Eberhard- Karls- Universität Tübingen
Wirtschaftswissenschaftliche Fakultät

Time and the Price Impact of a Trade

A revision of the DUFOUR/ENGLE (2000)–model with XETRA data

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Prof. Dr. Joachim Grammig

by

Cand. rer. pol.
Christian David Dick
Matrikel-Nr.: 2680033
8. Semester VWL
Dorfacker Str. 20, 72074 Tübingen
christian105@web.de

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1 Introduction

The study of DUFOUR/ENGLE (2000) is an empirical contribution to information–based microstructure theory. Key claim of their study is that the impact of a trade on prices is higher in markets with high trading intensity. Since the impact of a trade is a measure for the presence of informed traders, they predict that active markets are more dominated by informed traders than inactive markets.

Since their analyis is based on NYSE–data, the purpose of this paper is to apply their idea to XETRA– data and to test the robustness of their central results. The paper is organized as follows: Section 2 gives a short survey of the theoretical background for information–based models of market microstructure theory, as far it is relevant for the following empirical discussion. Section 3 first introduces the underlying framework of HASBROUCK (1991) before turning to the specification of DUFOUR/ENGLE (2000). After describing the data and relevant variables in Section 4, we turn to the estimation of the DUFOUR/ENGLE (2000)–model with XETRA–data in Section 5. To show the impact of a trade on prices, the role of Impulse Response Functions is discussed in Section 6. A last section is reserved for concluding remarks.

2 Theoretical Background

2.1 Information– based models

Information– based models of market microstructure typically discuss the effects of asymmetric information across market participants on financial markets. These considerations originate in BAGEHOT (1971, p.13), who points out that traders with private information ("informed traders") can achieve "trading gains" from their market activities, whereas "uninformed traders" cannot. Informed traders always choose to trade if they have superior information[1]. Uninformed traders can still achieve profits from "market gains" and seek diversification of their wealth. Since they are active in the market solely due to liquidity needs[2], they are referred to as "liquidity traders" in the literature[3].

2.2 General effects of asymmetric information

Theory derives two general consequences from the presence of asymmetric information in the marketplace: The first concerns the role of a bid/ask–spread, the second deals with the informational content of a trade:

[1] They might be restricted in doing so by short- selling restraints.

[2] BAGEHOT (1971, p.13) also identifies investors that only *think* they have superior information (but indeed have not); BLACK (1986, p.531) refers to them as "noise traders". In the following, we classify them as non–informed and take their motivation as exogenous.

[3] e.g. BAGEHOT 1971, p.13; DUFOUR/ENGLE 2000, p.2468

2.2.1 The effect on spreads

COPELAND/GALAI (1983) formalize the idea of BAGEHOT and discuss the optimal behavior of market makers in a one–period framework. Market makers, who cannot distinguish between informed and uninformed traders in the first place, need to be compensated for the losses they face due to the presence of private information in the marketplace: Even if transaction costs and inventory effects are absent[4], market makers have to quote a bid/ask–spread (COPELAND/GALAI 1983, p.1463), which is optimal to offset expected losses from dealing with informed traders.

2.2.2 The persistent effect of a trade

Extending the COPELAND/GALAI–framework from a one–period to a dynamic setting, an additional effect arises: If a purchase order occurs in the first period , there is a certain probability that it stems from an informed trader who knows about secret good news[5]. The market maker considers this information when he quotes the bid/ask–spread in the next periods. Doing so, he gradually learns the true value of an asset. GLOSTEN/MILGROM (1985, p.74) show that the value expectation of the market maker on the one hand and informed traders on the other tend to converge over time. This means that private information is incorporated in the price in the long run; the effect of a trade is a persistent one. O'HARA (2006, p.58) describes the analysis about this "Bayesian learning" phenomenon as the focus of recent microstructural research. Depending on the set–up of the underlying model, we consider specific features of trading patterns, such as direction, size or duration. In the GLOSTEN/MILGROM (1985)– model the market maker has to find out whether good news or bad news have happened. If there is bad news, the probability of a sale is higher than the probability of a purchase. Looking at a sequence of trades, the market maker learns from the relative number of sales if informed traders have good or bad private information and adjusts his own quotes gradually.

2.2.3 Asymmetric Information and Market Efficiency

The assumptions that market prices do not fully incorporate all information conflicts with the notion of *strong form market efficiency*. Following the concepts of FAMA (1970, p.383), strongly efficient markets require the current market price to reflect all *public* as well as *private* information. However, one can still apply the idea of *semi- strong efficiency* (FAMA, ibid.), since *publicly* available information is immediately captured in the stock price. Therefore, empirical analyses do not only decide about the explanatory power of a specific microstructure model, but also about the degree of efficiency of the market.

[4] In inventory models the spread arises as a compensation for risk (e.g. HO/STOLL 1980, p.261). Assuming risk– neutral market makers and unlimited capital illustrates the point of information– based models, although a combination of both types of effects is more realistic (O'HARA (2006), p.59).

[5] It is obvious that the same is true for bad news. A market maker cannot distinguish between uninformed traders who want to sell for liquidity reasons and informed traders who have private information that lowers the true value of the stock. An adverse selection problem arises which is similar to AKERLOF's (1970) "lemons problem": The seller has superior information about his value expectations; the asset is sold at a lower value.

O'HARA (2006, p.65) discusses the adjustment process of prices after a trade with respect to market efficiency. A market is no longer strongly efficient if there is private information in the marketplace. The predicted convergence process, however, leads to a final point in which the market turns again from semi–strong to strong form market efficiency.

2.2.4 Asymmetric Information and Market Liquidity

DUFOUR/ENGLE (2000, p.2470) stress the close link between efficiency and liquidity. Markets are liquid when a single trade does not have a noticeable impact on prices. This means that it takes time until the informational content of a trade is fully captured by market quotes. A fast path of convergence of the expectations of informed traders and market makers means a quick return to strong market efficiency, but it is also a sign of illiquid markets.

2.3 The effects of trade size

The model of EASLEY/O'HARA (1987, p.72) discusses the scenario with a market maker who does not know whether there is new information; if there is new information he does not know if it is good or bad news. The latter of these two uncertainties can again be approached by the trade *directions*; for a the prediction of the former the size of a trade comes into play.

In this setting, informed traders have an incentive to trade large quantities, whereas uninformed traders are indifferent regarding their trade size. The market maker can interpret a sale as a signal of bad news (as seen in the GLOSTEN/MILGROM–model); additionally, he can interpret a small sale as a sign of "no news". Transaction size is hence correlated with information, and it "signals the existence of an information event" (EASLEY/O'HARA 1987, p.86). The implication of this model is that prices as well as spreads depend on traded volumes[6]. Since the trade size alters the market maker's perception concerning the informational content of a trade, it also influences the speed of the adjustment process towards a market price which fully reflects the private information.

2.4 The effects of time

A very similar argument can be made for time. EASLEY/O'HARA (1992, p. 578) predict a correlation between volume and the time between trades. An informed trader, who has an incentive to make a large trade, might decide to split up his transaction into smaller consecutive transactions. The reason for this is strategic behavior, since the informed trader does not want to show himself[7] in order to slow down the process of convergence of his value expectations and these of the other market participants. The timing of transactions is not any more exogenously given, but endogenously determined by the occurrence of private information. Having this in

[6] LEE/MUCKLOW/READY (1993, p.371) find in their empirical work that "*spreads widen [...] in response to an increase in volume*", which confirms this prediction.

[7] FOSTER/VISWANATHAN (1990, p.594) describe the optimal strategic behavior of an informed trader.

mind, the market maker can use the duration between two trades to derive a probability about the *existence* of new private information. If time between trades increases (meaning there are no trades for a longer period of time), it becomes more likely that the following trade occurs for liquidity reasons only. Hence, the market maker will reduce the spread.

While the market maker adjusts his expectations concerning the *direction* of new information from the Trade–sign (purchase vs. sale) directly, he can adjust his expectations concerning *event uncertainty* based on the time between trades or the volumes of the transactions.

3 Empirics on microstructure models

Microstructure theory elaborates the impact of private information on trade patterns. Conversely, empirical contributions to this problem analyze trade patterns to quantify the extent of asymmetric information in the marketplace. Theory predicts that asymmetry is positively related to the bid/ask–spread[8] as well as to the price impact of a trade (HASBROUCK (1991), p.180). HASBROUCK (ibid) points out that unlike other effects[9] informational imperfections have a persistent effect on prices. Therefore, the impulse response function is the appropriate measure of private information (HASBROUCK (1991), p.189). The projection in the future yields the current *efficient* price (ibid, p.183); the speed of convergence to this projection is negatively related to the extent of private information.

The focus of this paper is the impact of time on prices. DUFOUR/ENGLE (2000) provide a model that includes time effects which is based on a vector autoregression model (VAR) introduced by HASBROUCK (1991). In the following, we present the features of the underlying model before turning to the DUFOUR/ENGLE (2000)–framework.

3.1 The underlying HASBROUCK (1991)– Model

3.1.1 The role of autocorrelations

HASBROUCK/HO (1987) develop and estimate a complex price evolution process that contains autocorrelations of returns as well as of Trade–signs. They find that returns have a strong negative autocorrelation in their first lag, followed by slightly positive and declining autocorrelations for the following lags. There are positive but declining autocorrelations in the Trade–sign, meaning that sales tend to be followed by sales and purchases by purchases (HASBROUCK/HO 1987, p.1036). They provide as an explanation that a single informed trader might split up a large trade over time. This idea is consistent with the further analysis performed by DUFOUR/ENGLE (2000) and revised in the present paper.

[8] CHIANG/VENKATESH (1988, p.1047) find empirically that the spread is larger for companies with a more concentrated ownership structure (which is taken as a proxy for private information), which confirms this prediction.

[9] Inventory effects, price discreteness, price pressure, order fragmentation, price smoothing

3.1.2 Autocorrelations and cross–correlations in a VAR- model

HASBROUCK (1991) presents a vector autoregression (VAR) model that captures returns and trades with their autocorrelations and mutual effects in a system. He provides estimates for the relevant mechanisms and derives the impulse response functions as a measure of market efficiency.

x_t denotes a trade in event time t (called "Trade variable" or "Trade–sign variable"), whereas q_{t+1} is the exact middle of the bid/ask–spread[10]that emerges immediately after the trade in t. The return (or Price Revision) r_t is the delta between q_t and q_{t+1}. HASBROUCK (1991, p. 183) distinguishes between *public* information (captured in υ_1) that has an immediate influence on the quote, and *private* information (captured in υ_2) that may provoke an informed trader to trade. Note that υ_1 and υ_2 are white noise components. As Hasbrouck (1991, p. 189) puts it, "*the trade is driven partially by private information and partially by liquidity needs*". A rise in υ_2 does not necessarily mean that there is private information with certainty; but if new private information appears, it enters the system via υ_2. Public information has a direct effect on Price Revisions. Figure 1 shows that quotes are made just immediately after a trade. The

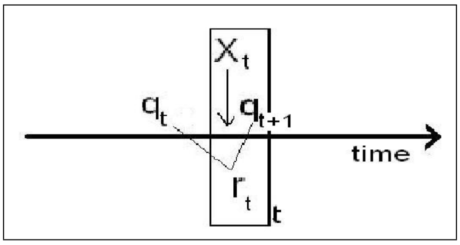

Figure 1: Trade flow

model hence assumes a contemporaneous effect of trades on returns. (Note that an immediate effect of the return on the Trade–sign is not assumed.) Although returns are a function of public, but not private information, private information still enters the return equation indirectly by the contemporaneous effect of the trade on returns[11].

Similarly to the HASBROUCK/HO (1987)–framework, the return equation and the trade equation include autocorrelation terms. Additionally, the return equation captures the correlation with lagged trade variables in order to take into account that the information from a trade enters only gradually the pricing of market makers. Finally, the model also includes the correlation terms of lagged returns in the trade equation. These considerations define the vector autoregres-

[10]EASLEY/O'HARA (1987, p.81) point out that this is not an appropriate measure for the market value if the size of transactions determine the spread. If there are more large purchases than large sales, the midpoint is an upward-biased measure. HASBROUCK (1991, p.182) assumes that these effects are transient and quotes are set symmetrically around the efficient value at least in terms of expectations.

[11]In a formal language, this can be denoted as $r = r(x, \upsilon_1)$ and $x = x(\upsilon_2) \Rightarrow r = r(x(\upsilon_2), \upsilon_1)$.

sive system (HASBROUCK 1991, p.194)

$$\begin{aligned} r_t &= \sum_{i=1}^{n} a_i r_{t-i} + \sum_{i=0}^{n} b_i x_{t-i} + \upsilon_{1,t} \\ x_t &= \sum_{i=1}^{n} c_i r_{t-i} + \sum_{i=1}^{n} d_i x_{t-i} + \upsilon_{2,t} \end{aligned} \quad (1)$$

Note that this vector autoregression model contains a contemporaneous effect of x_t on r_t. As can be seen in Figure 1, however, trade and returns are not determined simultaneously. For this reason, $\upsilon_{1,t}$ and $\upsilon_{2,t}$ are jointly and serially uncorrelated. It is therefore possible to include the contemporaneous effect in the VAR estimation, and to compute the parameters consistently via OLS (see HASBROUCK, p.184).

3.1.3 Trade–sign patterns and trade size effects

HASBROUCK (1991) applies this model to estimate the effect of simple trade direction patterns and –in an extended version (ibid, p.198)– the effect of different transaction volumes. The trade variable x can be interpreted as a limited dependent variable taking the value of 1 if the transaction is a purchase and a -1 if it is a sale[12]. In this case, the model can be used in the sense of the GLOSTEN/MILGROM (1985) framework. The trade variable can, however, be also treated as a volume measure (having a positive sign if it is a trade and negative sign if it is a purchase). This allows capturing trade size effects as introduced by EASLEY/O'HARA (1987).

3.2 The DUFOUR/ENGLE (2000)- Model

In Section 2.4 it has been argued that trade size and the time between two trades (duration) can be seen as related variables. DUFOUR/ENGLE (2000) extend the described VAR- model with durations in order to "*test the informational role of market activity*"(ibid, p.2468). Market activity, however, can differ for various reasons. It is obvious that, on average over all trading days, certain trading hours are more highly frequented than others. Therefore, one need to separate these day time patterns from the remaining variation of market activity that might have informational content concerning asymmetric information. DUFOUR/ENGLE (2000) implement these considerations into the model given in (1) by specifying the coefficients b_i and d_i. Besides the autocorrelation and cross- correlation effects of the Trade–signs[13] themselves as given in (1), the Trade–sign–weighted duration as well as diurnal variables are included. The latter are dummy variables which filter day time patterns. Both elements are included in the coefficients

[12] In HASBROUCK (1991, p.193), this interpretation of the trade variable is denoted by x^0.
[13] DUFOUR/ENGLE use the simpler model without trade sizes as it is given in HASBROUCK (1991, p. 194).

in the following way (DUFOUR/ENGLE 2000, p.2474):

$$b_i = \gamma_i^r + \sum_{j=1}^{J} \gamma_{j,i}^r D_{j,t-i} + \delta_i^r ln(T_{t-i}) \tag{2}$$

$$d_i = \gamma_i^x + \sum_{j=1}^{J} \gamma_{j,i}^x D_{j,t-i} + \delta_i^x ln(T_{t-i}) \tag{3}$$

with b_i belonging to the Price Revision equation and d_i belonging to the Trade–sign equation. j denotes the exact dummy out of $J+1$ possible day time classes[14]. This set–up provides testable parameters to examine different ways in which time might have an impact: If the γ^rs and $\gamma^x$are jointly equal to zero, the day time period does not influence the Trade- or the Price Revision equation. If the δ^rs and δ^xs are jointly zero, the assumption that durations matter cannot be confirmed. If both is the case, the original HASBROUCK (1991) VAR of equation (1) might be the appropriate specification. Conversely, if the δs are significantly different from zero, the model provides evidence for an influence of trading activity on prices and trades respectively (DUFOUR/ENGLE 2000, p.2475).

It can be seen that this framework includes a multitude of contemporaneous and lagged dummy variables. DUFOUR/ENGLE (2000) provide some experimentation to exclude non–significant variables. They find that all lagged diurnal and most contemporaneous dummy variables are jointly insignificant and proceed to model the interdependencies with the VAR system (ibid, p.2481)[15]

$$\begin{aligned} r_t &= \sum_{i=1}^{5} a_i r_{t-i} + \gamma_{open}^r D_t x_t^0 + \sum_{i=0}^{5} (\gamma_i^r + \delta_i^r ln(T_{t-i})) x_{t-i}^0 + \upsilon_{1,t} \\ x_t &= \sum_{i=1}^{5} c_i r_{t-i} + \gamma_{open}^x D_{t-1} x_{t-1}^0 + \sum_{i=1}^{5} (\gamma_i^x + \delta_i^x ln(T_{t-i})) x_{t-i}^0 + \upsilon_{2,t} \end{aligned} \tag{4}$$

The lags larger than five are truncated. The contemporaneous Trade–sign enters the Price Revision equations in three ways: γ_i^r captures a direct effect (as in equation (1)), γ_{open}^r and δ_0^r are interaction terms for the opening period and the duration effect respectively. Note that there is no contemporaneous effect in the trade equation. This is consistent with the original model in (1).

[14] The last one is omitted to avoid a “dummy trap”.

[15] Note that DUFOUR/ENGLE (2000, p.2481) also present another version of their model which is not including $i = 0$ in the second sum operator in the price variation equation. This would mean that the contemporaneous Trade–sign and duration do not enter the equation. This paper, however, focuses on the version described in (4).

4 The data

DUFOUR/ENGLE (2000) perform their analysis for a selection of 18 stocks which belong to the most actively– traded stocks on the NYSE. The data contains quotes and transaction information for 62 trading days from November 1, 1990 to January 31, 1991 (ibid, p.2477)[16].

The aim of the present paper is to revise the DUFOUR/ENGLE (2000) framework with data from the electronic trading platform XETRA. The considered stocks are those of the German blue chip index DAX[17]. The models are exposed to data from the Continuous Trading order book for the period from January 2 to January 30, 2004, which contains 21 trading days.

4.1 DAX 30

A summary table showing the characteristics of all thirty stocks is provided in Appendix A (Table 1). The stocks within the DAX vary substantially with respect to the number of transactions, average trading volume and duration. The stock with the largest number of trades is Deutsche Telekom, which shows at the same time the largest average volume and the lowest average time between two trades. Fresenius Medical Care, on the other hand, has the lowest number of transactions in the sample, accompanied by the second lowest average volume and the –by far– largest duration between trades. It appears that the link between trade size and duration (as predicted by EASLEY/O'HARA (1992)) and between trading activity and duration can be confirmed. To attain robust results, our estimations are performed on all 30 DAX values, which allows to identify general patterns. Since we are using the stock of Deutsche Telekom as an example to compute the impulse response function in Section 6, results for this stock are mentioned separately if they deviate from the general pattern.

4.2 Relevant Variables

Due to the assumed non–stationarity of prices themselves (DUFOUR/ENGLE 2000, p.2471), equations (1) and (4) include r_t as a price variation term[18]. This paper follows DUFOUR/ENGLE (2000, p.2478) in defining r_t as

$$r_t = 100(ln(q_{t+1}) - ln(q_t))$$

where[19] q_{t+1} denotes the midpoint of the bid/ask–spread right after the trade, while q_t is the midpoint quote before the trade.

The Trade–sign variable x_t is a limited dependent variable as described in Section 3.1.3. A transaction is considered a *purchase* ($x_t = 1$) if the transaction price exceeds the midpoint quote of the bid/ask–spread. It is defined as a *sale* ($x_t = -1$) if the actual transaction price is lower

[16]The data is extracted from the TORQ database by HASBROUCK (1992) (see DUFOUR/ENGLE (2000), p. 2476)).
[17]Deutscher Aktien Index
[18]This term is also referred to as "return" or "prive revision"
[19]Note that this is consistent with Figure 1.

than the midpoint quote. If the midpoint quote is exactly equal to the transaction price, x_t equals zero[20].

As can be seen in equations (2) and (3), the innovative idea of the DUFOUR/ENGLE (2000) model is the inclusion of time durations. The duration variable T_t is defined as the difference in seconds between the time of trade x_t and the previous trade x_{t-1}. We drop the first observation of a day, since the time gap to the previous trade (which occurred the day before) cannot be interpreted as a meaningful duration. Since logarithms are needed in (2) and (3), one second is added to all time differences; the log–duration is thus at least equal to zero. The durations are weighted with the Trade–sign: For purchases, durations enter the equation with a positive sign, for sales they enter with a negative sign. Technically, the inclusion of duration is done by the means of an interaction term $x_t * ln(T_t)$.

Section 3.2 discusses the necessity of dummy variables[21] in order to capture day time effects. The trading day[22] is therefore divided into eleven[23] intervals; the first and the last three intervals are shorter than the others[24]. Besides the interval of the opening period, the interval of the dummy D_8 (3:30 p.m. to 4:30 p.m.) might be of specific interest: This is the opening period of the NYSE which typically triggers enhanced market activity on stock exchanges outside the US. Table 3 shows that there is an increased market activity for all stocks in the last two hours of the trading day. The first hour right after the opening of the NYSE accounts for 16% of all transactions of the day, compared to 10% and 8% respectively in the two hours before the NYSE opening. Similarly to the duration effects, the dummy variables are weighted with the Trade–sign and enter the equation as interaction terms ($x_t * D_j$).

5 Estimation and Results

Following the approach of DUFOUR/ENGLE (2000, p.2471-72), we use OLS for all estimations and compute our standard errors with the application of WHITE's (1980) heteroskedasticity–robust variance matrix. For all estimates, we report p–values and decide about the rejection of the null hypotheses on a 5% significance level. Our results for the different estimations are reported in Appendix C.

5.1 Day time effects

The separation of day time effects and duration effects is necessary to obtain realistic insights in the impact of time on prices. As discussed in section 3.2, DUFOUR/ENGLE (2000, p.2480) provide arguments to drop most dummy variables from the terms (2) and (3): They first perform

[20]For the pure HASBROUCK (1991)–model, the quotes of market makers without a transaction could be included in the analysis with a x_t equal to 0. Since a duration can only be computed for consecutive transactions, we follow DUFOUR/ENGLE (2000) and drop all quotes without corresponding transactions from our samples.

[21]The dummies are referred to as "day time dummy variables" or "diurnal variables".

[22]XETRA trades from Monday through Friday from 9 a.m. to 5.30 p.m.

[23]D_{11} is omitted in all estimations.

[24]For the exact time intervals and the associated dummies, see Table 2.

a Wald–test on all lagged diurnal variables to check whether all coefficients are jointly equal to zero. Since this hypothesis cannot be rejected on a 5% level for 16 out of 18 stocks of their sample, the insignificance of lagged diurnal variables is assumed.

To follow this approach, we estimate the VAR[25] with all 10 day time dummy variables (with 5 lags each).

$$\begin{aligned} r_t &= \sum_{i=1}^{5} a_i r_{t-i} + \sum_{j=1}^{10}\sum_{i=0}^{5} \gamma_{i,j}^{r} D_{t-i,j} x_{t-i}^{0} + \sum_{i=0}^{5} (\gamma_i^r + \delta_i^r ln(T_{t-i})) x_{t-i}^{0} + \upsilon_{1,t} \\ x_t &= \sum_{i=1}^{5} c_i r_{t-i} + \sum_{j=1}^{10}\sum_{i=1}^{5} \gamma_{i,j}^{x} D_{t-i,j} x_{t-i}^{0} + \sum_{i=1}^{5} (\gamma_i^x + \delta_i^x ln(T_{t-i})) x_{t-i}^{0} + \upsilon_{2,t} \end{aligned} \tag{5}$$

We perform a Wald–test on all lagged diurnal parameters $\gamma_{1\ldots5,j}^{r}$ and $\gamma_{1\ldots5,j}^{x}$. The results are shown in Table 4 in Appendix C.

For the **Price Revision equation**, the lagged parameters are jointly significant on a 5% significance level for only 6 out of 30 stocks. The picture is less clear–cut for the **Trade equation**, where we compute significant p–values for 11 out of 30 stocks.

With the finding that lagged day time dummy variables are insignificant for most stocks in the Price Revision equation and for the majority of stocks in the Trade equation, we exclude all lagged dummy variables. This corresponds to the proposition made by DUFOUR/ENGLE(2000, p.2480).

We hence reduce (5) to a VAR that only contains the contemporaneous day time dummy variables in the price revision equation and the first–lag dummy variables in the trade equation, which delivers

$$\begin{aligned} r_t &= \sum_{i=1}^{5} a_i r_{t-i} + \sum_{j=1}^{10} \gamma_{0,j}^{r} D_{t,j} x_{t}^{0} + \sum_{i=0}^{5} (\gamma_i^r + \delta_i^r ln(T_{t-i})) x_{t-i}^{0} + \upsilon_{1,t} \\ x_t &= \sum_{i=1}^{5} c_i r_{t-i} + \sum_{j=1}^{10} \gamma_{1,j}^{x} D_{t-1,j} x_{t-1}^{0} + \sum_{i=1}^{5} (\gamma_i^x + \delta_i^x ln(T_{t-i})) x_{t-i}^{0} + \upsilon_{2,t} \end{aligned} \tag{6}$$

The estimation results for the **Price Revision equation** from (6) are presented in Table 5. Although most considered day time interaction terms are insignificant, it strikes that 14 out of 30 stocks exhibit positive and significant coefficients for the opening period. For this reason, it seems reasonable to keep the corresponding dummy variable in the equation. As discussed earlier (Section 4.2), the opening period of NYSE (D_8) might also be of interest. The evidence from our estimates, however, is against an inclusion of this dummy variable: The coefficients are significantly different from zero for only 5 out of 30 stocks.

A Wald–test is performed to find out whether all day time dummy variables besides D_1 are jointly equal to zero (see Table 7). This hypothesis can be rejected on a 5% significance level

[25] As can be seen, the quote revision equation contains 77 parameters, as opposed to the trade equation with only 65. This is due to 12 parameters for contemporaneous effects.

for 22 out of 30 stocks. This finding for the DAX values suggest that the dummy variables should not be removed from the Price Revision equation[26].

The **Trade equation** parameters are reported in Table 6. For all stocks, most coefficients are insignificant on a 5% significance level; apparently trades do not depend on day time effects[27].

The Wald–test for the **Trade equation** (reported in Table 7) predicts that we only reject the null in 9 out of 30 cases[28].

Although the Wald–test tells a different story for the Price Revision equation, the p–values shown in Table 5/6 justify to drop the dummy variables $D_{2...10}$. For the sake of simplicity (and according to the example of DUFOUR/ENGLE (2000)), the removal of lagged dummies occurs in a parallel way for both the quote revision equation and the trade equation.

5.2 Estimated Coefficients

According to the set–up of DUFOUR/ENGLE (2000), we keep the dummy for the opening period in our model. We obtain the VAR

$$\begin{aligned} r_t &= \sum_{i=1}^{5} a_i r_{t-i} + \gamma_{0,1}^r D_{t,1} x_t^0 + \sum_{i=0}^{5} (\gamma_i^r + \delta_i^r ln(T_{t-i})) x_{t-i}^0 + \upsilon_{1,t} \\ x_t &= \sum_{i=1}^{5} c_i r_{t-i} + \gamma_{1,1}^x D_{t-1,1} x_{t-1}^0 + \sum_{i=1}^{5} (\gamma_i^x + \delta_i^x ln(T_{t-i})) x_{t-i}^0 + \upsilon_{2,t} \end{aligned} \tag{7}$$

The results of our estimation are reported in Table 8 (Price Revision equation) and in Table 9 (Trade equation).

5.2.1 Mainly negative effect of lagged returns

HASBROUCK (1991, p.194) finds negative coefficients of lagged return variables in the Price Revision equation (negative autocorrelation) as well as in the Trade equation. DUFOUR/ENGLE (2000, p.2480) find negative autocorrelation between returns in the first and second lag as well as positive autocorrelation in the higher lags. This is consistent with the findings by HASBROUCK/HO (1987) discussed in Section 3.1.1. They also find a negative effect of lagged returns on the Trade–sign. Intuitively, this means that rising prices tend to encourage sales, falling prices encourage purchases.

For 24 out of 30 stocks, we find significant negative autocorrelations of returns for the first lag (see Table 8). For the second lag, there are only significant coefficients for only 6 stocks; furthermore, there is no clear pattern about the sign of these coefficients[29]. Therefore, general

[26]Note that the estimation for `Deutsche Telekom` tells the opposite story; the p–value of the Wald–test is 0.0881.

[27]Deutsche Telekom has three significant day time variables: δ_6, δ_7 and δ_8

[28]Once again, `Deutsche Telekom` provides an opposite pattern: Here the tested dummy variables are highly significant (p–value of 0.00).

[29]`Deutsche Telekom` shows significant negative autocorrelation even for the first four lags.

patterns regarding autocorrelation of returns can only be derived for the first lag.

The negative effect of the first lag–return in the **Trade equation** (see Table 9) can be confirmed for all DAX–stocks. The second lag is still significant for 25 stocks, most of them with positive coefficients. The coefficients of the first lag are about 7-10 times higher than the coefficients for the second lag. We find that for all 5 lags, the coefficients are widely significant for most stocks. Most of the higher- order lags have positive directions[30]. A preceding price increase therefore strongly encourages a sale, which tends to be followed by –smaller– corrections in the opposite direction (purchases).

5.2.2 Positive effect of lagged Trade–signs

More interesting from a theoretical perspective is the partial effect of lagged Trade–signs. If consecutive Trade–signs have positive autocorrelation, this might indicate a split of large transactions made by informed traders (see Section 3.1.1). DUFOUR/ENGLE (2000, p.2480) find strong autocorrelation of Trade–signs as well as a positive cross-correlation on the Price Revision equation.

Our estimation shows (see Table 8) that strong autocorrelation is also true for our data. 28 out of 30 stocks have significant coefficients for all 5 lags in the **Trade equation**; all of them are positive.

The pattern of positive effects of Trade–signs on the **Price Revision equation** (see Table 8) is also clearly visible for the contemporaneous effect and in the first lag: All 30 stocks exhibit significantly positive coefficients for the contemporaneous effect, and still 25 for the first lag[31].

5.2.3 The effect of XETRA and NYSE opening

After having dropped most contemporaneous and all lagged day–time dummy variables, DUFOUR/ENGLE (2000, p. 2481) only keep a single day–time variable for the opening period of the market (see (4)). For the **Price Revision equation**, they find significant coefficients to this parameter for only 7 out of 18 stocks at a five percent level; for the **Trade equation**, this is even the case for only 3 stocks. They conclude that “*time effects are not attributable to daily variations*” (ibid., p. 2480).

Equations (7) contain a dummy for the opening period as well. The results of our estimations for all time–related coefficients are presented in Table 10 and Table 11 respectively. They suggest that a daily pattern does exist at least for the **Price Revision equation**, where we find significant values for γ_1^r in 21 out of 30 stocks. In contrast to that, the assumption that time effects are not due to variations over the day might be strengthened by our estimation for the **Trade equation**, where we find significant values for γ_1^x in only 5 cases.

[30] Deutsche Telekom shows negative effects in the first three lags, the correction does not start until the forth lag.

[31] For Deutsche Telekom there are significant coefficients for the first four lags.

According to our XETRA data, daily patterns cannot be ruled out as easily from the Price Revision equation as it is done by DUFOUR/ENGLE (2000) for their NYSE sample.

5.2.4 The effect of duration

The main focus of this analysis is on the duration between two trades to find out whether market activity has an informational content.

For the **Price Revision equation**, DUFOUR/ENGLE (2000, p.2484) provide promising evidence for the relevance of the interaction terms (capturing the Trade–sign and the duration since the previous trade): In their analysis, the corresponding *contemporaneous coefficients* δ_0 are negative and significant in 13 out of 18 stocks. A Wald–test on all δ_i leads to a rejection of the null hypothesis that the interaction terms are *jointly* equal to zero in 13 out of 18 cases. Further, a Wald–test is performed on *the sum* of all δ_i: The null hypothesis that this sum of the interaction term coefficients equals zero can be rejected in –again– 13 out of 18 cases. DUFOUR/ENGLE (2000) conclude that the positive effect of the Trade–sign on prices (discussed in Section 5.2.2) is partly offset when time between two transactions increases. That means the price impact of a purchase that occurs right after the preceding transaction is larger than the price impact of a purchase which happens after a longer time interval. This finding is in line with theory (see Section 2.4): Short intervals between trades are a signal that new private information has entered the marketplace.

Our relevant parameter estimates for the interaction terms are reported in Table 10. The result is less overwhelming, but it still confirms the story sufficiently: The parameters for the contemporaneous interaction term (δ_0^r) are significant for 14 out of 30 stocks; all but one of them are negative[32]. We perform a Wald–test with the null hypothesis that $\delta_0^r = ... = \delta_5^r = 0$. The last column in Table 10 shows that we can reject the null for 11 out of 30 stocks[33].

The pattern of the effects of the interaction terms in the Price Revision equation are thus found similarly to DUFOUR/ENGLE (2000), although the evidence seems to be less strong.

A similar negative effect of the interaction term is identified by DUFOUR/ENGLE (2000, p.2483) in the **Trade equation**. The sums of the interaction terms δ_i^x (for $i = 1...5$) are negative (for 16 out of 18 stocks) and significantly different from zero in 11 out of 16 cases. Wald–tests on the null hypothesis that the coefficients are jointly equal to zero and that the sum of the coefficient is zero are performed to show that effect. The negative sign indicates that autocorrelations of Trade–signs are stronger when trades occur in little intervals.

The evidence from our analysis (see Table 11) confirms these results. For all five lags of the interaction term we find predominantly negative coefficients; the first lag parameter is significant on a 5% significance level for a large majority of stocks (26 out of 30). For the second (third, forth, fifth) lag, we can still reject the null hypothesis of coefficients equal to zero for 18

[32] `Deutsche Telekom` even has significant negative coefficients for the contemporaneous interaction term and the first and the second lag.

[33] Including `Deutsche Telekom`

(15,17,11) out of 30 stocks. Consequently, there is also a strong support for the significance of the duration/trade–sign interaction terms from the Wald–test on the null hypothesis that all δ_i^x are jointly equal to zero: We can reject this null in 28 out of 30 cases.

Therefore, our estimation based on XETRA data supports the relevance of the interaction terms.

6 The long-term impact of shocks

6.1 The idea

HASBROUCK (1991) introduces the Impulse Response Function as an illustration for the dynamics identified by a VAR-type model estimation. Besides visualizing how fast Price Revisions and Trades return to their equilibrium after a shock, Impulse Response Functions identify the long–term price effects of shocks.

The starting point is a stock which is trading in an equilibrium: This means that there is no private nor public information in the marketplace and stocks are constantly trading at the midpoint of the bid/ask–spread. The Trade–sign x_t and the Price Revision r_t are hence equal to zero for the preceding transactions.

Unexpectedly, an impulse of $\upsilon_{2,t}$ is entering the trade equation in $t = 0$. As discussed in Section 3.1.2, this effect might be interpreted as private information (if it is triggered by informed traders) or noise (if it is caused by liquidity traders). Intuitively, this means that a purchase order occurs. Hasbrouck uses the coefficients estimated in equation (1) and computes a path of r_t and x_t for the subsequent ts. These paths (called impulse response functions) show to what extent the impulse is perceived as new information that changes the true value of the stock.

The set–up of an Impulse Response Function is based on a vector moving average. The VAR from Equation (7) can be written as (HASBROUCK, 1991a, p.576):

$$\begin{aligned} r_t &= \upsilon_{1,t} + \tilde{a}_1\upsilon_{1,t-1} + \tilde{a}_2\upsilon_{1,t-2} + ... + \tilde{b}_0\upsilon_{2,t} + \tilde{b}_1\upsilon_{2,t-1} + ... \\ \mathrm{x}_t &= \tilde{c}_1\upsilon_{1,t-1} + \tilde{c}_2\upsilon_{1,t-2} + ... + \upsilon_{2,t} + \tilde{d}_1\upsilon_{2,t-1} + \tilde{d}_2\upsilon_{2,t-2} + ... \end{aligned} \quad (8)$$

The coefficients in Equation (8) can be interpreted as Impulse Response Functions. The cumulated coefficients are Cumulated Impulse response functions; for example, $\sum_{t=0}^{T} \tilde{a}_t$ is the effect of a shock in the Price Revision equation on Cumulative Price Revisions, which is the long–term impact of a trade.

6.2 Impulse Response Functions and Durations– our example

`Deutsche Telekom` is the most frequently traded stock in the present XETRA sample. We compute the efficients for Equation (8) and draw different Impulse Response Functions. We assume a stable equilibrium in $t = 0$. The impulse is given by an unexpected shift in the Trade–sign for Figures 2–4 and in the Price Revision equation for Figures 5–8. The size of the impulse

$\upsilon_{2,t}$ is chosen equal to the standard deviation of the Trade–sign and the Price Revision series in our sample, which is 0.9799 and 0.024025 respectively.

To make the point about the effect of durations between trades, we compare the same situation followed by two different –exogenously given– series of durations: These series include 20 durations which are taken from the original data and represent the most active and the least active trading interval for `Deutsche Telekom` in the sample. The stock is most actively traded in the interval starting at 4:52:20 p.m. on January 28, 2004. The interval with the highest durations (low activity) takes place at 12:58:41 p.m. on January 6, 2004[34].

Recall that we do not observe an equilibrium (as described above) in these points in time. Therefore, the Impulse Response Functions cannot be interpreted as forecasts for the consecutive transactions given that a shock occurs right then. Rather, forecasts for a shock occurring in any equilibrium are computed, but under the assumption that this equilibrium is followed by an exogenously given series of durations[35]. Unlike DUFOUR/ENGLE (2000), who draw these series from a stochastic process[36], we take the observed extreme cases from reality[37] to show the range of possible outcomes.

The Impulse Response Functions are shown and discussed in Appendix C.1. Here are some key results: For the impulses on the **Trade–Sign** ($\upsilon_{2,t}$), the effects on Price Revision is larger and more persistent if markets are highly active (see Figure 2). The Cumulative Price Revisions take longer to converge in active markets to a final value, and the long–term price effect is larger (see Figure 4). For impulses on **Price Revisions** ($\upsilon_{1,t}$), which means that prices suddenly jump, we see a correction with negative price revisions in the subsequent transactions. This correction takes longer and is larger in markets with high trading activity (Figure 7). In low intensity periods, Trade–signs converge faster to their equilibrium value 0 after a shock on both Price Revisions or Trade–signs (see Figures 3 and 6). Cumulation of Trade–signs show that there is a longer sequence of following trade–signs that is influenced by the shock if markets are more active (see Figure 8).

7 Variance decomposition

As discussed in HASBROUCK (1991a, p.577), total variance for the stock price can be decomposed into an element capturing the variance of the Price Revision equation ($\sigma^2_{\upsilon_1}$) and an element

[34] Table 3 confirms that there are typically low trading intensities around 1 p.m (Dufour/Engle (2000,p. 2487): the "*lunch effect*") and high intensities around 5 p.m.

[35] Note that the dummy variables for the discussed points in time are excluded in equation (7). For the sake of simplicity, we therefore compute impulse response functions for the case that D_1 and D_8 are equal to zero.

[36] Dufour/Engle (2000, p.2475) propose to understand duration series as conditionally Weibull–distributed. This is a more general form than the alternatively appropriate exponential distribution (ibid, p.2476).

[37] Of course, this cannot be taken literally: The underlying sample only contains 21 trading days. Nothing tells us that the "extreme situations" from this period are really that extreme when a longer period is considered. But all we want to do with taking the extreme cases from our sample is to show that durations make a difference.

capturing the variance of the Trade equation ($\sigma^2_{\upsilon_2}$), which can be expressed as

$$\sigma^2_w = (\sum_{t=0}^{T} \tilde{a}_t)^2 \sigma^2_{\upsilon_1} + (\sum_{t=0}^{T} \tilde{b}_t)^2 \sigma^2_{\upsilon_2}, \tag{9}$$

where $\tilde{a}_t$ and $\tilde{b}_t$ denote the coefficients from Equation (8). The variance which is due to trades is

$$\sigma^2_{x,w} = (\sum_{t=0}^{T} \tilde{b}_t)^2 \sigma^2_{\upsilon_2}. \tag{10}$$

The fraction $\sigma^2_{x,w}/\sigma^2_w$ can be interpreted as the share of variance that is due to a shock in $\upsilon_{2,t}$, which is private information (of informed traders) or liquidity needs (of liquidity traders). The remaining variance is due to a shock in $\upsilon_{1,t}$, which is public information.

The estimated coefficients $\tilde{a}_t$ and $\tilde{b}_t$ for Deutsche Telekom are presented in Table 12. We compute a share of $\sigma^2_{x,w}/\sigma^2_w = 41.09\%$ in active markets as opposed to $\sigma^2_{x,w}/\sigma^2_w = 4.54\%$ in low–intense markets.

This result shows that in active markets the role of shocks in $\upsilon_{2,t}$ is more important than in less active markets. This can be interpreted that there are more informed traders in markets with low durations between trades.

8 Conclusion

This paper confirms the basic findings of DUFOUR/ENGLE (2000). Time between trades does matter; low durations are perceived as evidence for the presence of new private information. The effect of a trade in highly active markets is not only larger, but also persistent for a longer period of subsequent trades.

Although impulse response functions provide interesting insights about the information content of time, its results rely on the assumption of exogenously given series of durations. DUFOUR/ENGLE (2000) use a stochastic process, we simply draw exemplary series of durations from our data. These approaches do not include a potential inverse causality of prices and trade signs on durations. As DUFOUR/ENGLE (2000, p. 2496) mention, a more complex model that relates prices, trade signs and durations as endogenous variables could provide "*more accurate*" (ibid) Impulse Response Functions.

A Data

Stock	Ticker	N	Price	Spread	Volume	Duration
Adidas	ADS	22,956	93.24	0.093	355.70	27.95
Allianz	ALV	101,130	104.29	0.055	682.73	6.35
Altana	ALT	24,925	47.12	0.054	546.77	25.75
BASF AG	BAS	50,172	44.99	0.030	1,029.36	12.79
Bayer	BAY	47,100	24.56	0.022	1,517.69	13.63
BMW	BMW	45,892	35.88	0.026	1,168.25	13.99
Commerzbank	CBK	30,422	16.01	0.018	2,224.97	21.11
Continental	CON	21,630	31.40	0.038	796.88	29.67
DaimlerChrysler	DCX	70,846	37.79	0.024	1,613.77	9.06
Deutsche Bank	DBK	72,110	64.39	0.037	1,085.65	8.90
Deutsche Börse	DB1	19,179	46.03	0.050	771.89	33.42
Deutsche Post	DPW	26,690	17.54	0.021	1,947.95	24.05
Deutsche Telekom	DTE	106,385	15.79	0.012	5,093.50	6.04
E.ON AG	EOA	60,458	51.00	0.033	1,101.47	10.62
Fresenius M. C.	FME	12,596	55.79	0.088	365.49	50.96
Henkel Vz.	HEN3	14,410	63.85	0.084	406.39	44.46
Hypo Real Estate	HRX	34,679	20.44	0.027	1,997.98	18.52
Infineon	IFX	68,573	11.72	0.013	4,797.01	9.36
Linde	LIN	19,425	43.98	0.054	567.25	32.96
Lufthansa	LHA	28,099	14.40	0.018	2,208.79	22.84
MAN	MAN	22,593	26.93	0.040	1,021.91	28.41
Metro	MEO	26,215	34.85	0.041	874.59	24.47
Münchener Rück	MUV2	70,932	96.68	0.061	592.03	9.05
RWE AG	RWE	50,863	31.45	0.025	1,257.08	12.62
SAP AG	SAP	62,821	136.05	0.094	514.39	10.22
Schering	SCH	35,404	42.94	0.038	802.72	18.12
Siemens	SIE	92,828	66.68	0.033	1,154.41	6.92
ThyssenKrupp	TKA	27,415	16.77	0.024	1,782.51	23.39
TUI AG	TUI1	25,880	18.87	0.030	1,494.57	24.80
Volkswagen	VOW	54,461	41.81	0.030	1,003.62	11.79

Table 1: **Overview:** This table presents the number of transactions (N) as well as the average prices, spreads, volumes and durations in the period from January 2nd to January 30 2004. These are 21 trading days.

B Day time dummy variables

From		**Until**		**Dummy**
09:00	a.m.	**09:30**	a.m.	D_1
09:30	a.m.	**10:30**	a.m.	D_2
10:30	a.m.	**11:30**	a.m.	D_3
11:30	a.m.	**12:30**	a.m.	D_4
12:30	a.m.	**01:30**	p.m.	D_5
01:30	p.m.	**02:30**	p.m.	D_6
02:30	p.m.	**03:30**	p.m.	D_7
03:30	p.m.	**04:30**	p.m.	D_8
04:30	p.m.	**05:00**	p.m.	D_9
05:00	p.m.	**05:15**	p.m.	D_{10}
05:15	p.m.	**05:30**	p.m.	D_{11}

Table 2: **Definition Diurnal Variables:** This table shows how the day is divided into 11 diurnal periods. Note that the intervals are not equally large. The pattern of the intervals is taken similarly as in DUFOUR/ENGLE (2000, p. 2479f). Unlike NYSE, markets open at 9 a.m. and close at 5.30 p.m. We compute interaction terms of these dummies with the trade sign. The corresponding coefficients are denoted γ_i^x and γ_i^r.

Stock	D_1	D_2	D_3	D_4	D_5	D_6	D_7	D_8	D_9	D_{10}	D_{11}
Adidas	6%	13%	12%	10%	8%	8%	11%	14%	8%	4%	5%
Allianz	8%	14%	11%	10%	6%	7%	10%	17%	9%	4%	4%
Altana	5%	13%	13%	11%	9%	8%	11%	15%	8%	4%	4%
BASF AG	6%	12%	11%	11%	7%	8%	10%	17%	9%	4%	5%
Bayer	6%	12%	11%	10%	8%	8%	10%	17%	9%	5%	5%
BMW	7%	12%	11%	10%	7%	8%	10%	18%	8%	4%	4%
Commerzbank	7%	13%	12%	11%	7%	7%	10%	17%	8%	4%	5%
Continental	5%	12%	12%	11%	8%	9%	11%	16%	8%	4%	4%
DaimlerChrysler	7%	14%	11%	10%	7%	8%	10%	17%	8%	4%	5%
Deutsche Bank	8%	14%	10%	10%	7%	8%	11%	16%	8%	4%	5%
Deutsche Börse	6%	13%	12%	11%	8%	9%	11%	15%	7%	4%	4%
Deutsche Post	6%	12%	13%	10%	8%	8%	11%	16%	8%	4%	4%
Deutsche Telekom	8%	14%	12%	11%	8%	8%	10%	16%	7%	4%	4%
E.ON AG	6%	12%	11%	11%	8%	8%	10%	16%	8%	5%	5%
Fresenius M. C.	5%	12%	11%	8%	9%	10%	11%	17%	8%	4%	5%
Henkel Vz.	5%	9%	12%	11%	9%	9%	12%	16%	8%	4%	5%
Hypo Real Estate	7%	13%	13%	11%	7%	8%	11%	15%	7%	4%	5%
Infineon	11%	16%	12%	9%	6%	7%	10%	15%	7%	3%	4%
Linde	6%	13%	12%	11%	8%	9%	12%	15%	8%	3%	4%
Lufthansa	7%	13%	11%	10%	7%	8%	11%	16%	7%	4%	4%
MAN	5%	13%	13%	10%	9%	8%	11%	16%	8%	4%	4%
Metro	6%	12%	12%	11%	8%	8%	11%	15%	9%	4%	5%
Münchener Rück	6%	13%	12%	10%	8%	7%	10%	15%	8%	5%	5%
RWE AG	6%	13%	12%	10%	8%	8%	11%	15%	7%	4%	5%
SAP AG	6%	11%	11%	12%	8%	8%	10%	18%	8%	4%	4%
Schering	7%	12%	12%	11%	8%	7%	10%	15%	9%	4%	4%
Siemens	8%	13%	11%	10%	6%	7%	12%	17%	8%	4%	4%
ThyssenKrupp	7%	13%	13%	11%	8%	8%	10%	15%	7%	4%	4%
TUI AG	7%	13%	11%	11%	11%	8%	10%	15%	7%	3%	4%
Volkswagen	7%	13%	13%	10%	7%	8%	10%	16%	8%	5%	5%
Total	7%	13%	12%	10%	7%	8%	10%	16%	8%	4%	5%

Table 3: **Trading intensity during the day:** Since time is a central topic of this paper, day time patterns need to be controlled for. This table presents the relative trading activities in a time–of–the–day period compared to total transactions over the day. The exact day time periods that correspond to the dummy variables are shown in Table 2. Note that not all dummies cover an interval of the same size.

C Estimation and Results

	Price Revision		Trade	
Stock	**Wald Test**	**p-value**	**Wald Test**	**p-value**
Adidas	70.2484	0.0310	56.3747	0.2488
Allianz	47.9925	0.5543	91.1163	0.0003
Altana	59.0124	0.1793	69.3895	0.0361
BASF AG	54.5953	0.3042	85.3669	0.0014
Bayer	56.0716	0.2578	50.9238	0.4371
BMW	42.1372	0.7776	64.7178	0.0788
Commerzbank	47.1415	0.5888	82.2136	0.0028
Continental	35.2298	0.9436	48.8375	0.5201
DaimlerChrysler	50.1338	0.4681	55.6443	0.2707
Deutsche Bank	46.3266	0.6216	68.7886	0.0401
Deutsche Börse	51.4241	0.4178	42.6140	0.7614
Deutsche Post	79.6191	0.0049	69.1929	0.0374
Deutsche Telekom	50.1961	0.4656	125.9699	0.0000
E.ON AG	64.9501	0.0760	36.1176	0.9298
Fresenius M. C.	51.3038	0.4224	56.4084	0.2478
Henkel Vz.	79.6655	0.0048	69.3509	0.0363
Hypo Real Estate	52.2401	0.3870	49.1521	0.5074
Infineon	43.1892	0.7412	64.5770	0.0806
Linde	55.2772	0.2822	62.4132	0.1118
Lufthansa	31.1798	0.9830	74.5430	0.0138
MAN	73.4904	0.0169	66.7004	0.0572
Metro	67.8816	0.0469	58.2126	0.1988
Münchener Rück	79.6673	0.0048	52.8015	0.3664
RWE AG	50.9237	0.4371	45.8985	0.6386
SAP AG	45.7926	0.6428	82.6177	0.0025
Schering	66.8149	0.0561	59.1857	0.1753
Siemens	61.3722	0.1300	76.1588	0.0100
ThyssenKrupp	43.1076	0.7442	45.1705	0.6672
TUI AG	46.3681	0.6199	37.9940	0.8934
Volkswagen	46.3520	0.6206	62.4759	0.1108

Table 4: **Wald test lagged dummy variables:** Initially, the estimated equation contains 10 day time dummy variables with 5 lags each. We use (see Equation (5)): $r_t = \sum_{i=1}^{5} a_i r_{t-i} + \sum_{j=1}^{10}\sum_{i=0}^{5}\gamma_{i,j}^{r} D_{t-i,j} x_{t-i}^{0} + \sum_{i=0}^{5}(\gamma_i^r + \delta_i^r ln(T_{t-i}))x_{t-i}^{0} + \upsilon_{1,t}$ as the Price Revision equation and $x_t = \sum_{i=1}^{5} c_i r_{t-i} + \sum_{j=1}^{10}\sum_{i=1}^{5}\gamma_{i,j}^{x} D_{t-i,j} x_{t-i}^{0} + \sum_{i=1}^{5}(\gamma_i^x + \delta_i^x ln(T_{t-i}))x_{t-i}^{0} + \upsilon_{2,t}$ as the Trade equation.
We perform a Wald–test with the null hypothesis that all lagged diurnal parameters $\gamma_{1\ldots5,j}^{r}$ and $\gamma_{1\ldots5,j}^{x}$ are jointly equal to zero. The Wald–statistics and the p–values (computed with standard errors on the basis of WHITE's (1980) heteroskedasticity–robust variance matrix) are reported in this table. For the Price Revision equation the null is rejected for 6 out of 30 stocks on a 5% significance level, for the Trade equation, it is rejected for 11 stocks.

Stock	$\gamma^r_{0,1}$	$\gamma^r_{0,2}$	$\gamma^r_{0,3}$	$\gamma^r_{0,4}$	$\gamma^r_{0,5}$	$\gamma^r_{0,6}$	$\gamma^r_{0,7}$	$\gamma^r_{0,8}$	$\gamma^r_{0,9}$	$\gamma^r_{0,10}$
Adidas	**0.0093**	**0.0027**	**-0.0002**	**0.0018**	**0.0026**	**0.0014**	**0.0020**	**0.0014**	**0.0003**	**0.0016**
	0.0043	*0.3173*	*0.9492*	*0.5054*	*0.3439*	*0.6116*	*0.4467*	*0.6055*	*0.9161*	*0.5748*
Allianz	**0.0001**	**0.0003**	**-0.0003**	**-0.0006**	**-0.0009**	**-0.0010**	**-0.0001**	**0.0001**	**-0.0003**	**-0.0001**
	0.9073	*0.7117*	*0.6773*	*0.4528*	*0.2879*	*0.2461*	*0.8597*	*0.9339*	*0.7143*	*0.9028*
Altana	**0.0057**	**0.0009**	**-0.0014**	**-0.0040**	**-0.0043**	**-0.0034**	**-0.0030**	**-0.0041**	**-0.0036**	**-0.0017**
	0.1681	*0.7874*	*0.6917*	*0.2504*	*0.2196*	*0.3307*	*0.3828*	*0.2284*	*0.3001*	*0.6273*
BASF AG	**0.0030**	**0.0024**	**0.0013**	**0.0008**	**0.0007**	**0.0016**	**0.0019**	**0.0015**	**0.0011**	**0.0001**
	0.0173	*0.0286*	*0.2338*	*0.4685*	*0.5054*	*0.1555*	*0.0827*	*0.1710*	*0.2976*	*0.9286*
Bayer	**0.0049**	**0.0020**	**0.0012**	**0.0006**	**0.0003**	**-0.0001**	**0.0010**	**0.0012**	**0.0004**	**-0.0004**
	0.0011	*0.1169*	*0.3655*	*0.6525*	*0.8197*	*0.9276*	*0.4504*	*0.3407*	*0.7499*	*0.7910*
BMW	**0.0055**	**0.0034**	**0.0022**	**0.0021**	**0.0025**	**0.0033**	**0.0033**	**0.0028**	**0.0026**	**0.0025**
	0.0049	*0.0621*	*0.2284*	*0.2452*	*0.1675*	*0.0756*	*0.0705*	*0.1177*	*0.1542*	*0.1801*
Commerzbank	**0.0031**	**0.0041**	**-0.0001**	**0.0008**	**-0.0005**	**0.0012**	**0.0017**	**0.0020**	**0.0022**	**0.0008**
	0.2477	*0.0924*	*0.9691*	*0.7286*	*0.8328*	*0.6270*	*0.4910*	*0.4189*	*0.3742*	*0.7552*
Continental	**0.0175**	**0.0098**	**0.0060**	**0.0077**	**0.0095**	**0.0084**	**0.0069**	**0.0069**	**0.0080**	**0.0069**
	0.0000	*0.0041*	*0.0723*	*0.0212*	*0.0058*	*0.0121*	*0.0372*	*0.0363*	*0.0182*	*0.0578*
DaimlerChrysler	**0.0029**	**0.0013**	**0.0014**	**0.0004**	**0.0010**	**0.0014**	**0.0014**	**0.0024**	**0.0016**	**-0.0001**
	0.0111	*0.2176*	*0.2051*	*0.6942*	*0.3797*	*0.2178*	*0.1874*	*0.0271*	*0.1552*	*0.9309*
Deutsche Bank	**0.0037**	**0.0028**	**0.0022**	**0.0022**	**0.0015**	**0.0025**	**0.0022**	**0.0031**	**0.0026**	**0.0019**
	0.0021	*0.0118*	*0.0539*	*0.0477*	*0.1746*	*0.0250*	*0.0521*	*0.0057*	*0.0244*	*0.1001*
Deutsche Börse	**0.0081**	**0.0040**	**0.0010**	**0.0026**	**0.0037**	**0.0000**	**0.0027**	**0.0004**	**0.0018**	**0.0025**
	0.1363	*0.4286*	*0.8405*	*0.6108*	*0.4638*	*0.9934*	*0.5886*	*0.9332*	*0.7213*	*0.6391*
Deutsche Post	**0.0094**	**0.0029**	**0.0021**	**0.0006**	**-0.0001**	**0.0009**	**0.0032**	**0.0025**	**0.0015**	**0.0031**
	0.0029	*0.3037*	*0.4422*	*0.8421*	*0.9720*	*0.7414*	*0.2520*	*0.3556*	*0.5877*	*0.2934*
Deutsche Telekom	**0.0014**	**0.0006**	**0.0001**	**0.0002**	**0.0004**	**0.0005**	**0.0007**	**0.0011**	**0.0008**	**0.0000**
	0.0607	*0.3982*	*0.9104*	*0.7382*	*0.6185*	*0.5232*	*0.3007*	*0.1234*	*0.2942*	*0.9654*
E.ON AG	**0.0028**	**0.0013**	**0.0007**	**-0.0001**	**-0.0002**	**0.0009**	**0.0014**	**0.0008**	**0.0009**	**0.0000**
	0.0186	*0.1918*	*0.4661*	*0.8919*	*0.8517*	*0.3681*	*0.1862*	*0.4132*	*0.4052*	*0.9999*
Fresenius M. C.	**0.0213**	**0.0098**	**0.0065**	**0.0095**	**0.0072**	**0.0088**	**0.0078**	**0.0087**	**0.0065**	**0.0092**
	0.0021	*0.0364*	*0.1502*	*0.0386*	*0.1117*	*0.0512*	*0.0844*	*0.0490*	*0.1575*	*0.0540*
Henkel Vz.	**0.0235**	**0.0077**	**0.0060**	**0.0032**	**0.0010**	**-0.0001**	**0.0020**	**0.0021**	**0.0020**	**-0.0004**
	0.0000	*0.0163*	*0.0478*	*0.2959*	*0.7431*	*0.9672*	*0.5124*	*0.4688*	*0.5186*	*0.9000*
Hypo Real Estate	**0.0092**	**0.0092**	**0.0079**	**0.0068**	**0.0061**	**0.0071**	**0.0076**	**0.0090**	**0.0086**	**0.0098**
	0.0015	*0.0004*	*0.0021*	*0.0082*	*0.0201*	*0.0060*	*0.0031*	*0.0005*	*0.0011*	*0.0010*
Infineon	**0.0006**	**0.0001**	**0.0002**	**-0.0001**	**-0.0013**	**0.0001**	**0.0000**	**0.0013**	**-0.0001**	**-0.0002**
	0.8148	*0.9680*	*0.9310*	*0.9670*	*0.6173*	*0.9807*	*0.9849*	*0.6175*	*0.9793*	*0.9464*
Linde	**0.0041**	**0.0006**	**-0.0028**	**-0.0050**	**-0.0042**	**-0.0024**	**-0.0019**	**-0.0036**	**-0.0007**	**-0.0003**
	0.3440	*0.8597*	*0.4354*	*0.1622*	*0.2419*	*0.5088*	*0.6051*	*0.3147*	*0.8447*	*0.9450*
Lufthansa	**-0.0024**	**-0.0037**	**-0.0037**	**-0.0056**	**-0.0056**	**-0.0033**	**-0.0049**	**-0.0044**	**-0.0039**	**-0.0034**
	0.4263	*0.1599*	*0.1638*	*0.0335*	*0.0443*	*0.2202*	*0.0646*	*0.0921*	*0.1553*	*0.2462*
MAN	**0.0137**	**0.0041**	**-0.0003**	**0.0002**	**-0.0023**	**0.0006**	**-0.0002**	**0.0005**	**0.0025**	**0.0036**
	0.0014	*0.2109*	*0.9273*	*0.9496*	*0.4780*	*0.8533*	*0.9593*	*0.8680*	*0.4528*	*0.3118*
Metro	**-0.0017**	**-0.0036**	**-0.0049**	**-0.0062**	**-0.0066**	**-0.0057**	**-0.0033**	**-0.0046**	**-0.0046**	**-0.0080**
	0.6827	*0.2824*	*0.1342*	*0.0604*	*0.0459*	*0.0871*	*0.3133*	*0.1606*	*0.1673*	*0.0203*
Münchener Rück	**0.0015**	**0.0001**	**-0.0007**	**-0.0008**	**-0.0003**	**-0.0010**	**-0.0006**	**-0.0001**	**-0.0001**	**-0.0004**
	0.1600	*0.9445*	*0.4994*	*0.4434*	*0.7744*	*0.3052*	*0.5552*	*0.8919*	*0.9122*	*0.7002*
RWE AG	**0.0008**	**-0.0008**	**-0.0014**	**-0.0013**	**-0.0004**	**-0.0015**	**-0.0005**	**0.0011**	**0.0011**	**0.0006**
	0.5969	*0.5742*	*0.2962*	*0.3211*	*0.7811*	*0.2550*	*0.7065*	*0.4233*	*0.4384*	*0.7051*
SAP AG	**0.0047**	**0.0021**	**0.0016**	**0.0020**	**0.0013**	**0.0013**	**0.0017**	**0.0009**	**0.0007**	**0.0011**
	0.0044	*0.1755*	*0.3148*	*0.2168*	*0.3958*	*0.3970*	*0.2754*	*0.5801*	*0.6600*	*0.5071*
Schering	**0.0052**	**0.0010**	**0.0024**	**0.0006**	**0.0003**	**-0.0004**	**0.0004**	**0.0003**	**0.0003**	**0.0002**
	0.0653	*0.7097*	*0.3653*	*0.8098*	*0.9197*	*0.8870*	*0.8921*	*0.8955*	*0.9090*	*0.9467*
Siemens	**0.0018**	**0.0019**	**0.0020**	**0.0013**	**0.0008**	**0.0020**	**0.0016**	**0.0017**	**0.0021**	**0.0024**
	0.0795	*0.0610*	*0.0481*	*0.2179*	*0.4120*	*0.0481*	*0.1252*	*0.0971*	*0.0410*	*0.0239*
ThyssenKrupp	**0.0084**	**0.0045**	**0.0026**	**0.0044**	**0.0034**	**0.0032**	**0.0031**	**0.0031**	**0.0028**	**0.0046**
	0.0533	*0.2746*	*0.5150*	*0.2835*	*0.4088*	*0.4350*	*0.4448*	*0.4403*	*0.4948*	*0.2878*
TUI AG	**0.0044**	**0.0036**	**0.0022**	**0.0069**	**0.0067**	**0.0069**	**0.0023**	**0.0056**	**0.0017**	**-0.0005**
	0.2592	*0.2638*	*0.5007*	*0.0347*	*0.0481*	*0.0396*	*0.4729*	*0.0833*	*0.6093*	*0.8873*
Volkswagen	**0.0024**	**0.0006**	**0.0003**	**0.0001**	**-0.0008**	**0.0003**	**0.0007**	**0.0008**	**-0.0004**	**-0.0007**
	0.1382	*0.6876*	*0.8314*	*0.9499*	*0.5746*	*0.8508*	*0.6439*	*0.5987*	*0.7592*	*0.6160*

Table 5: **Contemporaneous day time interaction terms in the Price Revision equation:** We use OLS to estimate the Price Revision equation from Equation (6) with all contemporaneous day time dummy variables $r_t = \sum_{i=1}^{5} a_i r_{t-i} + \sum_{j=1}^{10} \gamma^r_{0,j} D_{t,j} x^0_t + \sum_{i=0}^{5} (\gamma^r_i + \delta^r_i ln(T_{t-i})) x^0_{t-i} + \upsilon_{1,t}$. The table reports the coefficients for day time effects only. The p–values (in italics below each coefficient) are computed with heteroskedasticity–robust standard errors. Only the dummy for the opening period $\gamma^r_{0,1}$ exhibits a substantial number (14) of significant estimates on a 5 % level. The opening period of NYSE ($\gamma^r_{0,8}$) is only significantly different from zero for 5 stocks.

Stock	$\gamma^x_{1,1}$	$\gamma^x_{1,2}$	$\gamma^x_{1,3}$	$\gamma^x_{1,4}$	$\gamma^x_{1,5}$	$\gamma^x_{1,6}$	$\gamma^x_{1,7}$	$\gamma^x_{1,8}$	$\gamma^x_{1,9}$	$\gamma^x_{1,10}$
Adidas	**0.0344**	**-0.0030**	**0.0141**	**-0.0150**	**-0.0163**	**0.0000**	**0.0067**	**0.0045**	**0.0424**	**0.0376**
	0.3948	*0.9327*	*0.6980*	*0.6867*	*0.6772*	*0.9990*	*0.8549*	*0.9003*	*0.2744*	*0.3914*
Allianz	**0.0262**	**0.0048**	**0.0151**	**0.0209**	**0.0205**	**0.0777**	**0.0263**	**0.0258**	**0.0261**	**-0.0113**
	0.1771	*0.7881*	*0.4106*	*0.2662*	*0.3059*	*0.0001*	*0.1604*	*0.1413*	*0.1670*	*0.5976*
Altana	**0.0766**	**0.0583**	**0.0434**	**0.0377**	**0.0686**	**0.0723**	**0.0758**	**0.0839**	**0.0682**	**-0.0095**
	0.0751	*0.1141*	*0.2366*	*0.3073*	*0.0703*	*0.0607*	*0.0420*	*0.0192*	*0.0797*	*0.8327*
BASF AG	**-0.0044**	**0.0176**	**0.0153**	**0.0166**	**0.0324**	**0.0647**	**-0.0027**	**0.0077**	**0.0340**	**-0.0260**
	0.8748	*0.4628*	*0.5282*	*0.4971*	*0.2098*	*0.0115*	*0.9125*	*0.7403*	*0.1766*	*0.3634*
Bayer	**0.0084**	**0.0223**	**0.0052**	**0.0033**	**-0.0210**	**-0.0214**	**0.0205**	**0.0209**	**0.0048**	**0.0139**
	0.7577	*0.3516*	*0.8301*	*0.8945*	*0.4156*	*0.4047*	*0.4080*	*0.3626*	*0.8493*	*0.6276*
BMW	**0.0469**	**0.0507**	**0.0487**	**0.0371**	**0.0433**	**0.0645**	**0.0552**	**0.0495**	**0.0254**	**0.0152**
	0.1236	*0.0693*	*0.0844*	*0.1923*	*0.1477*	*0.0291*	*0.0527*	*0.0663*	*0.3874*	*0.6477*
Commerzbank	**0.0026**	**-0.0389**	**-0.0229**	**-0.0297**	**-0.0054**	**0.0072**	**0.0196**	**0.0328**	**0.0342**	**-0.0119**
	0.9385	*0.2139*	*0.4677*	*0.3524*	*0.8745*	*0.8352*	*0.5382*	*0.2758*	*0.3056*	*0.7589*
Continental	**0.0800**	**0.0726**	**0.0126**	**0.0640**	**0.0263**	**0.0497**	**0.0418**	**0.0739**	**0.0510**	**0.0855**
	0.0683	*0.0609*	*0.7469*	*0.1023*	*0.5187*	*0.2178*	*0.2866*	*0.0507*	*0.2169*	*0.0704*
DaimlerChrysler	**0.0158**	**0.0121**	**-0.0160**	**0.0287**	**0.0179**	**0.0212**	**0.0098**	**0.0022**	**-0.0022**	**0.0343**
	0.4797	*0.5557*	*0.4518*	*0.1816*	*0.4361*	*0.3370*	*0.6497*	*0.9121*	*0.9199*	*0.1668*
Deutsche Bank	**0.0350**	**0.0423**	**0.0112**	**0.0417**	**0.0496**	**0.0304**	**0.0364**	**0.0255**	**0.0404**	**0.0207**
	0.1166	*0.0384*	*0.5990*	*0.0524*	*0.0305*	*0.1697*	*0.0845*	*0.2061*	*0.0648*	*0.4017*
Deutsche Börse	**-0.0512**	**-0.0275**	**-0.0409**	**-0.0386**	**-0.0333**	**-0.0080**	**-0.0210**	**-0.0504**	**-0.0222**	**-0.0874**
	0.2615	*0.5082*	*0.3378*	*0.3680*	*0.4557*	*0.8579*	*0.6201*	*0.2292*	*0.6246*	*0.0931*
Deutsche Post	**-0.0598**	**-0.0215**	**-0.0025**	**-0.0187**	**0.0485**	**0.0119**	**0.0185**	**0.0413**	**0.0200**	**0.0301**
	0.1282	*0.5383*	*0.9413*	*0.5988*	*0.1839*	*0.7465*	*0.5966*	*0.2186*	*0.5877*	*0.4727*
Deutsche Telekom	**-0.0109**	**0.0041**	**0.0008**	**-0.0075**	**0.0357**	**0.0476**	**0.0245**	**0.0376**	**0.0525**	**0.0388**
	0.5658	*0.8149*	*0.9626*	*0.6810*	*0.0596*	*0.0122*	*0.1760*	*0.0300*	*0.0056*	*0.0679*
E.ON AG	**0.0222**	**0.0100**	**-0.0053**	**0.0157**	**0.0153**	**0.0186**	**0.0116**	**0.0170**	**0.0106**	**0.0180**
	0.3769	*0.6495*	*0.8101*	*0.4790*	*0.5150*	*0.4303*	*0.6056*	*0.4232*	*0.6456*	*0.4766*
Fresenius M. C.	**0.0686**	**-0.0104**	**0.0068**	**0.0661**	**-0.0456**	**0.0656**	**-0.0014**	**0.0185**	**-0.0079**	**-0.0078**
	0.2315	*0.8283*	*0.8877*	*0.1894*	*0.3645*	*0.1848*	*0.9764*	*0.6861*	*0.8758*	*0.8952*
Henkel Vz.	**0.1312**	**0.0122**	**0.0033**	**-0.0255**	**-0.0094**	**-0.0262**	**0.0223**	**0.0192**	**-0.0089**	**0.0047**
	0.0149	*0.7950*	*0.9404*	*0.5760*	*0.8420*	*0.5774*	*0.6191*	*0.6571*	*0.8503*	*0.9317*
Hypo Real Estate	**-0.0158**	**-0.0036**	**0.0154**	**-0.0193**	**-0.0220**	**0.0024**	**-0.0066**	**0.0123**	**-0.0220**	**-0.0248**
	0.6185	*0.8986*	*0.5850*	*0.5060*	*0.4846*	*0.9365*	*0.8181*	*0.6571*	*0.4768*	*0.4995*
Infineon	**0.0263**	**0.0229**	**0.0254**	**0.0188**	**0.0357**	**0.0442**	**0.0375**	**0.0586**	**0.0653**	**0.0060**
	0.2605	*0.3167*	*0.2792*	*0.4404*	*0.1768*	*0.0802*	*0.1192*	*0.0095*	*0.0091*	*0.8333*
Linde	**-0.0645**	**-0.0153**	**-0.0181**	**-0.0208**	**0.0127**	**-0.0155**	**-0.0638**	**0.0359**	**-0.0409**	**0.0167**
	0.1549	*0.6953*	*0.6475*	*0.6053*	*0.7622*	*0.7076*	*0.1083*	*0.3466*	*0.3275*	*0.7394*
Lufthansa	**0.0887**	**-0.0247**	**-0.0104**	**-0.0145**	**0.0145**	**0.0017**	**0.0157**	**0.0325**	**-0.0042**	**-0.0363**
	0.0126	*0.4496*	*0.7550*	*0.6672*	*0.6838*	*0.9617*	*0.6403*	*0.3105*	*0.9064*	*0.3637*
MAN	**0.0423**	**0.0325**	**0.0079**	**-0.0253**	**-0.0023**	**0.0405**	**-0.0060**	**-0.0218**	**0.0114**	**-0.0550**
	0.3344	*0.3906*	*0.8356*	*0.5160*	*0.9541*	*0.3125*	*0.8769*	*0.5562*	*0.7771*	*0.2373*
Metro	**0.0467**	**-0.0152**	**-0.0337**	**-0.0177**	**0.0082**	**0.0069**	**-0.0291**	**-0.0319**	**-0.0558**	**-0.0234**
	0.2153	*0.6477*	*0.3075*	*0.5943*	*0.8166*	*0.8435*	*0.3828*	*0.3219*	*0.1069*	*0.5622*
Münchener Rück	**-0.0142**	**-0.0012**	**-0.0446**	**-0.0330**	**-0.0166**	**0.0118**	**-0.0143**	**-0.0034**	**-0.0158**	**-0.0002**
	0.5449	*0.9526*	*0.0316*	*0.1200*	*0.4594*	*0.6030*	*0.4996*	*0.8671*	*0.4688*	*0.9949*
RWE AG	**0.0373**	**0.0246**	**0.0339**	**0.0224**	**0.0121**	**0.0160**	**0.0129**	**0.0078**	**0.0193**	**0.0118**
	0.1551	*0.2829*	*0.1431*	*0.3410*	*0.6254*	*0.5160*	*0.5809*	*0.7296*	*0.4392*	*0.6726*
SAP AG	**0.0572**	**0.0627**	**0.0289**	**0.0748**	**0.0291**	**0.0385**	**0.0310**	**0.0815**	**0.0350**	**0.0184**
	0.0315	*0.0096*	*0.2339*	*0.0018*	*0.2531*	*0.1296*	*0.2061*	*0.0004*	*0.1630*	*0.5110*
Schering	**0.0342**	**0.0135**	**-0.0349**	**-0.0066**	**-0.0021**	**-0.0023**	**0.0178**	**0.0285**	**0.0225**	**0.0027**
	0.2980	*0.6575*	*0.2552*	*0.8320*	*0.9477*	*0.9440*	*0.5729*	*0.3416*	*0.4803*	*0.9414*
Siemens	**0.0445**	**0.0393**	**0.0194**	**0.0171**	**0.0553**	**0.0587**	**0.0462**	**0.0315**	**0.0284**	**-0.0135**
	0.0301	*0.0412*	*0.3209*	*0.3923*	*0.0098*	*0.0044*	*0.0178*	*0.0938*	*0.1634*	*0.5521*
ThyssenKrupp	**-0.0193**	**0.0074**	**0.0327**	**0.0245**	**0.0104**	**-0.0114**	**0.0270**	**0.0122**	**0.0108**	**-0.0111**
	0.6045	*0.8320*	*0.3509*	*0.4900*	*0.7828*	*0.7603*	*0.4562*	*0.7234*	*0.7770*	*0.7932*
TUI AG	**0.0216**	**-0.0028**	**0.0179**	**0.0249**	**0.0113**	**0.0342**	**0.0116**	**0.0130**	**-0.0118**	**0.0165**
	0.5710	*0.9343*	*0.6083*	*0.4760*	*0.7474*	*0.3450*	*0.7427*	*0.6982*	*0.7511*	*0.7091*
Volkswagen	**0.0062**	**0.0012**	**-0.0081**	**-0.0008**	**-0.0105**	**0.0031**	**0.0014**	**-0.0006**	**-0.0099**	**0.0312**
	0.8134	*0.9598*	*0.7300*	*0.9735*	*0.6784*	*0.9019*	*0.9532*	*0.9786*	*0.6911*	*0.2552*

Table 6: **Contemporaneous day time interaction terms in the Trade equation:** We use OLS to estimate the Trade equation from Equation (6) with the first lag of all day time dummy variables, $x_t = \sum_{i=1}^{5} c_i r_{t-i} + \sum_{j=1}^{10} \gamma^x_{1,j} D_{t-1,j} x^0_{t-1} + \sum_{i=1}^{5} (\gamma^x_i + \delta^x_i ln(T_{t-i})) x^0_{t-i} + \upsilon_{2,t}$. The table reports the coefficients for day time effects only. The p–values (in italics below each coefficient) are computed with heteroskedasticity–robust standard errors. Most coefficients are insignificant on a 5% level.

Stock	Price Revision		Trade	
	Wald Test	p-value	Wald Test	p-value
Adidas	17.2292	0.0452	6.2962	0.7099
Allianz	37.3304	0.0000	36.8205	0.0000
Altana	34.2744	0.0001	14.4432	0.1074
BASF AG	26.0779	0.0020	20.8880	0.0132
Bayer	17.2659	0.0447	10.9452	0.2795
BMW	13.6888	0.1338	9.5051	0.3920
Commerzbank	26.7562	0.0015	23.0435	0.0061
Continental	18.4637	0.0302	12.7724	0.1732
DaimlerChrysler	50.7310	0.0000	13.7373	0.1320
Deutsche Bank	31.9892	0.0002	11.8318	0.2230
Deutsche Börse	25.3999	0.0026	6.0272	0.7372
Deutsche Post	18.4198	0.0306	15.8949	0.0691
Deutsche Telekom	23.6775	0.0048	47.7283	0.0000
E.ON AG	33.8642	0.0001	3.5308	0.9395
Fresenius M. C.	8.8824	0.4482	13.2114	0.1533
Henkel Vz.	43.4271	0.0000	4.4695	0.8779
Hypo Real Estate	25.4031	0.0026	6.8698	0.6507
Infineon	15.3176	0.0826	23.0095	0.0062
Linde	25.0708	0.0029	17.9243	0.0361
Lufthansa	9.8988	0.3587	12.1657	0.2041
MAN	24.6272	0.0034	13.8360	0.1283
Metro	21.6201	0.0102	8.5977	0.4752
Münchener Rück	13.8645	0.1272	19.7143	0.0198
RWE AG	53.8831	0.0000	4.3081	0.8900
SAP AG	20.6212	0.0144	37.0310	0.0000
Schering	15.7301	0.0727	13.5189	0.1405
Siemens	41.2459	0.0000	28.5854	0.0008
ThyssenKrupp	5.6689	0.7725	4.9669	0.8372
TUI AG	37.6680	0.0000	3.9846	0.9124
Volkswagen	18.8323	0.0267	4.3858	0.8842

Table 7: **Wald test contemporaneous dummy variables:** Equation (6) contains all contemporaneous (for the Trade equation: first lag) interaction terms of day time effects. We consider $r_t = \sum_{i=1}^{5} a_i r_{t-i} + \sum_{j=1}^{10} \gamma_{0,j}^r D_{t,j} x_t^0 + \sum_{i=0}^{5} (\gamma_i^r + \delta_i^r ln(T_{t-i})) x_{t-i}^0 + \upsilon_{1,t}$ as the Price Revision equation and $x_t = \sum_{i=1}^{5} c_i r_{t-i} + \sum_{j=1}^{10} \gamma_{1,j}^x D_{t-1,j} x_{t-1}^0 + \sum_{i=1}^{5} (\gamma_i^x + \delta_i^x ln(T_{t-i})) x_{t-i}^0 + \upsilon_{2,t}$ as the Trade equation.
We perform a Wald–test with the null hypothesis that all diurnal variables besides the interaction term for the opening period γ_1^r and γ_1^x are jointly equal to zero. The Wald–statistics and the p–values (computed with standard errors on the basis of WHITE's (1980) heteroskedasticity–robust variance matrix) are reported in this table. For the Price Revision equation the null is rejected for 22 out of 30 stocks on a 5% significance level; for the Trade equation, it is rejected for 9 stocks.

Stock	r_{t-1}	r_{t-2}	r_{t-3}	r_{t-4}	r_{t-5}	x_t	x_{t-1}	x_{t-2}	x_{t-3}	x_{t-4}	x_{t-5}
Adidas	**-0.0150**	**0.0440**	**0.0009**	**0.0450**	**0.0299**	**0.0076**	**0.0022**	**-0.0005**	**0.0011**	**-0.0005**	**-0.0013**
	0.2863	*0.0013*	*0.9401*	*0.0006*	*0.0353*	*0.0000*	*0.0007*	*0.4443*	*0.0760*	*0.4133*	*0.0411*
Allianz	**-0.0432**	**-0.0017**	**0.0062**	**0.0126**	**0.0216**	**0.0031**	**0.0012**	**0.0002**	**0.0002**	**0.0000**	**-0.0004**
	0.0000	*0.8479*	*0.3855*	*0.0334*	*0.0000*	*0.0000*	*0.0000*	*0.1313*	*0.1822*	*0.7869*	*0.0061*
Altana	**-0.0713**	**0.0018**	**0.0123**	**0.0229**	**-0.0196**	**0.0094**	**0.0023**	**0.0002**	**0.0001**	**-0.0005**	**-0.0004**
	0.0000	*0.8957*	*0.3112*	*0.0338*	*0.1760*	*0.0000*	*0.0010*	*0.8198*	*0.8724*	*0.5316*	*0.5310*
BASF AG	**-0.0273**	**0.0252**	**0.0152**	**0.0098**	**0.0060**	**0.0063**	**0.0013**	**0.0003**	**0.0002**	**-0.0003**	**0.0000**
	0.0002	*0.0006*	*0.0196*	*0.1347*	*0.3595*	*0.0000*	*0.0000*	*0.2013*	*0.4019*	*0.2733*	*0.9462*
Bayer	**-0.0333**	**0.0073**	**0.0057**	**0.0093**	**0.0110**	**0.0075**	**0.0016**	**0.0005**	**0.0003**	**-0.0002**	**-0.0003**
	0.0000	*0.3181*	*0.3928*	*0.2786*	*0.1169*	*0.0000*	*0.0000*	*0.1131*	*0.4299*	*0.5898*	*0.3553*
BMW	**-0.0449**	**0.0110**	**0.0087**	**-0.0033**	**-0.0055**	**0.0055**	**0.0017**	**0.0002**	**-0.0004**	**0.0000**	**0.0005**
	0.0001	*0.2311*	*0.3514*	*0.7728*	*0.4615*	*0.0000*	*0.0000*	*0.4880*	*0.2420*	*0.9628*	*0.1359*
Commerzbank	**-0.0535**	**-0.0155**	**0.0004**	**0.0044**	**-0.0126**	**0.0096**	**0.0029**	**-0.0002**	**0.0001**	**0.0005**	**0.0002**
	0.0000	*0.0557*	*0.9594*	*0.5677*	*0.1283*	*0.0000*	*0.0000*	*0.7007*	*0.8265*	*0.4065*	*0.7403*
Continental	**-0.0611**	**-0.0209**	**0.0197**	**0.0025**	**-0.0118**	**0.0093**	**0.0016**	**0.0014**	**-0.0010**	**-0.0011**	**0.0006**
	0.0000	*0.2191*	*0.1780*	*0.8412*	*0.3026*	*0.0000*	*0.0574*	*0.0811*	*0.2324*	*0.1287*	*0.4641*
DaimlerChrysler	**-0.0389**	**0.0061**	**0.0050**	**0.0045**	**0.0103**	**0.0044**	**0.0016**	**0.0003**	**0.0004**	**0.0002**	**-0.0003**
	0.0000	*0.3122*	*0.3218*	*0.4221*	*0.1406*	*0.0000*	*0.0000*	*0.1292*	*0.0433*	*0.4324*	*0.1860*
Deutsche Bank	**-0.0359**	**-0.0179**	**0.0072**	**0.0054**	**0.0131**	**0.0041**	**0.0012**	**0.0008**	**0.0004**	**0.0003**	**0.0000**
	0.0057	*0.0846*	*0.2015*	*0.2823*	*0.1983*	*0.0000*	*0.0000*	*0.0000*	*0.0442*	*0.0915*	*0.8965*
Deutsche Börse	**0.0176**	**0.0066**	**0.0155**	**0.0023**	**0.0066**	**0.0075**	**0.0000**	**-0.0002**	**-0.0017**	**0.0011**	**-0.0001**
	0.2473	*0.5091*	*0.0804*	*0.8163*	*0.4767*	*0.0000*	*0.9993*	*0.7684*	*0.0274*	*0.2235*	*0.8780*
Deutsche Post	**-0.0492**	**-0.0157**	**0.0031**	**-0.0062**	**0.0087**	**0.0072**	**0.0021**	**0.0017**	**-0.0006**	**0.0003**	**-0.0008**
	0.0000	*0.1420*	*0.7094*	*0.5289*	*0.2727*	*0.0000*	*0.0022*	*0.0081*	*0.3176*	*0.6923*	*0.1952*
Deutsche Telekom	**-0.1469**	**-0.0681**	**-0.0315**	**-0.0159**	**-0.0041**	**0.0035**	**0.0018**	**0.0013**	**0.0006**	**0.0005**	**0.0004**
	0.0000	*0.0000*	*0.0000*	*0.0001*	*0.2625*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0004*	*0.0032*
E.ON AG	**-0.0441**	**0.0084**	**0.0371**	**-0.0045**	**-0.0174**	**0.0048**	**0.0016**	**0.0010**	**-0.0002**	**0.0000**	**0.0000**
	0.0001	*0.3836*	*0.0020*	*0.7665*	*0.0726*	*0.0000*	*0.0000*	*0.0000*	*0.4477*	*0.9089*	*0.9107*
Fresenius M. C.	**-0.0444**	**0.0165**	**0.0165**	**-0.0199**	**-0.0160**	**0.0113**	**0.0025**	**0.0005**	**-0.0003**	**0.0003**	**-0.0018**
	0.0796	*0.4138*	*0.3375*	*0.3138*	*0.3295*	*0.0000*	*0.0563*	*0.6659*	*0.8445*	*0.7962*	*0.1277*
Henkel Vz.	**-0.0215**	**0.0299**	**-0.0095**	**0.0180**	**0.0157**	**0.0077**	**0.0025**	**0.0000**	**-0.0014**	**-0.0005**	**-0.0012**
	0.1923	*0.0786*	*0.5138*	*0.1902*	*0.3603*	*0.0000*	*0.0009*	*0.9517*	*0.0726*	*0.5554*	*0.1369*
Hypo Real Estate	**-0.0714**	**0.0003**	**0.0199**	**0.0184**	**0.0175**	**0.0089**	**0.0026**	**0.0019**	**0.0006**	**0.0009**	**0.0000**
	0.0000	*0.9744*	*0.0702*	*0.0394*	*0.0312*	*0.0000*	*0.0000*	*0.0036*	*0.3033*	*0.1562*	*0.9993*
Infineon	**-0.0652**	**-0.0252**	**-0.0109**	**-0.0056**	**-0.0011**	**0.0057**	**0.0026**	**0.0005**	**0.0004**	**0.0008**	**-0.0001**
	0.0000	*0.0000*	*0.0207*	*0.1630*	*0.7763*	*0.0000*	*0.0000*	*0.2157*	*0.2778*	*0.0520*	*0.6728*
Linde	**-0.0136**	**0.0166**	**0.0166**	**-0.0108**	**0.0147**	**0.0100**	**0.0026**	**0.0009**	**-0.0001**	**-0.0003**	**-0.0001**
	0.2464	*0.2529*	*0.0919*	*0.4544*	*0.2774*	*0.0000*	*0.0010*	*0.2168*	*0.8729*	*0.6993*	*0.8996*
Lufthansa	**-0.0542**	**-0.0097**	**0.0198**	**0.0097**	**-0.0113**	**0.0085**	**0.0018**	**0.0008**	**0.0008**	**-0.0015**	**0.0006**
	0.0000	*0.3469*	*0.0466*	*0.2907*	*0.1765*	*0.0000*	*0.0144*	*0.2499*	*0.2284*	*0.0311*	*0.3756*
MAN	**-0.0540**	**0.0268**	**0.0220**	**0.0222**	**0.0030**	**0.0103**	**0.0014**	**-0.0002**	**0.0001**	**-0.0002**	**0.0006**
	0.0001	*0.0231*	*0.0564*	*0.0602*	*0.7573*	*0.0000*	*0.0893*	*0.8031*	*0.9177*	*0.8435*	*0.4292*
Metro	**-0.0291**	**0.0173**	**0.0178**	**0.0039**	**-0.0101**	**0.0104**	**0.0007**	**0.0000**	**0.0005**	**-0.0002**	**0.0000**
	0.3256	*0.2818*	*0.2423*	*0.7674*	*0.3355*	*0.0000*	*0.3580*	*0.9946*	*0.5665*	*0.8153*	*0.9643*
Münchener Rück	**-0.0341**	**0.0203**	**0.0088**	**0.0057**	**0.0100**	**0.0042**	**0.0013**	**0.0004**	**0.0000**	**0.0001**	**0.0001**
	0.0000	*0.0003*	*0.1563*	*0.5342*	*0.1811*	*0.0000*	*0.0000*	*0.0343*	*0.9594*	*0.7017*	*0.6069*
RWE AG	**-0.0281**	**0.0068**	**0.0135**	**0.0049**	**-0.0032**	**0.0054**	**0.0012**	**0.0002**	**-0.0004**	**0.0000**	**0.0003**
	0.0244	*0.3707*	*0.0322*	*0.5184*	*0.7502*	*0.0000*	*0.0000*	*0.4249*	*0.1727*	*0.8879*	*0.3186*
SAP AG	**-0.0451**	**-0.0053**	**0.0065**	**0.0252**	**0.0110**	**0.0049**	**0.0017**	**0.0006**	**0.0003**	**0.0001**	**-0.0001**
	0.0000	*0.6694*	*0.2860*	*0.0086*	*0.1449*	*0.0000*	*0.0000*	*0.0249*	*0.2053*	*0.7072*	*0.5485*
Schering	**-0.0414**	**0.0092**	**0.0057**	**0.0109**	**0.0029**	**0.0068**	**0.0023**	**0.0000**	**-0.0003**	**-0.0009**	**-0.0001**
	0.0009	*0.3223*	*0.6582*	*0.3060*	*0.7564*	*0.0000*	*0.0000*	*0.9496*	*0.4499*	*0.0790*	*0.8772*
Siemens	**-0.0337**	**0.0012**	**0.0115**	**0.0128**	**0.0053**	**0.0038**	**0.0011**	**0.0006**	**0.0005**	**0.0000**	**0.0000**
	0.0000	*0.7464*	*0.0067*	*0.0143*	*0.1390*	*0.0000*	*0.0000*	*0.0001*	*0.0006*	*0.8731*	*0.8321*
ThyssenKrupp	**-0.0786**	**-0.0159**	**0.0079**	**-0.0063**	**-0.0006**	**0.0090**	**0.0021**	**0.0007**	**-0.0008**	**-0.0012**	**0.0001**
	0.0000	*0.0699*	*0.3498*	*0.3768*	*0.9433*	*0.0000*	*0.0032*	*0.3054*	*0.2626*	*0.1495*	*0.9165*
TUI AG	**-0.0637**	**0.0127**	**0.0181**	**0.0187**	**0.0044**	**0.0111**	**0.0039**	**0.0007**	**0.0005**	**-0.0013**	**-0.0012**
	0.0000	*0.2720*	*0.0481*	*0.0350*	*0.6945*	*0.0000*	*0.0000*	*0.4528*	*0.6091*	*0.1638*	*0.1826*
Volkswagen	**-0.0442**	**0.0092**	**0.0193**	**0.0157**	**0.0076**	**0.0049**	**0.0013**	**0.0002**	**-0.0005**	**-0.0002**	**0.0001**
	0.0000	*0.1739*	*0.0175*	*0.0788*	*0.2101*	*0.0000*	*0.0000*	*0.4181*	*0.0679*	*0.5460*	*0.7530*

Table 8: **Lagged Returns and Trade Signs in the Price Revision Equation:** We use OLS to estimate the Price Revision equation from Equation (7) which is $r_t = \sum_{i=1}^{5} a_i r_{t-i} + \gamma_{0,1}^r D_{t,1} x_t^0 + \sum_{i=0}^{5} (\gamma_i^r + \delta_i^r ln(T_{t-i})) x_{t-i}^0 + \upsilon_{1,t}$. The results are split on this table and on Table 10: The present table reports the coefficients for the HASBROUCK (1991)–style variables (see Equation (1)), such as returns and trade signs. Table 10 reports the time–related coefficients. The p–values (in italics below each coefficient) are computed with heteroskedasticity–robust standard errors. Returns show significant (on a 5% level) negative autocorrelation in the first lag in 24 cases. Higher–order autocorrelation is not significant in most cases. For 30 (25) stocks, there is a positive effect from the contemporaneous (the first–lag) Trade–sign.

Stock	r_{t-1}	r_{t-2}	r_{t-3}	r_{t-4}	r_{t-5}	x_{t-1}	x_{t-2}	x_{t-3}	x_{t-4}	x_{t-5}
Adidas	**-5.0747**	**0.7097**	**0.8238**	**0.5340**	**0.5180**	**0.1649**	**0.0659**	**0.0566**	**0.0333**	**0.0320**
	0.0000	*0.0000*	*0.0000*	*0.0005*	*0.0012*	*0.0000*	*0.0000*	*0.0000*	*0.0140*	*0.0162*
Allianz	**-9.5531**	**0.6399**	**1.0733**	**0.8291**	**1.1354**	**0.1744**	**0.1106**	**0.0874**	**0.0727**	**0.0618**
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
Altana	**-4.6670**	**-0.0621**	**0.4900**	**0.3680**	**0.4309**	**0.1541**	**0.0879**	**0.0338**	**0.0549**	**0.0444**
	0.0000	*0.6376*	*0.0013*	*0.0050*	*0.0005*	*0.0000*	*0.0000*	*0.0087*	*0.0000*	*0.0004*
BASF AG	**-8.8328**	**1.1124**	**1.3182**	**0.8013**	**0.5327**	**0.2170**	**0.1113**	**0.0780**	**0.0684**	**0.0416**
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0016*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
Bayer	**-6.9518**	**0.7247**	**0.5056**	**0.3167**	**0.3227**	**0.2174**	**0.0875**	**0.0661**	**0.0501**	**0.0344**
	0.0000	*0.0000*	*0.0001*	*0.0171*	*0.0116*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0001*
BMW	**-7.6903**	**0.4686**	**0.6708**	**0.6687**	**0.6273**	**0.2023**	**0.1126**	**0.0844**	**0.0737**	**0.0273**
	0.0000	*0.0089*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0018*
Commerzbank	**-4.9819**	**-0.1554**	**0.2021**	**0.4385**	**0.2219**	**0.2144**	**0.1145**	**0.0670**	**0.0574**	**0.0501**
	0.0000	*0.1879*	*0.0857*	*0.0001*	*0.0533*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
Continental	**-5.2392**	**0.2951**	**0.5232**	**0.4899**	**0.5048**	**0.1966**	**0.0826**	**0.0692**	**0.0548**	**0.0225**
	0.0000	*0.0268*	*0.0002*	*0.0005*	*0.0001*	*0.0000*	*0.0000*	*0.0000*	*0.0001*	*0.0919*
DaimlerChrysler	**-8.8614**	**0.6366**	**1.1747**	**0.9776**	**0.7983**	**0.2245**	**0.1314**	**0.0859**	**0.0737**	**0.0502**
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
Deutsche Bank	**-8.4613**	**0.8948**	**0.9986**	**1.1490**	**0.4262**	**0.1812**	**0.0979**	**0.0777**	**0.0554**	**0.0605**
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0024*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
Deutsche Börse	**-3.5674**	**0.6442**	**0.3097**	**0.6308**	**0.3455**	**0.2188**	**0.1214**	**0.0713**	**0.0721**	**0.0480**
	0.0002	*0.0180*	*0.1052*	*0.0000*	*0.1081*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0010*
Deutsche Post	**-5.0396**	**0.1995**	**0.6157**	**0.3274**	**0.3154**	**0.2297**	**0.1064**	**0.0650**	**0.0565**	**0.0403**
	0.0000	*0.1408*	*0.0000*	*0.0126*	*0.0162*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0012*
Deutsche Telekom	**-11.1518**	**-2.1501**	**-0.6517**	**0.0277**	**0.5666**	**0.2358**	**0.1417**	**0.0920**	**0.0761**	**0.0667**
	0.0000	*0.0000*	*0.0000*	*0.8311*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
E.ON AG	**-9.1133**	**1.3437**	**1.3704**	**1.1306**	**0.6262**	**0.2172**	**0.1083**	**0.0810**	**0.0640**	**0.0675**
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0014*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
Fresenius M. C.	**-3.7268**	**0.6759**	**0.2176**	**0.3941**	**0.4179**	**0.2102**	**0.0547**	**0.0496**	**0.0527**	**0.0232**
	0.0000	*0.0000*	*0.1424*	*0.0076*	*0.0048*	*0.0000*	*0.0026*	*0.0063*	*0.0039*	*0.1922*
Henkel Vz.	**-4.6738**	**1.4635**	**0.3207**	**0.7630**	**0.3334**	**0.2106**	**0.0752**	**0.0700**	**0.0417**	**0.0441**
	0.0000	*0.0000*	*0.1053*	*0.0001*	*0.0856*	*0.0000*	*0.0000*	*0.0000*	*0.0140*	*0.0076*
Hypo Real Estate	**-4.0956**	**0.0751**	**0.3368**	**0.2107**	**0.1013**	**0.2019**	**0.0691**	**0.0698**	**0.0302**	**0.0309**
	0.0000	*0.5026*	*0.0010*	*0.0463*	*0.3219*	*0.0000*	*0.0000*	*0.0000*	*0.0035*	*0.0023*
Infineon	**-5.1358**	**-0.5882**	**0.0317**	**0.1915**	**0.1517**	**0.2369**	**0.1103**	**0.0791**	**0.0623**	**0.0735**
	0.0000	*0.0007*	*0.6893*	*0.0035*	*0.0207*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
Linde	**-4.4776**	**0.9921**	**0.6354**	**0.4303**	**0.1375**	**0.1942**	**0.1008**	**0.0683**	**0.0501**	**0.0561**
	0.0000	*0.0000*	*0.0003*	*0.0026*	*0.3136*	*0.0000*	*0.0000*	*0.0000*	*0.0004*	*0.0001*
Lufthansa	**-4.8510**	**0.1937**	**0.3560**	**0.4647**	**0.3412**	**0.2296**	**0.1235**	**0.0867**	**0.0411**	**0.0465**
	0.0000	*0.0854*	*0.0020*	*0.0000*	*0.0025*	*0.0000*	*0.0000*	*0.0000*	*0.0006*	*0.0001*
MAN	**-4.1140**	**0.3948**	**0.5524**	**0.4110**	**0.2139**	**0.2032**	**0.0905**	**0.0846**	**0.0645**	**0.0651**
	0.0000	*0.0011*	*0.0000*	*0.0006*	*0.0692*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
Metro	**-4.1077**	**0.6017**	**0.5309**	**0.4863**	**0.1942**	**0.1820**	**0.0937**	**0.0732**	**0.0549**	**0.0329**
	0.0000	*0.0002*	*0.0004*	*0.0002*	*0.0730*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0059*
Münchener Rück	**-8.5286**	**0.7369**	**1.0744**	**0.9869**	**0.8777**	**0.1704**	**0.0921**	**0.0609**	**0.0651**	**0.0429**
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
RWE AG	**-7.0666**	**0.3794**	**0.6177**	**0.4929**	**0.2426**	**0.2148**	**0.1219**	**0.0909**	**0.0705**	**0.0519**
	0.0000	*0.0117*	*0.0000*	*0.0004*	*0.0812*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
SAP AG	**-6.7216**	**0.5361**	**0.4788**	**0.4907**	**0.3929**	**0.1678**	**0.0739**	**0.0719**	**0.0427**	**0.0455**
	0.0000	*0.0000*	*0.0009*	*0.0020*	*0.0028*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
Schering	**-5.4472**	**0.7910**	**0.5213**	**0.4936**	**0.3623**	**0.1702**	**0.1100**	**0.0813**	**0.0593**	**0.0511**
	0.0000	*0.0000*	*0.0006*	*0.0010*	*0.0029*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
Siemens	**-9.7384**	**0.6771**	**1.1369**	**1.0128**	**0.8802**	**0.1805**	**0.1044**	**0.0700**	**0.0639**	**0.0505**
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0012*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
ThyssenKrupp	**-3.4676**	**0.2089**	**0.4016**	**0.0014**	**0.0715**	**0.2183**	**0.0938**	**0.0687**	**0.0503**	**0.0492**
	0.0000	*0.0823*	*0.0001*	*0.9896*	*0.4810*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0001*
TUI AG	**-3.5845**	**0.4479**	**0.4869**	**0.3130**	**0.2467**	**0.2165**	**0.0966**	**0.0451**	**0.0459**	**0.0302**
	0.0000	*0.0000*	*0.0000*	*0.0010*	*0.0084*	*0.0000*	*0.0000*	*0.0003*	*0.0002*	*0.0117*
Volkswagen	**-7.6658**	**0.3491**	**0.6147**	**0.4354**	**0.2494**	**0.2113**	**0.1169**	**0.0750**	**0.0693**	**0.0621**
	0.0000	*0.0305*	*0.0004*	*0.0041*	*0.0902*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*

Table 9: **Lagged Returns and Trade Signs in the Trade Equation:** We use OLS to estimate the Trade equation from Equation (7) which is $x_t = \sum_{i=1}^{5} c_i r_{t-i} + \gamma_{1,1}^x D_{t-1,1} x_{t-1}^0 + \sum_{i=1}^{5} (\gamma_i^x + \delta_i^x ln(T_{t-i})) x_{t-i}^0 + \upsilon_{2,t}$. The results are split on this table and on Table 11: The present table reports the coefficients for the HASBROUCK (1991)–style variables (see Equation (1)), such as returns and trade signs. Table 11 reports the time–related coefficients. The p–values (in italics below each coefficient) are computed with heteroskedasticity–robust standard errors. There is strong autocorrelation of Trade–signs: 28 stocks have significant coefficients (on a 5% level) in all 5 lags. A negative effect of returns on Trade–signs can be identified in all cases for the first lag. The second lag of returns is significant for 25 stocks; most of the coefficients are positive.

Stock	δ_0^r	δ_1^r	δ_2^r	δ_3^r	δ_4^r	δ_5^r	$\gamma_{0,1}^r$	Wald- test
Adidas	**-0.0003**	**-0.0001**	**0.0003**	**-0.0003**	**0.0003**	**0.0002**	**0.0079**	**11.2189**
	0.1970	*0.7384*	*0.1189*	*0.1109*	*0.1034*	*0.4178*	*0.0000*	*0.0818*
Allianz	**0.0000**	**0.0000**	**0.0002**	**0.0000**	**0.0001**	**0.0001**	**0.0003**	**13.3657**
	0.4983	*0.9994*	*0.0056*	*0.7258*	*0.2114*	*0.0455*	*0.4143*	*0.0376*
Altana	**-0.0006**	**-0.0001**	**0.0001**	**0.0003**	**-0.0001**	**0.0002**	**0.0082**	**9.0993**
	0.0124	*0.5425*	*0.5447*	*0.1892*	*0.7296*	*0.3010*	*0.0004*	*0.1681*
BASF AG	**-0.0005**	**0.0000**	**0.0001**	**-0.0001**	**0.0002**	**0.0000**	**0.0017**	**24.8573**
	0.0000	*0.9430*	*0.5382*	*0.4621*	*0.0803*	*0.9179*	*0.0244*	*0.0004*
Bayer	**-0.0006**	**0.0000**	**0.0001**	**0.0000**	**0.0001**	**0.0000**	**0.0041**	**17.3898**
	0.0000	*0.9586*	*0.5829*	*0.8603*	*0.3544*	*0.9241*	*0.0000*	*0.0080*
BMW	**-0.0003**	**-0.0002**	**0.0001**	**0.0001**	**0.0001**	**-0.0002**	**0.0029**	**14.6625**
	0.0059	*0.1322*	*0.6195*	*0.5466*	*0.5449*	*0.1475*	*0.0009*	*0.0231*
Commerzbank	**-0.0009**	**-0.0005**	**0.0004**	**-0.0001**	**-0.0002**	**-0.0001**	**0.0016**	**30.7347**
	0.0000	*0.0185*	*0.0478*	*0.4979*	*0.4178*	*0.5873*	*0.2400*	*0.0000*
Continental	**-0.0003**	**0.0001**	**-0.0001**	**0.0006**	**0.0003**	**0.0000**	**0.0101**	**8.0337**
	0.3345	*0.6651*	*0.7946*	*0.0234*	*0.1601*	*0.9162*	*0.0000*	*0.2356*
DaimlerChrysler	**0.0000**	**0.0000**	**0.0000**	**-0.0001**	**-0.0001**	**0.0000**	**0.0016**	**7.7123**
	0.7331	*0.9033*	*0.9616*	*0.2643*	*0.5783*	*0.5910*	*0.0012*	*0.2599*
Deutsche Bank	**-0.0001**	**0.0000**	**-0.0001**	**0.0000**	**-0.0001**	**-0.0001**	**0.0013**	**7.7123**
	0.1665	*0.8977*	*0.1150*	*0.8189*	*0.3699*	*0.4120*	*0.0042*	*0.2599*
Deutsche Börse	**-0.0006**	**0.0004**	**-0.0001**	**0.0006**	**-0.0004**	**-0.0001**	**0.0061**	**23.8468**
	0.0063	*0.1563*	*0.8677*	*0.0065*	*0.1881*	*0.6264*	*0.0027*	*0.0006*
Deutsche Post	**-0.0004**	**-0.0002**	**-0.0003**	**0.0004**	**0.0001**	**0.0002**	**0.0076**	**10.5202**
	0.0896	*0.3609*	*0.1208*	*0.0987*	*0.6854*	*0.4046*	*0.0000*	*0.1044*
Deutsche Telekom	**-0.0005**	**-0.0002**	**-0.0002**	**0.0000**	**-0.0001**	**-0.0002**	**0.0009**	**82.5893**
	0.0000	*0.0037*	*0.0016*	*0.9037*	*0.1325*	*0.0224*	*0.0066*	*0.0000*
E.ON AG	**-0.0002**	**-0.0002**	**-0.0003**	**0.0002**	**0.0000**	**0.0000**	**0.0021**	**24.0331**
	0.0189	*0.0129*	*0.0056*	*0.1044*	*0.7732*	*0.8113*	*0.0014*	*0.0005*
Fresenius M. C.	**-0.0004**	**0.0002**	**0.0002**	**-0.0002**	**-0.0002**	**0.0002**	**0.0134**	**2.5515**
	0.3327	*0.6324*	*0.6503*	*0.6085*	*0.6096*	*0.4925*	*0.0127*	*0.8627*
Henkel Vz.	**0.0005**	**0.0000**	**0.0002**	**0.0005**	**-0.0001**	**0.0003**	**0.0207**	**12.0390**
	0.0299	*0.8331*	*0.3841*	*0.0555*	*0.7163*	*0.2631*	*0.0000*	*0.0611*
Hypo Real Estate	**-0.0003**	**0.0000**	**0.0000**	**0.0001**	**-0.0002**	**0.0001**	**0.0016**	**3.0613**
	0.1623	*0.9054*	*0.8478*	*0.6262*	*0.4202*	*0.6766*	*0.2963*	*0.8011*
Infineon	**-0.0004**	**-0.0004**	**0.0000**	**0.0000**	**-0.0003**	**-0.0002**	**0.0004**	**15.2872**
	0.0115	*0.0497*	*0.8347*	*0.9874*	*0.0753*	*0.2598*	*0.4984*	*0.0181*
Linde	**0.0000**	**-0.0002**	**0.0000**	**0.0000**	**0.0000**	**-0.0001**	**0.0063**	**0.7451**
	0.9056	*0.4850*	*0.9460*	*0.8686*	*0.9383*	*0.7055*	*0.0131*	*0.9935*
Lufthansa	**-0.0004**	**0.0000**	**0.0001**	**-0.0002**	**0.0004**	**-0.0002**	**0.0017**	**6.3438**
	0.0994	*0.8573*	*0.7957*	*0.4997*	*0.1122*	*0.3101*	*0.3053*	*0.3858*
MAN	**-0.0004**	**0.0002**	**0.0001**	**0.0001**	**-0.0001**	**-0.0004**	**0.0129**	**6.2123**
	0.1570	*0.4295*	*0.5700*	*0.8256*	*0.6292*	*0.0859*	*0.0000*	*0.3998*
Metro	**-0.0006**	**0.0005**	**0.0003**	**0.0000**	**-0.0001**	**0.0001**	**0.0030**	**9.6621**
	0.0498	*0.0441*	*0.2383*	*0.9690*	*0.7000*	*0.7875*	*0.2400*	*0.1396*
Münchener Rück	**-0.0001**	**0.0001**	**0.0001**	**0.0002**	**0.0000**	**-0.0001**	**0.0019**	**7.3343**
	0.1814	*0.4984*	*0.5396*	*0.0522*	*0.5834*	*0.4182*	*0.0004*	*0.2910*
RWE AG	**-0.0001**	**0.0000**	**0.0001**	**0.0002**	**-0.0001**	**-0.0001**	**0.0012**	**5.1674**
	0.6210	*0.7928*	*0.2680*	*0.1898*	*0.4906*	*0.3251*	*0.1536*	*0.5225*
SAP AG	**-0.0003**	**-0.0001**	**0.0000**	**0.0000**	**0.0000**	**0.0001**	**0.0034**	**9.5783**
	0.0078	*0.2770*	*0.9755*	*0.6904*	*0.7640*	*0.5199*	*0.0000*	*0.1436*
Schering	**-0.0004**	**-0.0002**	**0.0001**	**0.0003**	**0.0005**	**-0.0001**	**0.0046**	**18.5066**
	0.0082	*0.1769*	*0.6697*	*0.0906*	*0.0120*	*0.7305*	*0.0002*	*0.0051*
Siemens	**-0.0002**	**0.0000**	**-0.0001**	**-0.0002**	**0.0000**	**0.0000**	**0.0002**	**18.5349**
	0.0047	*0.6813*	*0.2734*	*0.0415*	*0.6122*	*0.9172*	*0.5313*	*0.0050*
ThyssenKrupp	**-0.0002**	**0.0001**	**-0.0001**	**0.0005**	**0.0004**	**0.0000**	**0.0050**	**8.6679**
	0.4011	*0.8012*	*0.7579*	*0.0391*	*0.1147*	*0.9292*	*0.0022*	*0.1931*
TUI AG	**-0.0005**	**-0.0006**	**0.0000**	**0.0001**	**0.0002**	**0.0002**	**0.0002**	**8.7214**
	0.0712	*0.0405*	*0.8742*	*0.8349*	*0.5890*	*0.4732*	*0.9300*	*0.1899*
Volkswagen	**-0.0001**	**0.0000**	**0.0001**	**0.0003**	**0.0000**	**-0.0001**	**0.0022**	**6.8623**
	0.3228	*0.6921*	*0.6345*	*0.0202*	*0.9514*	*0.2257*	*0.0053*	*0.3338*

Table 10: **Time Effects in the Price Revision Equation:** We use OLS to estimate the Price Revision equation from Equation (7) which is $r_t = \sum_{i=1}^{5} a_i r_{t-i} + \gamma_{0,1}^r D_{t,1} x_t^0 + \sum_{i=0}^{5} (\gamma_i^r + \delta_i^r ln(T_{t-i})) x_{t-i}^0 + \upsilon_{1,t}$. The results are split on this table and on Table 8: Table 8 reports the coefficients for the HASBROUCK (1991)–style variables (see Equation (1)), such as returns and trade signs. This table reports the time–related coefficients, such as contemporaneous and lagged interaction terms for durations between trades and an interaction term for the opening period dummy. The p–values are shown in italics below each coefficient. The last column shows the Wald–statistic and the p–value for the null hypothesis that the duration coefficients $\delta_{0...5}^r$ are jointly equal to zero. Wald–statistics and p–values are computed with heteroskedasticity–robust standard errors.

Stock	δ^{x_1}	δ^{x_2}	δ^{x_3}	δ^{x_4}	δ^{x_5}	$\gamma^x_{0,1}$	Wald–test
Adidas	**-0.0060**	**-0.0027**	**-0.0070**	**0.0012**	**0.0003**	**0.0292**	**4.4652**
	0.2000	*0.5609*	*0.1346*	*0.7975*	*0.9439*	*0.2782*	*0.4845*
Allianz	**-0.0263**	**-0.0193**	**-0.0157**	**-0.0121**	**-0.0127**	**0.0050**	**218.8577**
	0.0000	*0.0000*	*0.0000*	*0.0001*	*0.0000*	*0.6576*	*0.0000*
Altana	**-0.0037**	**-0.0060**	**0.0014**	**-0.0108**	**-0.0105**	**0.0191**	**14.7973**
	0.4108	*0.1894*	*0.7553*	*0.0169*	*0.0189*	*0.4917*	*0.0113*
BASF AG	**-0.0236**	**-0.0177**	**-0.0164**	**-0.0142**	**-0.0067**	**-0.0215**	**128.6606**
	0.0000	*0.0000*	*0.0000*	*0.0001*	*0.0564*	*0.2571*	*0.0000*
Bayer	**-0.0252**	**-0.0100**	**-0.0089**	**-0.0083**	**-0.0036**	**0.0011**	**74.1747**
	0.0000	*0.0068*	*0.0154*	*0.0239*	*0.3263*	*0.9529*	*0.0000*
BMW	**-0.0181**	**-0.0114**	**-0.0100**	**-0.0140**	**0.0013**	**0.0032**	**61.6019**
	0.0000	*0.0023*	*0.0073*	*0.0002*	*0.7283*	*0.8567*	*0.0000*
Commerzbank	**-0.0136**	**-0.0129**	**-0.0038**	**-0.0089**	**-0.0054**	**0.0037**	**33.0036**
	0.0010	*0.0021*	*0.3680*	*0.0322*	*0.1916*	*0.8620*	*0.0000*
Continental	**-0.0138**	**-0.0075**	**-0.0046**	**-0.0036**	**0.0013**	**0.0300**	**14.2686**
	0.0029	*0.1058*	*0.3226*	*0.4419*	*0.7710*	*0.3009*	*0.0140*
DaimlerChrysler	**-0.0298**	**-0.0221**	**-0.0129**	**-0.0142**	**-0.0074**	**0.0069**	**211.9100**
	0.0000	*0.0000*	*0.0001*	*0.0000*	*0.0219*	*0.6094*	*0.0000*
Deutsche Bank	**-0.0205**	**-0.0099**	**-0.0107**	**-0.0099**	**-0.0112**	**0.0038**	**93.0279**
	0.0000	*0.0027*	*0.0012*	*0.0023*	*0.0006*	*0.7800*	*0.0000*
Deutsche Börse	**-0.0102**	**-0.0155**	**-0.0045**	**-0.0132**	**-0.0038**	**-0.0185**	**27.8075**
	0.0375	*0.0018*	*0.3635*	*0.0068*	*0.4284*	*0.5283*	*0.0000*
Deutsche Post	**-0.0206**	**-0.0084**	**-0.0052**	**-0.0028**	**-0.0020**	**-0.0720**	**30.0426**
	0.0000	*0.0624*	*0.2401*	*0.5260*	*0.6458*	*0.0048*	*0.0000*
Deutsche Telekom	**-0.0373**	**-0.0233**	**-0.0145**	**-0.0123**	**-0.0140**	**-0.0324**	**326.2710**
	0.0000	*0.0000*	*0.0000*	*0.0001*	*0.0000*	*0.0032*	*0.0000*
E.ON AG	**-0.0250**	**-0.0108**	**-0.0074**	**-0.0073**	**-0.0141**	**0.0109**	**108.4029**
	0.0000	*0.0013*	*0.0289*	*0.0303*	*0.0000*	*0.5182*	*0.0000*
Fresenius M. C.	**-0.0160**	**0.0016**	**-0.0055**	**-0.0052**	**0.0018**	**0.0587**	**11.1312**
	0.0030	*0.7706*	*0.3123*	*0.3380*	*0.7372*	*0.1496*	*0.0488*
Henkel Vz.	**-0.0036**	**-0.0011**	**-0.0045**	**0.0000**	**-0.0084**	**0.1304**	**4.2325**
	0.4875	*0.8355*	*0.3795*	*0.9972*	*0.0995*	*0.0008*	*0.5164*
Hypo Real Estate	**-0.0163**	**0.0053**	**-0.0058**	**0.0019**	**0.0025**	**-0.0124**	**20.6328**
	0.0000	*0.1810*	*0.1459*	*0.6374*	*0.5355*	*0.5554*	*0.0010*
Infineon	**-0.0243**	**-0.0049**	**-0.0012**	**0.0006**	**-0.0073**	**-0.0082**	**67.5501**
	0.0000	*0.1414*	*0.7111*	*0.8551*	*0.0263*	*0.4588*	*0.0000*
Linde	**-0.0062**	**-0.0127**	**-0.0071**	**-0.0029**	**-0.0085**	**-0.0524**	**16.5145**
	0.1919	*0.0077*	*0.1358*	*0.5425*	*0.0731*	*0.0851*	*0.0055*
Lufthansa	**-0.0183**	**-0.0145**	**-0.0118**	**-0.0003**	**-0.0077**	**0.0886**	**48.0252**
	0.0000	*0.0008*	*0.0059*	*0.9419*	*0.0703*	*0.0000*	*0.0000*
MAN	**-0.0099**	**-0.0029**	**-0.0090**	**-0.0066**	**-0.0101**	**0.0419**	**18.8708**
	0.0286	*0.5207*	*0.0458*	*0.1422*	*0.0238*	*0.1463*	*0.0020*
Metro	**-0.0124**	**-0.0063**	**-0.0054**	**-0.0043**	**-0.0031**	**0.0684**	**14.3385**
	0.0049	*0.1494*	*0.2155*	*0.3227*	*0.4728*	*0.0080*	*0.0136*
Münchener Rück	**-0.0192**	**-0.0100**	**-0.0084**	**-0.0121**	**-0.0057**	**-0.0006**	**73.9613**
	0.0000	*0.0025*	*0.0117*	*0.0003*	*0.0826*	*0.9694*	*0.0000*
RWE AG	**-0.0271**	**-0.0146**	**-0.0156**	**-0.0105**	**-0.0069**	**0.0201**	**130.5987**
	0.0000	*0.0000*	*0.0000*	*0.0034*	*0.0527*	*0.2589*	*0.0000*
SAP AG	**-0.0086**	**-0.0043**	**-0.0114**	**-0.0003**	**-0.0097**	**0.0085**	**30.5080**
	0.0117	*0.2090*	*0.0009*	*0.9186*	*0.0041*	*0.5900*	*0.0000*
Schering	**-0.0131**	**-0.0140**	**-0.0102**	**-0.0094**	**-0.0068**	**0.0289**	**43.1916**
	0.0012	*0.0005*	*0.0119*	*0.0198*	*0.0899*	*0.1494*	*0.0000*
Siemens	**-0.0207**	**-0.0172**	**-0.0134**	**-0.0105**	**-0.0081**	**0.0133**	**134.9336**
	0.0000	*0.0000*	*0.0000*	*0.0007*	*0.0083*	*0.2575*	*0.0000*
ThyssenKrupp	**-0.0239**	**-0.0048**	**-0.0043**	**-0.0086**	**-0.0036**	**-0.0329**	**38.3613**
	0.0000	*0.2704*	*0.3261*	*0.0499*	*0.4069*	*0.1435*	*0.0000*
TUI AG	**-0.0206**	**-0.0095**	**0.0000**	**-0.0003**	**0.0002**	**0.0098**	**29.2768**
	0.0000	*0.0303*	*0.9915*	*0.9493*	*0.9572*	*0.6864*	*0.0000*
Volkswagen	**-0.0217**	**-0.0138**	**-0.0091**	**-0.0149**	**-0.0097**	**0.0070**	**104.7124**
	0.0000	*0.0001*	*0.0094*	*0.0000*	*0.0051*	*0.6632*	*0.0000*

Table 11: **Time Effects in the Trade Equation:** We use OLS to estimate the Trade equation from Equation (7) which is $x_t = \sum_{i=1}^{5} c_i r_{t-i} + \gamma^x_{1,1} D_{t-1,1} x^0_{t-1} + \sum_{i=1}^{5} (\gamma^x_i + \delta^x_i ln(T_{t-i})) x^0_{t-i} + \upsilon_{2,t}$. The results are split on this table and on Table 9: Table 9 reports the coefficients for the HASBROUCK (1991)–style variables (see Equation (1)), such as returns and trade signs. This table reports the time–related coefficients, such as lagged interaction terms for durations between trades and an interaction term for the opening period dummy. The p–values are shown in italics below each coefficient. The last column shows the Wald–statistic and the p–value for the null hypothesis that the duration coefficients $\delta^x_{1...5}$ are jointly equal to zero. Wald–statistics and p–values are computed with heteroskedasticity–robust standard errors.

C.1 Impulse Response Functions

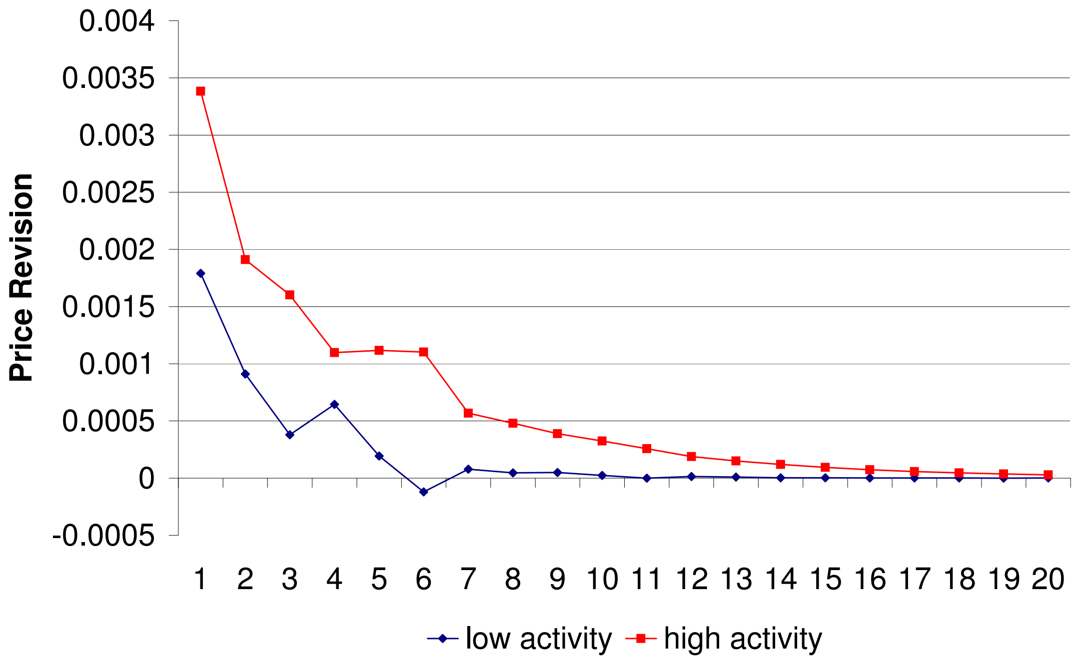

Figure 2: **Effect of a Trade shock on Price Revisions:** We use the estimated coefficients (see Tables 8,9,10,11) from Equation (7), $(r_t = \sum_{i=1}^{5} a_i r_{t-i} + \gamma_{0,1}^r D_{t,1} x_t^0 + \sum_{i=0}^{5} (\gamma_i^r + \delta_i^r ln(T_{t-i})) x_{t-i}^0 + \upsilon_{1,t}$ and $x_t = \sum_{i=1}^{5} c_i r_{t-i} + \gamma_{1,1}^x D_{t-1,1} x_{t-1}^0 + \sum_{i=1}^{5} (\gamma_i^x + \delta_i^x ln(T_{t-i})) x_{t-i}^0 + \upsilon_{2,t})$ for the stock of `Deutsche Telekom` to compute an Impulse Response Function. The effects are compared for two different series of twenty durations following the shock: We take a series from a high–market–activity period (the interval starting at 4:52:20 p.m. on January 28, 2004) and a series from a low–market–activity period (12:58:41 p.m. on January 6, 2004).
This diagram shows the effect of a shock on $\upsilon_{2,t}$ (Trade Shock) in a Price Revision/Event time– space. The y–axis contains the price variation in percent.
The Price Revision equation and the Trade equation are in a stable equilibrium until $t = 0$. The shock on Trade–Signs occurs in $t = 1$ and is immediately translated into the Price Revisions equation. The size of the impulse is one standard deviation of the Trade–sign series (0.9799) of the data. A large contemporaneous positive effect on Price Revision can be identified, followed by smaller positive effects. (For the case of high (low) market activity, the immediate price change is 0.34 (0.18) basis points.)
For high trading intensity after the shock (the shock is followed by a series of low duration), the impulse has a larger and more persistent effect on the Price Revision equation than for low trading intensity. In case of low trading intensity, the Price Revision equation has almost returned to its equilibrium at $t = 7$, whereas this is the case for high trading activity only at $t = 16$.

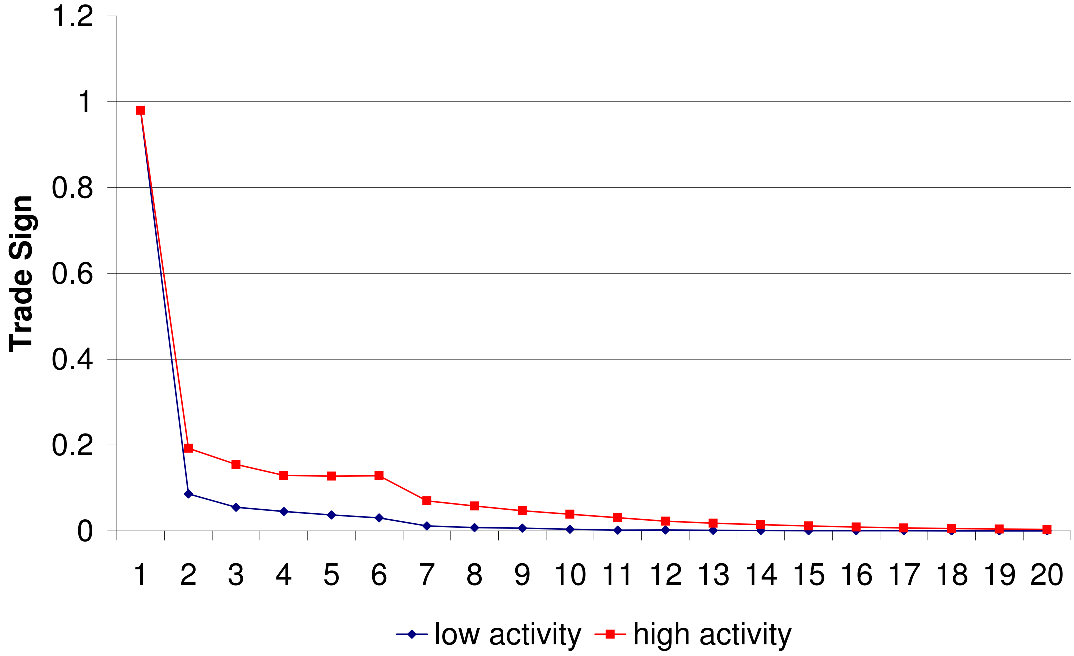

Figure 3: **Effect of a Trade shock on Trade Signs** We use the estimated coefficients (see Tables 8,9,10,11) from Equation (7), ($r_t = \sum_{i=1}^{5} a_i r_{t-i} + \gamma_{0,1}^r D_{t,1} x_t^0 + \sum_{i=0}^{5} (\gamma_i^r + \delta_i^r ln(T_{t-i})) x_{t-i}^0 + \upsilon_{1,t}$ and $x_t = \sum_{i=1}^{5} c_i r_{t-i} + \gamma_{1,1}^x D_{t-1,1} x_{t-1}^0 + \sum_{i=1}^{5} (\gamma_i^x + \delta_i^x ln(T_{t-i})) x_{t-i}^0 + \upsilon_{2,t}$) for the stock of `Deutsche Telekom` to compute an Impulse Response Function. The effects are compared for two different series of twenty durations following the shock: We take a series from a high–market–activity period (the interval starting at 4:52:20 p.m. on January 28, 2004) and a series from a low–market–activity period (12:58:41 p.m. on January 6, 2004).
This diagram shows the effect of a shock on $\upsilon_{2,t}$ (Trade Shock) in a Trade–sign/Event time– space. The y–axis contains values from -1 (sale order) to $+1$ (purchase order).
The Price Revision equation and the Trade equation are in a stable equilibrium until $t = 0$. The shock on Trade–Signs occurs in $t = 1$ and can be seen in the diagram. The size of the impulse is one standard deviation of the Trade–sign series (0.9799) of the data. Note the positive autocorrelation in the following lags, which is larger and more persistent in more active markets. The Trade-sign returns close to its equilibrium in $t = 7$ for low trading intensity as opposed to $t = 14$ for high trading intensity.

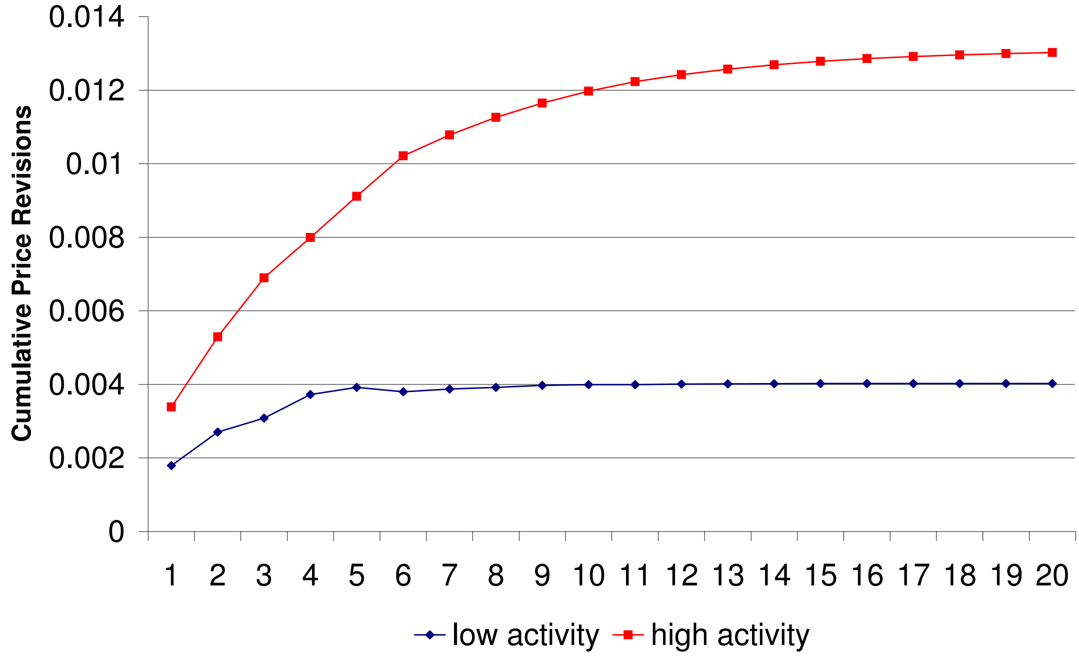

Figure 4: **Long–term effect of a Trade shock on Cumulative Price Revisions:** We use the estimated coefficients (see Tables 8,9,10,11) from Equation (7), ($r_t = \sum_{i=1}^{5} a_i r_{t-i} + \gamma_{0,1}^r D_{t,1} x_t^0 + \sum_{i=0}^{5} (\gamma_i^r + \delta_i^r ln(T_{t-i})) x_{t-i}^0 + \upsilon_{1,t}$ and $x_t = \sum_{i=1}^{5} c_i r_{t-i} + \gamma_{1,1}^x D_{t-1,1} x_{t-1}^0 + \sum_{i=1}^{5} (\gamma_i^x + \delta_i^x ln(T_{t-i})) x_{t-i}^0 + \upsilon_{2,t}$) for the stock of `Deutsche Telekom` to compute an Impulse Response Function. The effects are compared for two different series of twenty durations following the shock: We take a series from a high–market–activity period (the interval starting at 4:52:20 p.m. on January 28, 2004) and a series from a low–market–activity period (12:58:41 p.m. on January 6, 2004). This diagram shows the effect of a shock on $\upsilon_{2,t}$ (Trade Shock) in a Cumulative Price Revision/Event time– space. The y–axis contains the cumulated price variation in percent.
The Price Revision equation and the Trade equation are in a stable equilibrium until $t = 0$. The shock on Trade–Signs occurs in $t = 1$ and is immediately translated into the Price Revisions equation. The size of the impulse is one standard deviation of the Trade–sign series (0.9799) of the data. A large contemporaneous positive effect on Price Revision can be identified, followed by smaller positive effects. The curves in this diagram are therefore increasing and concave and converge in the long–run to a new price level. The delta between the stock price before the shock and the stock price at the end of the convergence process is given in percent; it can be interpreted as the long–run effect of a Trade shock. If market activity is high, the shock has a larger short–term impact (in $t = 1$) and a larger long–term impact. The long term impact for high market activity (low market activity) is 1.3 (0.4) basis points; if the original value of `Deutsche Telekom` has been EUR 15.00, it will be EUR 15.00195 (EUR 15.0006) when the shock is fully incorporated. Furthermore, prices converge faster in a low–market–activity period. It takes 7 transactions after a shock until the new price level is reached for low–intensity markets as opposed to 17 transactions for high–intensity markets.

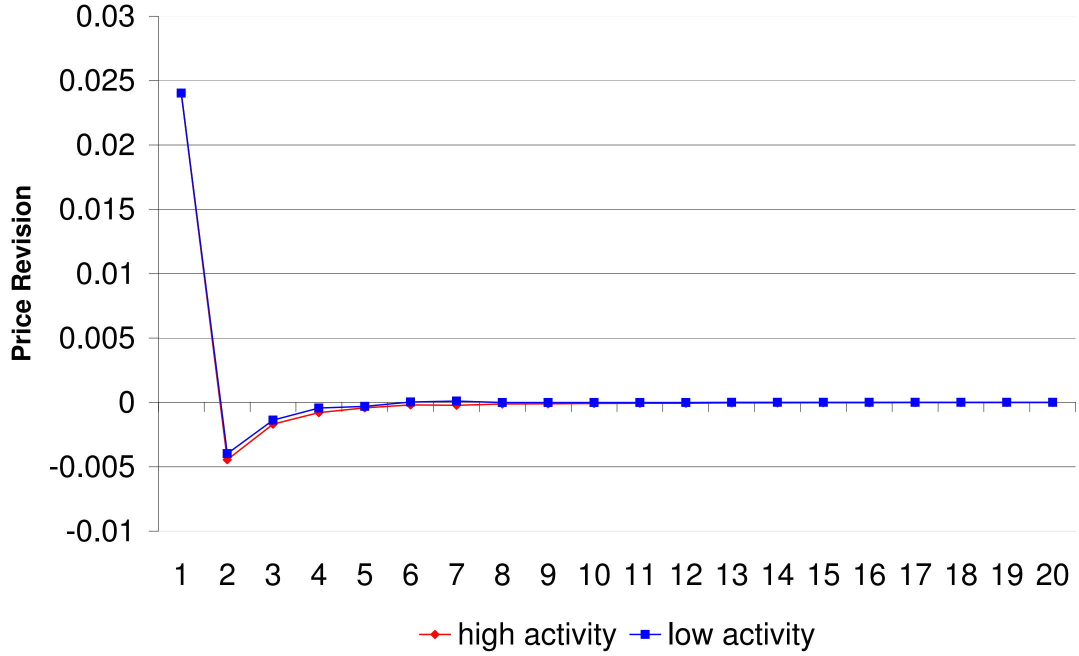

Figure 5: **Effect of a Price shock on Price Revisions:** We use the estimated coefficients (see Tables 8,9,10,11) from Equation (7), ($r_t = \sum_{i=1}^{5} a_i r_{t-i} + \gamma_{0,1}^r D_{t,1} x_t^0 + \sum_{i=0}^{5} (\gamma_i^r + \delta_i^r ln(T_{t-i})) x_{t-i}^0 + \upsilon_{1,t}$ and $x_t = \sum_{i=1}^{5} c_i r_{t-i} + \gamma_{1,1}^x D_{t-1,1} x_{t-1}^0 + \sum_{i=1}^{5} (\gamma_i^x + \delta_i^x ln(T_{t-i})) x_{t-i}^0 + \upsilon_{2,t}$) for the stock of `Deutsche Telekom` to compute an Impulse Response Function. The effects are compared for two different series of twenty durations following the shock: We take a series from a high–market–activity period (the interval starting at 4:52:20 p.m. on January 28, 2004) and a series from a low–market–activity period (12:58:41 p.m. on January 6, 2004).
This diagram shows the effect of a shock on $\upsilon_{1,t}$ (Price Shock) in a Price Revision/Event time– space. The y–axis contains the price variation in percent.
The Price Revision equation and the Trade equation are in a stable equilibrium until $t = 0$. The shock on prices occurs in $t = 1$ and can be seen in the diagram. The size of the impulse is one standard deviation of the Price–Revision series (0.024025) in the data. A positive shock in Price Revisions is followed by subsequent negative Price Revisions. In the long–run, Price Revisions return to their equilibrium. Note that the effects are only slightly larger in high–intensity periods.

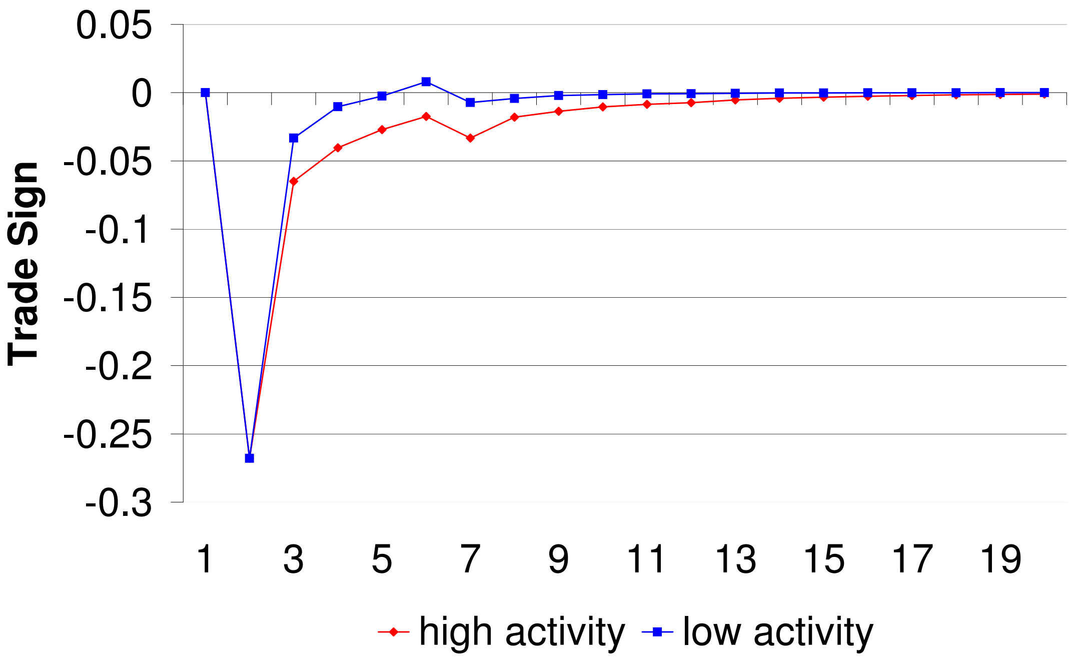

Figure 6: **Effect of a Price shock on Trade–signs:** We use the estimated coefficients (see Tables 8,9,10,11) from Equation (7), ($r_t = \sum_{i=1}^{5} a_i r_{t-i} + \gamma_{0,1}^{r} D_{t,1} x_t^0 + \sum_{i=0}^{5} (\gamma_i^r + \delta_i^r ln(T_{t-i})) x_{t-i}^0 + \upsilon_{1,t}$ and $x_t = \sum_{i=1}^{5} c_i r_{t-i} + \gamma_{1,1}^{x} D_{t-1,1} x_{t-1}^0 + \sum_{i=1}^{5} (\gamma_i^x + \delta_i^x ln(T_{t-i})) x_{t-i}^0 + \upsilon_{2,t}$) for the stock of `Deutsche Telekom` to compute an Impulse Response Function. The effects are compared for two different series of twenty durations following the shock: We take a series from a high–market–activity period (the interval starting at 4:52:20 p.m. on January 28, 2004) and a series from a low–market–activity period (12:58:41 p.m. on January 6, 2004).
This diagram shows the effect of a shock on $\upsilon_{1,t}$ (Price Shock) in a Trade–sign/Event time– space. The y–axis contains values from -1 (sale order) to $+1$ (purchase order). The Price Revision equation and the Trade equation are in a stable equilibrium until $t = 0$. The shock on prices occurs in $t = 1$ and translates into the Trade–sign equation in $t = 2$. Time effects do not come into play until $t = 3$, since their interaction terms require lagged Trade–Sign variables x_t that are different from zero. Note that Trade–signs converge faster to the equilibrium value 0 in periods with lower market activity after a shock has occurred.

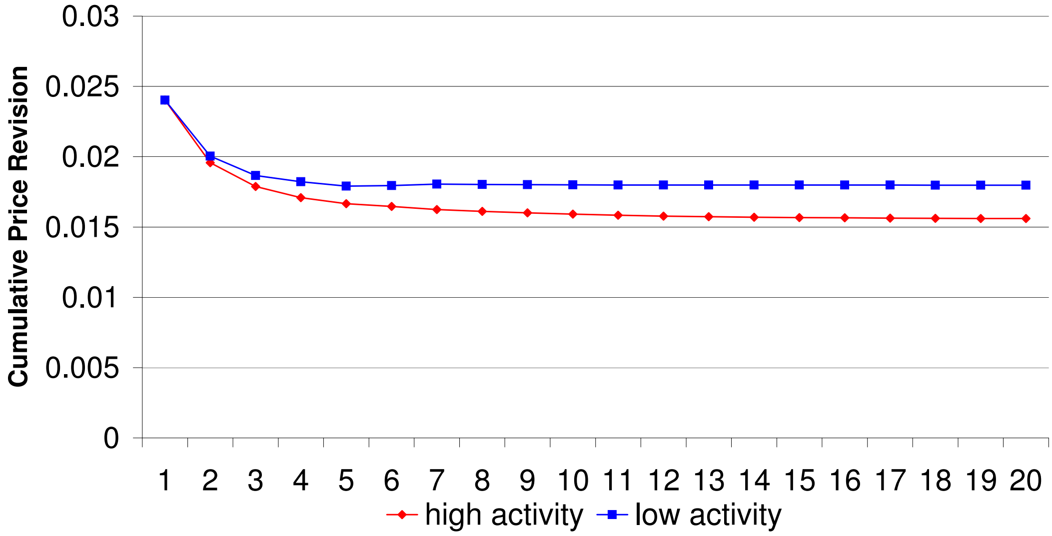

Figure 7: **Long–term effect of a Price shock on Cumulative Price Revisions:** We use the estimated coefficients (see Tables 8,9,10,11) from Equation (7), ($r_t = \sum_{i=1}^{5} a_i r_{t-i} + \gamma^r_{0,1} D_{t,1} x^0_t + \sum_{i=0}^{5} (\gamma^r_i + \delta^r_i ln(T_{t-i})) x^0_{t-i} + \upsilon_{1,t}$ and $x_t = \sum_{i=1}^{5} c_i r_{t-i} + \gamma^x_{1,1} D_{t-1,1} x^0_{t-1} + \sum_{i=1}^{5} (\gamma^x_i + \delta^x_i ln(T_{t-i})) x^0_{t-i} + \upsilon_{2,t}$) for the stock of `Deutsche Telekom` to compute an Impulse Response Function. The effects are compared for two different series of twenty durations following the shock: We take a series from a high–market–activity period (the interval starting at 4:52:20 p.m. on January 28, 2004) and a series from a low–market–activity period (12:58:41 p.m. on January 6, 2004). This diagram shows the effect of a shock on $\upsilon_{1,t}$ (Price Shock) in a Cumulative Price Revision/Event time–space. The y–axis contains the cumulated price variation in percent.
The Price Revision equation and the Trade equation are in a stable equilibrium until $t = 0$. The shock on prices occurs in $t = 1$ and can be seen in the diagram. The size of the impulse is one standard deviation of the Price–Revision series (0.024025) in the data.
It can be seen that prices converge to a new long–term price level, which is above the original price level and below the short–term effect of the shock. Note that the correction takes longer and reaches further if the shock happens in very active markets. In active markets, prices rise by 1.6 basis points in the long run; in less active markets, they rise by 1.8 basis points. A sudden rise of the stock price of Deutsche Telekom due to public information from EUR 15.00 to EUR 15.00375 leads therefore to a long–term price of EUR 15.0024 (EUR 15.0027) in highly active (not so active) markets.

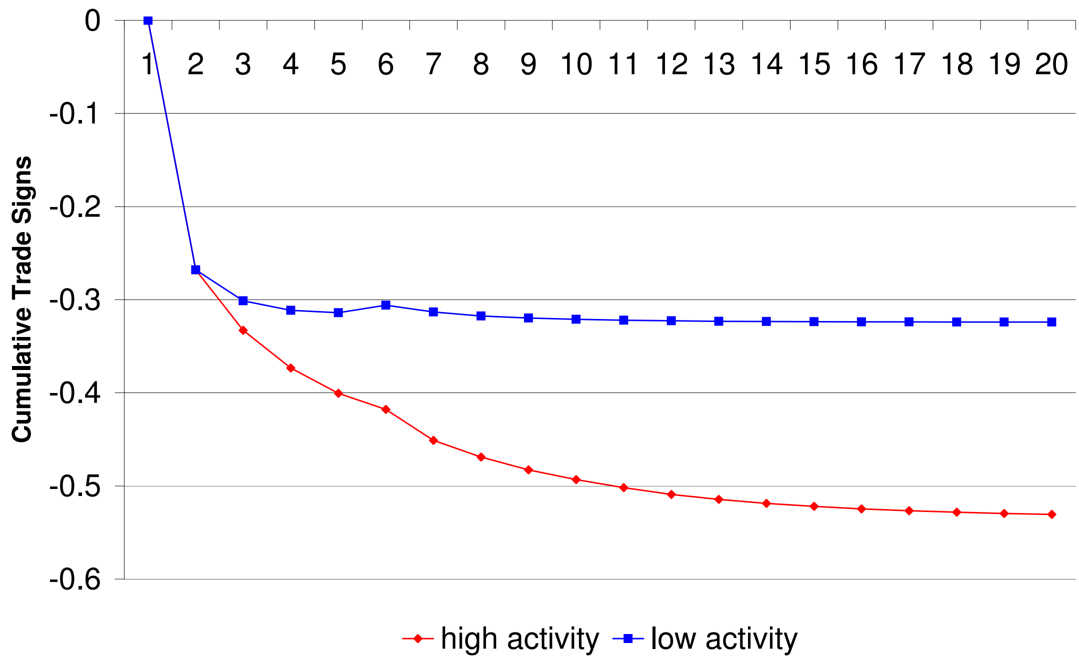

Figure 8: **Long–term effect of a Price shock on Trade–Signs:** We use the estimated coefficients (see Tables 8,9,10,11) from Equation (7), ($r_t = \sum_{i=1}^{5} a_i r_{t-i} + \gamma_{0,1}^{r} D_{t,1} x_t^0 + \sum_{i=0}^{5} (\gamma_i^r + \delta_i^r ln(T_{t-i})) x_{t-i}^0 + \upsilon_{1,t}$ and $x_t = \sum_{i=1}^{5} c_i r_{t-i} + \gamma_{1,1}^{x} D_{t-1,1} x_{t-1}^0 + \sum_{i=1}^{5} (\gamma_i^x + \delta_i^x ln(T_{t-i})) x_{t-i}^0 + \upsilon_{2,t}$) for the stock of `Deutsche Telekom` to compute an Impulse Response Function. The effects are compared for two different series of twenty durations following the shock: We take a series from a high–market–activity period (the interval starting at 4:52:20 p.m. on January 28, 2004) and a series from a low–market–activity period (12:58:41 p.m. on January 6, 2004). This diagram shows the effect of a shock on $\upsilon_{1,t}$ (Price Shock) in a Cumulative Trade–sign/Event time–space. The Price Revision equation and the Trade equation are in a stable equilibrium until $t = 0$. The shock on prices occurs in $t = 1$ and translates into the Trade–sign equation in $t = 2$. Time effects do not come into play until $t = 3$, since their interaction terms require lagged Trade–Sign variables x_t that are different from zero. A sudden rise in prices triggers a series of sales. Note that in an active environment, the number of transactions after the shock which are influenced by the impulse are larger than in a less active environment.

C.2 Variance decomposition

	high activity		low activitiy		high activity		low activitiy	
t	$\tilde{a}_t$	$\sum_{t=0}^{T} \tilde{a}_t$	$\tilde{a}_t$	$\sum_{t=0}^{I} \tilde{a}_t$	$\tilde{b}_t$	$\sum_{t=0}^{T} \tilde{b}_t$	$\tilde{b}_t$	$\sum_{t=0}^{T} \tilde{b}_t$
0	1.000	1.000	1.000	1.000	0.00345	0.00345	0.00183	0.00183
1	-0.185	0.815	0.834	0.834	0.00195	0.00540	0.00093	0.00276
2	-0.070	0.745	0.777	0.777	0.00164	0.00704	0.00039	0.00314
3	-0.033	0.711	0.758	0.758	0.00112	0.00816	0.00066	0.00380
4	-0.018	0.694	0.746	0.746	0.00114	0.00930	0.00020	0.00400
5	-0.008	0.685	0.747	0.747	0.00112	0.01042	-0.00012	0.00388
6	-0.009	0.676	0.751	0.751	0.00058	0.01100	0.00008	0.00396
7	-0.005	0.671	0.750	0.750	0.00049	0.01149	0.00005	0.00400
8	-0.005	0.666	0.750	0.750	0.00040	0.01189	0.00005	0.00405
9	-0.004	0.662	0.749	0.749	0.00033	0.01222	0.00002	0.00408
10	-0.003	0.659	0.749	0.749	0.00026	0.01248	0.00000	0.00408
11	-0.003	0.657	0.749	0.749	0.00019	0.01267	0.00001	0.00409
12	-0.002	0.655	0.749	0.749	0.00015	0.01283	0.00001	0.00410
13	-0.001	0.654	0.748	0.748	0.00012	0.01295	0.00000	0.00410
14	-0.001	0.652	0.748	0.748	0.00010	0.01304	0.00000	0.00411
15	-0.001	0.652	0.748	0.748	0.00008	0.01312	0.00000	0.00411
16	-0.001	0.651	0.748	0.748	0.00006	0.01318	0.00000	0.00411
17	-0.001	0.650	0.748	0.748	0.00005	0.01322	0.00000	0.00411
18	0.000	0.650	0.748	0.748	0.00004	0.01326	0.00000	0.00411
19	0.000	0.649	0.748	0.748	0.00003	0.01329	0.00000	0.00411
..								
∞		0.649		0.748		0.01329		0.00400

Table 12: **VMA and Variance Decomposition:** The VAR from Equation (7) can be written in the form of a vector moving average: $r_t = \upsilon_{1,t} + \tilde{a}_1\upsilon_{1,t-1} + \tilde{a}_2\upsilon_{1,t-2} + ... + \tilde{b}_0\upsilon_{2,t} + \tilde{b}_1\upsilon_{2,t-1} + ...$ and $x_t = \tilde{c}_1\upsilon_{1,t-1} + \tilde{c}_2\upsilon_{1,t-2} + ... + \upsilon_{2,t} + \tilde{d}_1\upsilon_{2,t-1} + \tilde{d}_2\upsilon_{2,t-2} + ...$ (HASBROUCK, 1991a, p.576)
This table presents the computed estimates $\tilde{a}_t$ and $\tilde{b}_t$ for the stock of `Deutsche Telekom` for two different series of durations between trades. We take a series from a high–market–activity period (the interval starting at 4:52:20 p.m. on January 28, 2004) and a series from a low–market–activity period (12:58:41 p.m. on January 6, 2004).
The columns can be interpreted as Impulse Response Functions: If there is a shock on prices of $\upsilon_{1,0} = 1$, $\tilde{a}_t$ represents the change of Price Revisions in t and $\sum_{t=0}^{T} \tilde{a}_t$ the sum of Cumulative Price Revisions. If there is a shock on trade–signs of $\upsilon_{2,0} = 1$, $\tilde{b}_t$ represents the change of Price Revisions in t and $\sum_{t=0}^{T} \tilde{a}_t$ the sum of Cumulative Price Revisions. $\sum_{t=0}^{\infty} \tilde{a}_t$ is therefore the long–term price effect of a shock equal to $\upsilon_{1,}0 = 1$, whereas $\sum_{t=0}^{\infty} \tilde{b}_t$ is the long–term price effect of a shock equal to $\upsilon_{2,0} = 1$.
These results can be used to compute a variance decomposition. The standard deviation of Price Revision is $\sigma^2_{\upsilon_1} = 0.024025$ and the standard deviation of Trade–Signs is $\sigma^2_{\upsilon_2} = 0.9799$. The total variance can be written as $\sigma^2_w = (\sum_{t=0}^{T} \tilde{a}_t)^2\sigma^2_{\upsilon_1} + (\sum_{t=0}^{T} \tilde{b}_t)^2\sigma^2_{\upsilon_2}$. The variance which is due to shocks in the Trade equation is equal to $\sigma^2_{w,x} = (\sum_{t=0}^{T} \tilde{b}_t)^2\sigma^2_{\upsilon_2}$. The relative contribution of the variance of Trades to total variance can be expressed in $\sigma^2_{w,x}/\sigma^2_x$, which can be interpreted as the share of the variance that is driven by private information and liquidity needs.
We find that this share is 41.09% in high–activity markets as opposed to 4.54% in low activity markets.

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