken from the *Trade and Quote* (TAQ) database, distributed by the NYSE. We consider five large US department store operators (industry code 146) traded on the NYSE. This results in a sample of five stocks including the three largest upscale department store operators of the US, see Table I. The sample covers the period August 1 until October 31, 1999 and consists of 64 trading days.

We remove all trades before 9.30 AM and after 16.00 PM. Moreover, we also delete trades that take place before the first quotes are generated. For all trades in each stock $i = 1, 2, \ldots, 5$ the associated trade moments $\tau_{s,i}$ are recorded, where s indexes subsequent transactions (i.e. s indexes 'transaction time'), $s = 1, 2, \ldots$. The duration (in 'calendar time') between subsequent trades (in the same type of stock) is defined as $y_{s,i} = \tau_{s,i} - \tau_{s-1,i}$. The total number of trades in stock i up to time τ is denoted by $N_i(\tau)$. To deal with multiple trades at the same second in the same stock, we treat multiple transactions at the same time as one transaction. Hence, we follow Engle and Russell (1998) and interpret multiple trades as a single transaction that is split up into several parts[1].

For any combination of two stocks, we compute the durations between two subsequent transactions of the 'pooled' process; i.e. the process consisting of all transactions in any of the two stocks. This process is denoted by $(\tau_t)_t$ and the corresponding pooled duration process is denoted by $(y_t)_t$. The total number of trades up to time τ is denoted by $N(\tau)$. To each transaction of

[1] However, it may also happen that trades in any two stock in our sample take place at the same second. This happens in about 1% of the transactions in our sample. Again we can these multiple trades as one single transaction, but are then left with the problem how to determine the type of stock that corresponds to the (unique) transaction time. We randomly assign the trade to one of both stocks traded at the given point in time. We verified that the way of dealing with multiple transactions is not important for the results.

the pooled process we associate a variable $(z_t)_t$ that gives the type of stock traded; i.e. $z_t \in \{0, 1\}$.
Table I reports some sample statistics for the five department stores selected for this paper. J.C. Penney is the most frequently traded stock (average duration 55 seconds), while Saks is most infrequently traded (average duration 1 minute and 40 seconds).
To get a notion of the comovements among trading intensities of the stocks in the sample, we construct pairs of stocks. Using the five stocks in the sample, this results in ten pairs of stocks. Given stocks i and j, we determine the first transaction in stock j that follows the $(t-1)$-th transaction in stock i; i.e., for each t we determine

$$\tilde{\tau}_{t,j} = \inf\{\tau_{s,j} : \tau_{s,j} > \tau_{t-1,i}\}. \tag{1}$$

Subsequently, we compute the duration between the $(t-1)$-th transaction in stock i and the first transaction in stock j which is given by

$$w_{t,j} = \tilde{\tau}_{t,j} - \tau_{t-1,i}. \tag{2}$$

We compute Spearman's rank correlation between $y_{t-1,i}$ and $w_{t,j}$. For each stock we also report the rank autocorrelation in the durations. The resulting correlations and corresponding t-statistics are given in Table II. For example, for J.C. Penney and Dillard's the 'cross' correlation equals 0.103, with t-value 16.733. Thus, the correlation is significantly positive[2]. We do the same with the roles of the two stocks interchanged. We then establish a correlation of 0.516 with t-value 6.174. This correlation is smaller, but also significantly positive. Furthermore, the autocorrelation in the durations of J.C. Penney equals 0.130 (21.440) and for Dillard's it equals 0.127 (15.410). For the remaining stocks the 'cross' correlations vary from -0.002 (-0.278) to 0.103 (16.733) and the autocorrelations are between 0.048 (7.306) and 0.149 (17.992). The significant cross correlations among the stocks suggest that J.C. Penney contains most sector-specific news, since the impact of J.C. Penney on any other stock is larger than the other way around. The stocks Federated and May contain most sector specific news after J.C. Penney, and, finally, Dillard's and Saks follow.
The correlations reported in Table II can be caused by sector-wide news events, but can equally well be due to other factors such as time of the day periodicities. In order to separate these effects, we will explicitly model the comovements in trading intensities in the next sections. Moreover, in the next sections we will further investigate the amount of sector specific information contained in the trading intensity of each stock.

[2] Unless stated otherwise, hypotheses will be tested at a (two-sided) 5% significance level in the sequel.

III A review of multivariate duration models

In this section we discuss three models that have been proposed to jointly analyze two or more trading intensities. We start with the model of Engle and Lunde (1999). Subsequently we discuss Davis et al. (2001) and Russell (1999).

Engle and Lunde (1999) model one marginal ('independent') duration process and the other ('dependent') process conditional on that. They apply the model to the trade (independent) and quote process (dependent). For the application of this paper, the direction of the causality could be motivated, for example by arguing that company A is much larger than company B (or market leader) and will therefore influence B rather than the other way around. In the context of Section 2, information on A would be more relevant for sector-wide information than information on B, since A is market leader. The Engle and Lunde (1999) model only specifies the dependence between the first duration in the dependent stock that follows a trade in the independent process. Although this leads to an appealing model, the remaining feedback is ignored.

The count in bin (Cbin-) model for counts, see Davis et al. (2001), focuses on the number of trades in each stock during equally spaced time intervals of length Δ. These are specified as conditionally Poisson distributed variables. This approach has the advantage that probabilities in terms of the number of events during some time period usually have a closed-form expression, while this would require simulation in the ACD-like model of Engle and Lunde (1999). However, the main drawback is the choice of the aggregation level, which is arbitrary.

Engle and Russell (1998) explicitly model the durations between trades in a univariate framework. This is a convenient specification for predicting durations if the purpose is not to model the effect of other events on the duration. In the case of two related stocks, however, we want to allow that transactions of the other process affect the conditional expected duration since they may contain information relevant for the other process. This is more conveniently modeled by specifying the conditional intensity function, following Russell (1999). He focuses on a bivariate transaction process, consisting of two dependent transaction processes, indexed by $i = 1, 2$. Let $\underline{y}_{t-1}$ and $\underline{z}_{t-1}$ denote the history of the processes $(y_t)_t$ and $(z_t)_t$ up to time τ_{t-1}, respectively. The conditional intensity function of the i-th transaction process is defined as

$$\begin{aligned} \lambda_{t-1,i}(s) &= \lambda_i(s \mid \underline{y}_{t-1}, \underline{z}_{t-1}) \qquad (3) \\ &= \lim_{\Delta s \to 0} \frac{\mathbb{P}(N_i(s+\Delta s) > N_i(s) \mid \underline{y}_{t-1}, \underline{z}_{t-1})}{\Delta s} \qquad [i = 1, 2]. \end{aligned}$$

For fixed s and conditional upon the history of the process up to time τ_{t-1}, $\lambda_{t,i}(s)\Delta s$ can be interpreted as the (conditional) probability of a transaction of type i during the interval $(s, s+\Delta s]$, for $\Delta s \to 0$. Russell (1999) assumes that the conditional intensity function can be specified as a specific time invariant function of past marginal durations of the two processes. In Russell (1999)'s model, the direction of the dependence between the two processes is not determined a priori and all trades in every stock are taken into account. In the bivariate case, for example, the two processes can be market the market and limit order arrival processes, which is the framework of Russell (1999). He shows that there is significant Granger-causality between the arrival processes of market orders and limit orders. The Russell (1999) model can also be used to jointly model the duration dependence among several stocks, which is the context of this paper. We will show in Section 4 that the model that will be introduced in the next section can be interpreted as a more parsimonious reformulation of the Russell (1999) model.

IV The probit-pooled ACD-model

In the previous sections we discussed several ways to model the dependence between trading intensities of related stocks. The model of Engle and Lunde (1999) is appealing, but restricted to the dependence between durations of one stock on the consecutive duration in the other stock. The Cbin-model of Davis et al. (2001) requires a choice of a time aggregation interval Δ. The Russell (1999) model seems the most flexible specification to examine the comovements in the trading intensities of stocks in the same industry. However, its specification is less appealing than the univariate ACD-model and estimation and simulation of the model is more demanding. Therefore, we propose a more parsimonious and more appealing specification to model dependent trading intensities.

Russell (1999) specifies the conditional intensity functions corresponding to the marginal transaction processes. Instead of modeling the conditional intensity functions of the marginal processes separately, we directly specify the conditional intensity function of the pooled transaction process, as well as the probability that a trade is in either type of stock. We consider the pooled transaction process and use a simple univariate duration model of the ACD-type (cf. Engle and Russell (1998)), possibly including explanatory variables. The type of trade variable is model using a probit-specification. We will call the resulting bivariate model the probit-pooled ACD-model.

We start with the conditional density corresponding to the marks. Since z_t is a binary variable that indicates whether a transaction is a trade in stock

A or stock B, we consider a probit-specification. Let $\Phi(\cdot)$ denote the normal distribution function. We assume

$$p_t = \mathbb{P}(z_t = 0 \mid \underline{y}_t, \underline{z}_{t-1}; \delta) = \Phi(\delta' x_t). \tag{4}$$

Here $x_t = x_t(\underline{y}_t, \underline{z}_{t-1})$ represents a vector of regressors − to be specified later − and δ is the corresponding vector of coefficients. We allow p_t to depend upon lagged values of z_t. An issue that we have to consider is the persistence in the type of trade variable z_t that was established in Section 2. To deal with the persistence effectively, we allow the conditional probability p_t to depend upon lagged values of itself; i.e. we include as potential regressors lagged values of p_t. Furthermore, the type of trade variable z_t may also be affected by how long ago trades in both stocks have taken place. We therefore take

$$\begin{aligned} \delta' x_t &= \delta_1 + \delta_2 z_{t-1} + \delta_3 z_{t-2} + \delta_4 \delta' x_{t-1} \\ &\quad + (\delta_5 + \delta_6 z_{t-1}) y_t + (\delta_7 + \delta_8 z_{t-2}) y_{t-1}. \end{aligned} \tag{5}$$

We include lagged values of the type of trade variable z_t, the pooled durations y_t and $\delta' x_t$. As explained, the likelihood of a trade in one stock may not only depend upon the duration since the most recent trade, but also on the duration since the last trade in either stock. Therefore, we let the coefficients of y_t and y_{t-1} depend upon the type of trade at which the duration started. It will sometimes be convenient to write $p_t = p_t(\underline{z}_{t-1}, \underline{y}_t)$ to emphasize the dependence of p_t upon the past history of the type of trade variable and the durations.

We now turn to the specification of the conditional density corresponding to the pooled duration process, expressed in terms of the diurnally corrected duration process $(y_t)_t$. Let $\mathcal{I}_{t-1}$ denote the information known up to time τ_{t-1}, consisting of the history of the pooled durations and the type of trade variable. We consider a log ACD$(1,1)$-model, see Bauwens and Giot (2000), which is specified as

$$y_t = \psi_t \varepsilon_t, \quad \psi_t = \mathbb{E}(y_t \mid \mathcal{I}_{t-1}), \tag{6}$$

with $(\varepsilon_t)_t$ identically distributed with unit mean and ε_t independent of $\mathcal{I}_{t-1}$. The log of the conditional expected duration is specified as

$$\log \psi_t = \omega + \alpha \log \varepsilon_{t-1} + \beta \log \psi_{t-1} + \gamma \nu_{t-1}, \tag{7}$$

where ν_{t-1} is a row vector of variables related to the type of trade process and γ a vector of parameters. We specify

$$\nu_{t-1} = (\Delta z_{t-1}, \log p_{t-1})'. \tag{8}$$

The model is expressed in terms of diurnally corrected durations which are constructed by proceeding as in Engle and Russell (1998). That is, we obtain the diurnally adjusted durations by approximating the expected duration given the time of the day by a piecewise linear and continuous spline. We therefore set nodes on $9.30-10.00, 10.00-11.00, \ldots, 14.00-15.00, 15.30-16.00$ hours. We compute the diurnally corrected durations by dividing each duration by its corresponding diurnal correction

$$\phi_t = \text{const} + \sum_{i=1}^{8} \lambda_i T_{i,t}, \tag{9}$$

where

$$T_{i,t} = (\tau_{t-1} - k_i) 1_{\{\tau_{t-1} > k_i\}}, \tag{10}$$

and where k_i corresponds to the i-th time interval as defined above. The variable ν_{t-1} is a vector of explanatory variables containing variables related to the type of trade variable. The variable $\Delta z_t = z_{t-1} - z_{t-2}$ indicates whether or not a change in the type of trade variable has taken place and in which direction. Such a change may convey information and therefore, it may affect the trading behavior of traders and thus their speed of trading. The variable $\log p_{t-1}$ represents the log of the conditional probability of a trade in stock A. When, for example, stock A contains much sector specific news, it may be the 'driving ' process behind the pooled transaction process. In this case, a high conditional probability of a trade in stock A may increase the trading intensity.

By analyzing sample correlations we established significant comovements in the trading intensities of the stocks under consideration. We would also like to know whether or not the type of trade variable conveys additional information relative to the history of the pooled transaction process. If this is not the case, then the fact that there has been a trade provides all information that is relevant for both stocks' interarrival times, while the type of trade is 'redundant'. The individual trading intensities of both stocks then only depend upon the history of the pooled transaction process. This is easy to test for in the probit-pooled ACD-model. Note, however, that this hypothesis is inherently difficult to test in the Russell (1999) model. On the other hand, the null hypothesis of independent transaction processes is testable in the Russell (1999) model, but this is not straightforward in the pooled ACD-model.

Estimation results

For all pairs of stocks, we estimate the probit-model by means of maximum likelihood, using the Berndt, Hall, Hall, and Hausman (1974) algorithm for the numerical optimization. The ACD-part of the model is estimated using quasi maximum likelihood using the same optimization algorithm, cf. Engle and Russell (1998).

The choice of explanatory variables in ν_{t-1} as given in equation (7) is the result of a specification search. Initially, we estimated the model with $\nu_{t-1} = (z_{t-1}, z_{t-2}, \log p_{t-1}, \log p_{t-2})'$, allowing for feedback from the two most recent trades (z_{t-1}, z_{t-2}) and the entire history of the type of trade variable that is captured in the variables $\log p_{t-1}$ and $\log p_{t-2}$. For all pairs of stocks, the null hypothesis that z_{t-1} and z_{t-2} add up to zero could not be rejected. Moreover, $\log p_{t-2}$ turned out insignificant for all pairs of stocks under consideration. In our final specification, we therefore set $\nu_{t-1} = (\Delta z_{t-1}, \log p_{t-1})'$. Since the variable $\Delta z_{t-1} = z_{t-1} - z_{t-2}$ indicates whether or not a change in the type of trade has taken place, it can be interpreted as in indication of 'news'.

In a similar way, the specification given in expression (5) is the result of a specification search. We use a Wald-test for omitted variables (more lags) in the probit-model for which there is no significant evidence. Moreover, we use a Lagrange-multiplier (LM) test for heteroscedasticity in expression (5). We proceed in the line of Harvey (1976) by considering heteroscedasticity of the form $\mathbb{V}\text{ar}\,(\eta_t) = \exp(\nu\xi_t)$. Here η_t is the disturbance in the unobserved process underlying the probit-model and

$$\xi_t = (z_{t-1}, z_{t-2}, \Phi^{-1}(p_{t-1}), y_t, z_{t-1}y_{t-1}, z_{t-2}y_{t-1})'. \tag{11}$$

The null hypothesis of no heteroscedasticity is not rejected for all pairs of stocks at a 5% significance level.

The estimation results are given in Table III and Table IV. We start with the ACD-part of the model. The persistence in the ACD-model is high, since the estimated value of β varies between 0.982 and 0.997. We test the hypothesis that the type of trade variable does not affect the conditional expected duration. For all stocks this hypothesis is rejected at any reasonable significance level. For eight out of ten pairs of stocks there is significant impact from Δz_{t-1} to the conditional expected duration. In seven out of ten cases $\log p_{t-1}$ significantly influences ψ_t. We will later turn to the economic significance of the estimated coefficients.

We now turn to the probit-model. The persistence in the type of trade variable z_t is high, since the coefficients of $\Phi^{-1}(p_{t-1})$ are close to one for all stocks; they vary between 0.95 and 0.99. To test whether or not the type of trade variable completely depends upon the pooled transaction process only, we test the hypothesis

$$H_0 : \delta_i = 0 \quad [i = 2, 3, 6, 8]. \tag{12}$$

This null hypothesis is rejected for all stocks at any reasonable significance level level, so the type of trade variable depends on both the pooled and the individual transaction processes.
The null hypothesis that the type of trade variable is not informative (for the entire process) is strongly rejected for all pairs of stocks. Hence, not only the fact that there has been a trade conveys information, also the type of trade is informative.

Finally, we will show that the probit-pooled ACD-model is a reformulation of the Russell (1999) model. First, note that the conditional intensity function of the pooled transaction process and the conditional density of the type of trade completely determine the conditional intensity functions of the marginal processes, since

$$\lambda_{t-1,1}(s) = \lambda_{t-1}(s)\mathbb{P}(z_t = 0 \mid \underline{y}_{t-1}, \underline{z}_{t-1}, y_t = s - \tau_{t-1}) \tag{13}$$

A similar expression is obtained for $\lambda_{t,2}(\cdot)$. Furthermore, specification of the two conditional intensity functions determines the conditional intensity function and the density of the type of trade variable of the pooled transaction:

$$\begin{aligned} \lambda_{t-1}(s) &= \lambda_{t-1,1}(s) + \lambda_{t-1,2}(s) \qquad (14) \\ \mathbb{P}(z_t = 0 \mid \underline{y}_{t-1}, \underline{z}_{t-1}, y_t = s) &= \frac{\lambda_{t-1,1}(s + \tau_{t-1})}{\lambda_{t-1,1}(s + \tau_{t-1}) + \lambda_{t-1,2}(s + \tau_{t-1})}. \end{aligned}$$

Hence, the pooled ACD-model and the Russell (1999) model are equivalent in a nonparametric sense. Only when assumptions on the functional forms are added, then the two models are different and nonnested.

V Distinguishing sector and stock specific news

In this section we analyze to what extent the trading intensity in a stock depends primarily on the past trading activity in the stock itself and the trading activity in the sector as a whole. We first examine the information content of the history of the pooled transaction process in addition to the history of the type of trade. Subsequently, we examine the informativeness of the type of trade in addition to the pooled transaction process.
We estimate the variances

$$\begin{aligned} v_y &= \mathbb{V}\text{ar}\,(\hat{\lambda}_{t-1}(\underline{y}_{t-1})), \\ v_z &= \mathbb{V}\text{ar}\,(\hat{\lambda}_{t-1}(\underline{z}_{t-1})), \\ v_{yz} &= \mathbb{V}\text{ar}\,(\hat{\lambda}_{t-1}(\underline{y}_{t-1}, \underline{z}_{t-1})). \end{aligned} \tag{15}$$

The conditional intensity function in v_y is obtained from equation (7), with the additional restriction $\gamma = 0$. The conditional intensity function in v_z is obtained in the same way, with the restriction $\alpha = 0, \beta = 0$. Finally, in v_{yz} it is obtained with no restriction imposed upon the parameters. The variances in expression (15) are estimated using the corresponding sample variances in the one-step ahead predictions. Subsequently we compute the ratios $\hat{v}_z/\hat{v}_{yz}$ and $\hat{v}_y/\hat{v}_{yz}$. The values of the ratios are displayed in Table V. The lower the ratio, the higher the explained variance and the more informative the newly added information. The results show that the marks add very little new information to the information on the pooled transaction process; i.e. the economic impact of the Granger-causality from marks the pooled durations is small. However, the history of the pooled transaction process is very informative in addition to the marks.
In a similar way we estimate

$$w_y = \mathbb{V}\text{ar}\,(\hat{p}_t(\underline{y}_t)),\;\; w_z = \mathbb{V}\text{ar}\,(\hat{p}_t(\underline{z}_{t-1})),\;\; w_{yz} = \mathbb{V}\text{ar}\,(\hat{p}_t(\underline{y}_t, \underline{z}_{t-1})), \qquad (16)$$

and compute ratios as before. The results in Table V show that the history of the type of trade adds much information to the type of trade process, but that the pooled transaction process hardly contains any additional information. This is in line with the simulation results obtained in Section 4.
In Section 1 we explained that news events may consist of two parts: a stock specific component and a component that applies to sector specific news. When the trading intensity of stock A has a large impact on that of stock B, the trading intensity of stock A contains a lot of sector specific news that is relevant for stock B. We will now measure the amount of sector specific news contained in the trading intensity of each stock.
For each stock we estimate the variance of the estimated conditional intensity function. We obtain the estimated conditional intensity functions in the the pooled ACD-model using equation (13). In the probit-pooled ACD-model we get, under the assumption of exponentially distributed disturbances,

$$\lambda_{t-1,1}(s) = \mathbb{P}(z_t = 0 \mid \underline{y}_{t-1}, \underline{z}_{t-1}, y_t = s - \tau_{t-1})/\psi_t, \qquad (17)$$

and

$$\lambda_{t-1,2}(s) = \lambda_{t-1}(s) - \lambda_{t-1,1}(s). \qquad (18)$$

In a univariate framework we specify a log ACD$(1,1)$-model, cf. Engle and Russell (1998); i.e.

$$y_{t,i} = \psi_{t,i}\varepsilon_{t,i}, \quad \psi_{t,i} = \mathbb{E}(y_{t,i} \mid \mathcal{I}_{i,t-1}) \qquad [i = 1, 2]. \qquad (19)$$

Here $(\varepsilon_{t,i})_t$ is a sequence of identically distributed variables with unit mean, independent of $\mathcal{I}_{t-1}$ and

$$\log \psi_{t,i} = \omega^{(i)} + \alpha^{(i)} \log y_{t,i} + \beta^{(i)} \log \psi_{t-1,i}, \qquad [i = 1, 2] \tag{20}$$

We estimate the univariate ACD-model for each individual stock using QML; the estimation results are available upon request.
We define

$$v_A = \mathbb{V}\text{ar}\,(\hat{\lambda}_t^A),\; v_B = \mathbb{V}\text{ar}\,(\hat{\lambda}_t^B), \tag{21}$$

that is, v_A and v_B denote the variance of the one-step ahead predictions of the conditional intensity function of respectively stock A and B in the univariate ACD-models (where t indexes the pooled transaction process). Similarly, let v_A^p and v_B^p denote these variances in the probit-pooled ACD-model. We estimate the variances by means of the sample variances of the one-step ahead predictions and subsequently compute the ratios $\hat{v}_A/\hat{v}_A^p$ and $\hat{v}_B/\hat{v}_B^p$. The ratios are reported in Table VI.
Consider, for example, the results for the pair Federated and Saks. Table VI shows that for Federated the explained variance of the conditional intensity function in the pooled ACD-model is 88.1% of the explained variance in the univariate ACD-model. This means that the trading intensity of Saks contains much sector-wide information that is relevant for Federated. Conversely, for Saks the explained variance of the conditional intensity function in the pooled ACD-model is 86.1% of the explained variance in the univariate ACD-model. This means that the trading intensity of Federated contains much sector-wide information that is relevant for Saks.
Furthermore, from Table VI it follows J.C. Penney contains more sector-wide information than any other stock, which is in line with the correlations in Table II. Therefore, it can be viewed as the most informative stock with respect to sector-wide information. Similarly, Federated contains more sector-wide information than all other stocks except J.C. Penney. When we rank the remaining stocks based upon the number of stocks they outperform with respect to the amount of sector specific news contained in the trading intensity as given in Table VI, we obtain the ranking Saks (outperforms two other stocks), Dillard's (one), and finally May (zero) follow. Hence, the least informative stock is May; i.e. all other stocks have more sector specific news contained in the trading intensity.
Note that the most informative stocks, J.C. Penney is also the most frequently traded stock. In fact, the ranking based upon Table VI (J.C. Penney, Federated, Saks, Dillard's, and May) is close to the ranking based upon the number of transactions (J.C. Penney, Federated, May, Dillard's, and

Saks), since the only difference is that the rankings of Dillard's and May are interchanged. Clearly, when a stock is traded more often, there are more opportunities to convey information to other stocks.
Also note that the ranking is roughly in line with the ranking obtained in Section 2 based upon the 'cross' correlations reported in Table II. According to this ranking the trading intensity of J.C. Penney is most important, followed by Federated and May, and finally by Dillard's and Saks. Hence, this ranking also sets J.C. Penney on top. However, it is not able to distinguish between Federated and May (shared second position) and Dillard's and Saks.

VI The economic impact of the comovements in trading intensities

To gain more insight in the dynamics of the duration process, we perform a simulation of the pooled ACD-model discussed in the previous section. We compare the simulation results of the bivariate model to the results of the univariate ACD-model. In the univariate model the history of the other process is not taken into account. Therefore, comparison of the results to those of the bivariate model provides another indication of the information content of the trading intensity of the other process.
Given a certain history of two transaction processes, we focus on the expected duration to the first trade in each stock and the expected time it takes until each stock has been traded ten times. We vary the history of the transaction process to assess the effect of different scenarios on the expected durations. The history of the two processes consists of three parts: the durations to the two most recent trades, the nature of the two most recent trades (stock A or B) and the most recent value of the conditional probability of a trade in stock A.
Technically speaking, for each pair of stocks (say A and B) we simulate the binary process $(z_t)_t$ jointly with the durations of the pooled transaction process $(y_t)_t$. For each path of durations and type of trade variables, we compute the time to the first trade in each stock and the time it takes before ten trades in stock A and B have taken place. We do this N times and estimate the expected durations by taking the corresponding averages of the durations over all simulation runs. We simulate the durations by randomly drawing from the empirical distribution of the ACD-residuals. Moreover, we obtain confidence intervals for the calculated statistics by means of a parametric bootstrap from the joint asymptotic distribution of the model parameters.
We consider a pair of stocks, which we refer to again as stocks A and B.

We consider the expected duration to a trade in stock A under two different scenarios: one of only few trades in stock B and one with many trades in stock B. From the path of trades in A we compute the variables needed to initialize the univariate ACD-model. From the paths of pooled transactions we compute the variables required for the initialization of the probit-pooled ACD-model. We do the same for stock B, in which case we focus on the scenarios that many or few trades in A have taken place. Thus, we are able to assess the effect of trades in one stock on trades in the other stock and, moreover, we are able to see the difference between the bivariate probit-pooled ACD-model and the univariate ACD-model.
We consider the stocks J.C. Penney and Dillard's for which we concluded in the previous section that the impact of J.C. Penney on Dillard's is quite large and that the trading intensity of Dillard's contains a small amount of sector specific information that is relevant for J.C. Penney. Table VII reports the expected time to the first transaction in each stock as well as the expected time it takes before each stock has been traded ten times, obtained by a simulation of $N = 10,000$ runs. These expected durations are estimated in both the probit-pooled ACD-model under the above mentioned scenarios and in the univariate ACD-model.
We first consider the simulation results for J.C. Penney. In a period with few trades in Dillard's the expected duration to the first trade in J.C. Penney equals 49 seconds, see the 'expected duration A' in the upper part of Table VII that has the caption 'few trades in the other stock'. With many trades in the other stock it equals 1 minute and 9 seconds, which is significantly larger. In the univariate ACD-model the expected duration equals 1 minute. Hence, in the univariate model, which ignores the history of the other stock, the expected duration falls between the expected durations with few trades in Dillard's and many trades in Dillard's as obtained in the bivariate model. With few trades in J.C. Penney the expected duration to a trade in Dillard's equals 1 minutes and 29 seconds, while it equals 3 minutes and 40 seconds when J.C. Penney is traded often. For the expected time it takes until each stock is traded ten times, we find similar results. Again the expected duration in the univariate ACD-model falls between the expected durations in the probit-pooled ACD-model with many and few trades in the other stock. The results also show that J.C. Penney is much less affected by Dillard's than the other way around. This asymmetry is consistent with the results in Table VI. For the other pairs of stock we obtain similar results.

VII Extensions of the probit pooled ACD-model

In this section we discuss several extensions of the model presented in this paper. The pooled ACD-model can be extended with the inclusion of explanatory variables such as returns on the mid quote, bid-ask spread and trade volume in equations (7). The idea is that the information content of the trade characteristics influences the trading intensity, see Spierdijk (2002). Hence, additional feedback allows for effects from the trade characteristics to the trading intensity of the pooled transaction process. For example, as put forward in Dufour and Engle (2000), a large change in the market maker's mid quote may be a signal to the informed traders that their information, initially unknown to other market participants, has been revealed to the market maker assuming that no new signal has been released thereafter. This means that their information is no longer superior and thus the incentive to trade disappears, decreasing their trading intensity. However, from an inventory perspective, large quote changes would attract opposite-side traders, thus increasing the trading intensity. Similar effects may occur when informed traders observed wide spreads or large volume trades. With feedback from the trade characteristics to the trading intensity, $\nu_{t-1} \in \mathcal{I}_{t-1}$ in expression (7) would be a vector of explanatory variables, possibly including type of trade variables or trade characteristics. With a similar motivation explanatory variables can be included in the probit-model. Although several trade characteristics (lagged bid-ask spread and unsigned trade volume) turn out significant in the ACD-part of the model, the economic impact of the trade characteristics appears to be small in the sense that the expected durations as simulated in previous section are hardly affected by the additional feedback. This is consistent with the evidence found in Spierdijk (2002).

Another extension is the multivariate analogue of the bivariate model considered in this paper. Instead of considering pairs of stocks, the focus could be on $K > 2$ stocks. This would provide a different way of measuring the amount of sector and stock specific information contained in the trading intensity of each stock. Moreover, in this way it becomes possible to see whether there are any stocks that provide sector specific information when modeled jointly with a single other stock, but are redundant when other stocks are added. In our case, we could take all five stocks of US department store operators into account. The model would then consist of a duration model of the ACD-type for the pooled durations and, for example, a multinomial logit-model to model the conditional probability of a trade in each type of stock.

Finally, in line with Engle and Lunde (1999), Russell (1999), and Davis et al. (2001) the pooled ACD-model can be applied to trade and quote data instead of transactions data on different stocks to investigate how information contained in the quote intensity affects the intensity of trades and vice versa. Similarly, the model can be applied to model possible comovements between the same stocks traded on different markets.

VIII Conclusions

In this paper we proposed a new way to model comovements in the trading intensities of related stocks, using a three-month sample (August-October 1999) of stocks of five large US department store operators listed at the NYSE.

We tested the hypothesis whether or not the type of trade variable conveys additional information relative to the fact that there has been a trade. We rejected the null hypothesis that the trading intensity of the pooled transaction process conveys all information. Thus, not only the fact that there has been a trade conveys information, also the type of trade is informative. Moreover, with respect to the durations of the pooled transaction process we established that the type of trade variable conveys significant information in addition to the durations of the pooled transaction process, but that the economic impact of this information is small. For the type of trade process we concluded that the durations of the pooled transaction process do convey some information though much less than the type of trade.

We made a distinction between stock specific news that applies to one stock only and sector specific news that is potentially relevant for stocks in the same type of industry. We investigated the amount of sector specific news contained in the trading intensity of each stock. We found that the trading intensity of J.C. Penney contains the largest amount of sector specific news. J.C. Penney is also the most frequently traded stock of our sample. Furthermore, the trading intensity of May is least informative with respect to sector specific news.

Finally, we compare the results of the probit-pooled ACD-model proposed in this paper to the univariate ACD-model that is usually used in the literature to model durations. By means of a simulation of both models we showed that the expected durations for a stock in the univariate ACD-model are between the expected durations in the probit-pooled ACD-model with many and few trades in the other stock.

ticker symbol	DDS	FD	JCP	MAY	SKS
company name	Dillard's Inc.	Federated Department Stores	J.C. Penney Corporation	May Department Stores	Saks Inc.
# transactions	14,731	24,875	27,133	23,611	14,641
durations (mm:ss)					
mean	01:40	01:00	00:55	01:03	01:40
median	00:52	00:32	00:31	00:35	00:54
0.5% quantile	00:01	00:01	00:01	00:01	00:01
5% quantile	00:03	00:02	00:03	00:03	00:03
95% quantile	06:06	03:31	03:09	03:40	06:05
99.5% quantile	12:33	07:48	07:12	08:03	12:14

Table I: Ticker symbols, company names and some sample statistics

Federated, May and Dillard's are the number one, two and three upscale department store operators in the US, respectively. Saks and J.C. Penney are other large department store operators.

	to stock DDS	FD	JCP	MAY	SKS
from stock DDS	0.127 (15.401)	0.065 (7.720)	0.060 (6.174)	0.052 (7.175)	0.062 (7.288)
FD	0.073 (11.450)	0.076 (10.369)	0.082 (11.820)	0.073 (11.146)	0.035 (5.446)
JCP	0.103 (16.733)	0.101 (16.400)	0.130 (21.440)	0.100 (16.289)	0.041 (6.584)
MAY	0.064 (11.231)	0.077 (11.255)	0.081 (12.329)	0.048 (7.306)	0.023 (3.506)
SKS	0.033 (3.906)	-0.002 (-0.278)	0.005 (0.592)	0.027 (3.236)	0.149 (17.992)

Table II: Rank correlations between consecutive durations

The diagonal of this table contains estimates of Spearman's rank autocorrelation in the durations of each individual stock. The corresponding t-values are between parentheses. The remaining values in this table are estimates of the rank correlation between $y_{t-1,i}$ and $w_{t,j}$, for each pair of stocks.

coefficient	variable	JCP-DDS estimate	std. error	MAY-DDS		MAY-JCP		SKS-DDS		SKS-JCP		SKS-MAY		FD-MAY	
ACD-model															
ω	const	−0.0615	0.0029	−0.0440	0.0223	−0.0415	0.0100	−0.0397	0.0008	−0.0410	0.0013	−0.0349	0.0012	−0.0441	0.0036
α	$\log \varepsilon_t$	0.1023	0.0047	0.0831	0.0429	0.0868	0.0147	0.0666	0.0010	0.0700	0.0021	0.0550	0.0018	0.0748	0.0055
β	$\log \psi_{t-1}$	0.9862	0.0006	0.9816	0.0082	0.9856	0.0018	0.9973	0.0001	0.9956	0.0002	0.9946	0.0002	0.9878	0.0009
γ_1	Δz_{t-1}	−0.0386	0.0018	−0.0096	0.0035	0.0378	0.0113	−0.0781	0.0541	−0.0191	0.0419	−0.0400	0.0121	0.0174	0.0021
γ_2	$\log p_{t-1}$	−0.0049	0.0008	0.0077	0.0053	0.0117	0.0022	−0.0015	0.00031	0.0001	0.0002	−0.0029	0.0003	−0.0016	0.0014
probit-model															
δ_1	const	0.0213	0.0018	0.0210	0.0020	0.0207	0.0020	0.0299	0.0025	0.0550	0.0033	0.0297	0.0024	0.0210	0.0021
δ_2	z_{t-1}	−0.1610	0.0167	−0.2416	0.0172	−0.0564	0.0145	−0.5452	0.0198	−0.3637	0.0178	−0.4121	0.0181	−0.2205	0.0147
δ_3	z_{t-2}	0.1214	0.0169	0.1986	0.0174	0.0048	0.0147	0.4890	0.0200	0.2490	0.0184	0.3556	0.0184	0.1816	0.0148
δ_4	$\Phi^{-1}(p_{t-1})$	0.9839	0.0014	0.9821	0.0017	0.9683	0.0024	0.9797	0.0018	0.9539	0.0024	0.9785	0.0017	0.9775	0.0026
δ_5	y_t	0.0297	0.0065	−0.0097	0.0069	−0.0039	0.0067	−0.0832	0.0086	−0.0584	0.0084	−0.0559	0.0087	−0.0395	0.0065
δ_6	$y_t z_{t-1}$	0.0290	0.0101	0.0671	0.0108	−0.0228	0.0090	0.1842	0.0121	0.0905	0.0108	0.1109	0.0112	0.0696	0.0090
δ_7	y_{t-1}	−0.0319	0.0065	0.0078	0.0069	0.0046	0.0067	0.0746	0.0086	0.0469	0.0084	0.0486	0.0087	0.0351	0.0065
δ_8	$y_{t-1} z_{t-2}$	−0.0258	0.0101	−0.0597	0.0108	0.0284	0.0090	−0.1701	0.0121	−0.0717	0.0109	−0.1012	0.0112	−0.0630	0.0090

Table III: Estimation results for the pooled ACD(1,1)-model

The pooled ACD-model and the probit-specification are estimated by means of QML-estimation. The Bollerslev and Wooldridge (1992) robust covariance matrix is used to compute the standard errors. The pooled ACD-model is specified according to equation (7) and the probit-model by expression (4). The regressors included in the probit-model, with coefficients $\delta_i = 1, \ldots, 8$, are given in expression (5).

coefficient	variable	FD-DDS estimate	std. error	FD-JCP		FD-SKS	
ACD-model							
ω	const	−0.0419	0.0013	−0.0477	0.0016	−0.0348	0.0015
α	$\log x_{t-1}$	0.0776	0.0020	0.0926	0.0029	0.0644	0.0026
β	$\log \psi_{t-1}$	0.9880	0.0002	0.9871	0.0004	0.9920	0.0003
γ_1	Δz_{t-1}	−0.0225	0.0056	0.0535	0.0182	0.0612	0.0176
γ_2	$\log p_{t-1}$	0.0052	0.0004	0.0083	0.0009	0.0054	0.0004
probit-model							
δ_1	const	0.0219	0.0020	0.0145	0.0014	0.0316	0.0023
δ_2	z_{t-1}	−0.2942	0.0170	−0.1407	0.0143	−0.4456	0.0181
δ_3	z_{t-2}	0.2507	0.0172	0.1082	0.0144	0.3790	0.0184
δ_4	$\Phi^{-1}(p_{t-1})$	0.9830	0.0017	0.9835	0.0015	0.9767	0.0017
δ_5	y_t	−0.0272	0.0065	−0.0431	0.0064	−0.0686	0.0069
δ_6	$y_t z_{t-1}$	0.0913	0.0104	0.0258	0.0090	0.1246	0.0110
δ_7	y_{t-1}	0.0231	0.0065	0.0435	0.0064	0.0631	0.0069
δ_8	$y_{t-1} z_{t-2}$	−0.0800	0.0104	−0.0237	0.0089	−0.1076	0.0111

Table IV: Estimation results for the pooled ACD(1, 1)-model (continued)

pair of stocks	$\hat{v}_y/\hat{v}_{yz}$	$\hat{v}_z/\hat{v}_{yz}$	$\hat{w}_y/\hat{w}_{yz}$	$\hat{w}_z/\hat{w}_{yz}$
DDS-FD	97.0	39.6	0.2	91.1
DDS-JCP	99.1	37.3	7.7	95.2
DDS-MAY	95.6	46.9	6.0	94.4
DDS-SKS	99.2	15.4	0.1	88.9
FD-JCP	98.1	14.8	2.5	93.6
FD-MAY	99.6	48.5	2.5	88.8
FD-SKS	89.8	37.1	25.1	93.7
JCP-MAY	99.3	46.2	51.0	94.6
JCP-SKS	99.3	31.8	1.4	97.6
MAY-SKS	94.5	33.6	27.5	95.5

Table V: Variances ratios in the pooled ACD-model

This table reports the variance ratios (in %) as defined in expressions (15) and (16), which provide an indication of the relevance of the information contained in the pooled duration process (first and third column) and the type of trade variable (second and fourth column).

pair of stocks (A-B)	$\hat{v}_A/\hat{v}_A^p$	$\hat{v}_B/\hat{v}_B^p$
DDS-FD	92.4	90.2
DDS-JCP	85.6	96.9
DDS-MAY	96.4	69.7
DDS-SKS	76.5	87.2
FD-JCP	83.4	95.7
FD-MAY	86.9	83.8
FD-SKS	88.1	86.1
JCP-MAY	92.0	80.7
JCP-SKS	91.1	85.3
MAY-SKS	71.4	87.2

Table VI: Variance ratios: univariate versus bivariate model

This table reports the ratios of the sample variance (in %) of the conditional intensity functions in the pooled ACD-model and the univariate ACD-model for each pair of stocks, as defined in expression (21).

scenario	time (mm:ss)
scenario 1: ‘few trades in the other stock’	
bivariate model	
exp. duration A	00:49
exp. duration B	01:29
exp. duration to 10 trades A	08:25
exp. duration to 10 trades B	14:55
scenario 2: ‘many trades in the other stock’	
bivariate model	
exp. duration A	01:09
exp. duration B	03:40
exp. duration to 10 trades A	12:12
exp. duration to 10 trades B	33:37
univariate model	
exp. duration A	01:00
exp. duration B	02:30
exp. duration to 10 trades A	09:54
exp. duration to 10 trades B	24:24

Table VII: Expected durations: bivariate versus univariate modeling

This table displays the results of a simulation (with $N = 10,000$ runs) and reports the expected duration (mm:ss) to the next trade and the expected time it takes before ten trades in the specific stock have taken place.

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