AUTOMATED ANN ALERTS – ONE STEP AHEAD WITH MOBILE SUPPORT

Abstract

In this paper, I examine the potential of mobile alerting services empowering investors to react quickly to critical market events. Therefore, an analysis of short-term (intraday) price effects is performed. I find abnormal returns to company announcements which are completed within a timeframe of minutes. To make use of these findings, these price effects are predicted using pre-defined external metrics and different estimation methodologies. Compared to previous research, the results provide support that artificial neural networks and multiple linear regression are good estimation models for forecasting price effects also on an intraday basis. As most of the price effect magnitude and effect delay can be estimated correctly, it is demonstrated how a suitable mobile alerting service combining a low level of user-intrusiveness and timely information supply can be designed.

Keywords: Automated Mobile Customer Alerts, Artificial Neural Networks (ANN), Financial Forecasting, Financial Decision Support, Event Study

1 INTRODUCTION

In the financial area, mobile alerting services have been successfully introduced in order to reduce communication costs caused by customer call center calls (Pavich 2004). Whereas these approaches focus mainly on cost reduction, this paper analyzes the potential of automated mobile alerting services in order to improve the information supply which empowers private investors to react to critical market events promptly. Especially when sending notifications to mobile devices it is of utmost importance to assure a level of user-intrusiveness at a manageable dimension. Therefore, an analysis of intraday price behaviour following company announcements provides evidence that significant price effects can be observed.

After reviewing prior studies regarding price effect analysis and effect estimation, I introduce an event study approach in order to evaluate potential price effects which can be exploited by the investors.

Therefore the observed market events (company announcements), the used dataset (intraday stock price series) and the methodology for calculating abnormal price effects are introduced. The empirical results of this analysis provide evidence that significant short-term price effects can be observed and that these might open a window of opportunity for investors if these effects can be estimated.

The estimation of forthcoming price effects is realized by a multiple linear regression model and an artificial neural network (ANN) approach introduced in section four in order to identify relevant market events and to support investors in making their investment decisions in time.

Much effort has been put into neural networks focusing on the estimation of stock price movements in recent years (Fadlalla and Lin 2001, Franses and van Griensven 1998, Kohara; Ishikawa; Fukuhara and Nakamura 1997, Swales Jr. and Young 1992). Most of this research focuses on long-term (daily, monthly or quarterly) price effect analysis. Prior research examining the estimation of intraday price effects propose text mining techniques in order to evaluate the information content of company announcements and their effects on the capital market.

I propose the application of company and price movement metrics being available from different impartial data sources in order to estimate intraday price effects following company announcements. As these data sources can not be affected by the company which has published the announcement, potential manipulation can be eliminated. The achieved forecast accuracies show that the neural network outperforms the regression approach. Since several authors (e.g. Hiemstra 1996) demonstrate the superiority of the neural network forecast quality concerning interday price effects, this paper validates this superiority for intraday price effects. In this paper the estimation accuracy is compared by performing out-of-sample tests of effect predictability.

I infer that by using these effect estimators an appropriate mobile alerting service can be designed. As relevant market events can be identified, price effect magnitude and price effect delay can be estimated, an appropriate mobile alerting service is introduced in section five. These results provide support for the value of mobile financial alerting services which base upon price effect estimation realized by artificial neural networks.

I conclude with a discussion of my results.

2 RELATED WORK

Several authors confirm the existence of significant abnormal intraday price movements following company announcements (Barclay and Litzenberger 1988, Gosnell; Keown and Pinkerton 1996, Patell and Wolfson 1984) but none of these provide evidence how these short-term (intraday) price effects can be estimated with good forecast quality.

Hiemstra (1996) analyzes the forecast quality between linear regression and backpropagation networks regarding quarterly stock market excess returns. Even though no strong nonlinear effects were observed, the linear model is outperformed by the neural network. Franses and van Griensven (1998) analyze the performance of neural networks for forecasting daily exchange rates compared to linear models. They also expose the superior forecast quality of the neural network approach. Refenes, Zapranis and Francis (1994) examine the forecast quality of a back propagation neural network compared to multiple linear regression for UK stocks on a daily basis. They can show a superior forecast quality of the neural network documented by higher in-sample (learning dataset) and out-of-sample (testing dataset) prediction power. The existing literature provides evidence that neural networks provide good forecast quality for analyzing and estimating long-term price effects. So far, little is known about the application of neural networks to forecast short-term (intraday) price effects following critical market events even though these effects have been proven by several event studies (Barclay and Litzenberger 1988, Gosnell and Keown and Pinkerton 1996).

In this research area Mittermayer (2004) proposes the application of text mining techniques in order to analyze the content of published company announcements. This work is based on the assumption, that announcements can be categorized into "good news", "bad news" and "no movers" and therefore correlate with corresponding intraday price movements. His results confirm a recognition rate for rating e.g. "good news" as "good news" of between 50 and 60%, lying significantly above random classification (33⅓%). The author indicates that it is a big problem when analyzing news content with data mining techniques because authors tend to falsify results by using adequate keywords perverting the text processing algorithm.

3 MARKET EVENTS, DATASET AND INTRADAY STOCK PRICE EFFECT ANALYSIS

Critical market events can have significant impact on the (short-term) development of stock prices. In this paper ad hoc disclosures pursuant to Section 15 of the German Securities Trading Law (WpHG) were chosen as the event to focus on. Equivalent regulations also exist in other countries, e.g. the Security Exchange Act 1934 in the US or Art. 72 (obligation to disclose price-sensitive facts) of the Listing Rules of the Swiss Exchange, which enjoin companies to publish material non-public information.

The publication of the ad hoc disclosures itself is done in most cases by companies being specialized in the distribution of company announcements on behalf of the companies. In Germany, most of these publications are done by the Deutsche Gesellschaft für Ad-hoc-Publizität (DGAP). Therefore, I have chosen DGAP as data source for the ad hoc disclosures to be observed. The observation period covers the time frame between 2003-08-01 and 2004-08-30 during stock exchange trading hours. This limitation is mandatory, because intraday price reactions cannot be measured for events lying outside trading hours. Furthermore, the absence of an opening reaction to overnight announcements can be expected (Francis and Pagach and Stephan 1992). To be able to isolate the price effect caused by an announcement, confounding events have been identified. If a company has published more than one ad hoc disclosure during a time frame of ten days, these announcements were discarded. The used dataset consists of 213 ad hoc disclosures published during the observation period. For each announcement the stock exchange symbol was extracted automatically and the corresponding intraday stock prices were requested starting ten days before the publication date. This was realized by a batch script running each night on an application server being connected to a news feed server (providing the ad hoc disclosures via DPA-AFX) and a price feed server (providing intraday price series exact to the minute via XETRA).

The analysis of intraday stock price reactions is based on the calculation of corrected absolute abnormal returns C*AAR*. These returns can be interpreted as returns adjusted by general market trends and lying above an average abnormal return which can be observed during a comparison period without any announcements. The general market trend is covered by the CDAX market index and the average is calculated for the ten days before the event day (period T2). This second adjustment is done according to Carter and Soo (1999) but not standardized and can consequently be interpreted easily. C*AARs* were calculated for each announcement *i* and available price fixing *t/t2* exact to the minute.

$$CAAR_{i,t} = \left| R_{i,t} - R_{CDAX,t} \right| - \frac{\sum_{t2=1}^{T2} \left| R_{i,t2} - R_{CDAX,t2} \right|}{T2}$$

The statistical test is based on the accumulation of these returns for different time frames (measured in price fixings) following the announcement date. Therefore cumulated corrected absolute abnormal returns ($CCAAR_{i,t1,t2}$) were calculated for each announcement *i* and the sequential time frames (*t1,t2*) = (1,2), (3,5), (6,10), (11,15), (16,20). E.g. timeframe (1,2) corresponds with the period of time in which the first two price fixings (exact to the minute) can be observed on the capital market (XETRA).

$$CCAAR_{i,t1,t2} = \sum_{t=t1}^{t2} CAAR_{i,t}$$

For each timeframe (*t1,t2*) a total number of 203 (number of observed announcements) *CCAARs* can be calculated and be interpreted as a distribution. In order to prove the existence of significant price movements for a specific time frame the following null hypothesis is formulated for each time frame:

$$H_0 : E(CCAAR_{t1,t2}) = 0 \qquad \text{vs.} \qquad H_1 : E(CCAAR_{t1,t2}) > 0$$

If the hypothesis H_0 can be rejected for a time frame, abnormal price movement can be proven for this time frame at a given significance level. The performed *T*-test provides information regarding this significance level, which is illustrated in table 1 (* indicates significance on the 1% level).

	$CCAAR_{1,2}$	$CCAAR_{3,5}$	$CCAAR_{6,10}$	$CCAAR_{11,15}$	$CCAAR_{16,20}$
Mean	0.0334	0.0112	0.0063	0.0014	-0.0048
T-Value	5.94*	2.34*	0.92	0.22	-0.79

Table 1. Intraday price effect significance

As shown in table 1, significant price effects can be observed for the two sequential time frames (1,2) and (3,5). Consequently, the price reaction is completed within the first five price fixings (effect delay) following the publication date of the ad hoc disclosure (time frame (1,5) is significant with a *T*-value of 5.78*).

An appropriate financial alerting service would have to inform about the announcement promptly or the investor would not be able to react to this event. As the number of price fixings does not provide evidence about how many minutes of reaction time are available, a conversion to minutes is required. As timestamps of all price fixings are available, all time frames can be converted to minutes and an average can be calculated. According to this, the first five price fixings correspond with 23.2 minutes on average which can be interpreted as maximum reaction time for the investors. Unfortunately, this average can not be used for alerting services and concrete investment decisions as the number of minutes which correspond with the first five price fixings varies exceedingly (4 up to 160 minutes).

Accordingly, the observed price effects ($CCAAR_{1,5}$) vary from announcement to announcement. Consequently, specific consideration of each potential price effect is required for automated alerting services and concrete investment decision support.

4 PRICE EFFECT AND EFFECT DELAY ESTIMATION

The observed capital market effects caused by the publication of ad hoc disclosures can be categorized by two dimensions: price effect and effect delay. Whereas the first is the magnitude of the price movement following the announcement (measured by $CCAAR_{i,1,5}$), the second is the period of time after which the price effect is completed (measured by $\Delta t_{i,1,5}$).

In order to evaluate the necessity of an alerting notification, it is required to estimate whether a published ad hoc disclosure will cause a significant price reaction. If so, it is important to estimate the speed at which the capital market will react to this event, which determines the window of opportunity of the investors.

So far, concepts for estimating price effects following company announcements focus on the analysis of the announcement content. Schulz, Spiliopoulou and Winkler (2003) propose the application of text mining techniques in order to identify announcements which will cause significant price effects on a daily basis. The recognition rate of the data mining algorithm is between forty and fifty percent. The authors ascribe this poor recognition rate to the fact that the publishing companies are tent to embellish the facts. Furthermore, the study is based on daily returns which are unsuitable for estimating short-term price effects.

Mittermayer (2004) analyzes intraday price effects following company announcements pursuant to the Securities Exchange Act 1934 with the goal of categorizing “good news”, “bad news” and “no movers” into the right category. The historical intraday prices were taken from several US stock exchanges (e.g. NYSE, NASDAQ etc.). Whereas this analysis covers intraday stock price effects, the effect estimation is also based on text mining techniques. The approach achieves a recognition rate between 54 and 60 percent (compared to 33⅓% which would be achieved by selecting the category randomly).

Whereas existing approaches are based on the analysis of the announcement content, I propose the application of external metrics which can not be influenced by the publishing company in order to estimate intraday price effects. A suitable alerting service would have to inform about critical announcement which will cause significant price effects. Furthermore, it is of utmost importance to estimate the effect delay in order to evaluate the potential window of opportunity. As we can observe significant abnormal returns for the first five price movements following the announcement it is required to estimate the expected value of $CCAAR_{i,1,5}$ and the maximum available reaction time measured by the time frame (in minutes) in which the first five price fixings are available ($\Delta t_{1,5}$). Consequently, the goal is to estimate the dependant variables $CCAAR_{i,1,5}$ and $\Delta t_{i,1,5}$ by independent variables. The expected price effect $E(CCAAR_{i,1,5})$ and the expected price delay $E(\Delta t_{i,1,5})$ are estimated by the following independent variables.

Variable name	*Variable description*
$CCAAR_{i,1,2}$	Cumulated corrected absolute abnormal return following disclosure *i* which can be observed for the first two price fixings (used to estimate E($CCAAR_{i,1,5}$) only)
$\Delta t_{i,1,2}$	Time frame (measured in minutes) which correspond with the first two price movements following the announcements (used to estimate E($\Delta t_{i,1,5}$) only)
$NoAnalysts_j$	Number of analysts covering company *j* (taken from a data feed provided by JCF Group)
$ln(MCap_j)$	Market capitalization in € of company *j* dated one day prior the announcement date (natural logarithm taken)
$ln(TradingVol_j)$	Trading volume of the stocks of company *j* in € dated one day prior to the announcement date (natural logarithm taken)
$Index_j$	Index membership of company *j* ($Index_j$="1" if company j is member of one of the indices DAX, MDAX, TecDAX or "0" else)

Table 2. Independent variables for intraday effect estimations

As illustrated in table 2, the expected price effect and effect delay which correspond with the first five price fixings should be explained by the price effect and effect delay which correspond with the first two price fixings. The idea of this procedure is that the first two price fixings might imply a trend which can help to estimate the further development. As the expected price effect and effect delay can only be estimated after the first two price fixings following the announcement are available, one could criticize that this approach is not adequate because valuable time of the window of opportunity is lost. This concern can be neglected as there is a window of opportunity of an average of 12.9 minutes between price fixing two and five.

All other independent variables are available from different data sources or can be calculated promptly when a new ad hoc disclosure is published.

In the following section I compare multiple linear regression and a neural network approach to estimate the intraday price effects and effect delays following ad hoc disclosures in order to valuate the generalization performance of the two approaches. Compared to further research this paper focuses on short-term price effects by the analysis of intraday stock prices. Furthermore, the effect estimation is not based on the analysis of the announcement content but on explaining variables which can not be influenced by the company publishing the ad hoc disclosure.

The analysis is based on the dataset which was calculated in section three ($CCAAR_{i,1,5}$ and $\Delta t_{i,1,5}$) as dependant variables) and calculated or received from external data sources ($CCAAR_{i,1,2}$, $\Delta t_{i,1,2}$, $NoAnalysts_j$, $ln(MCap_j)$, $ln(TradingVol_j)$ and $Index_j$ as independent variables). From the original data set of 213 it was possible to use 206 for the following analysis (for the remaining seven is was not possible to determine one of the dependant variables). The available dataset tuples were divided into a training and testing set in order to evaluate the generalization performance. The analysis covers the forecast performance regarding price effect and effect delay. Therefore, three categories were defined for price effect and effect delay which is illustrated in table 3.

Price effect categories	*Category definition*	*Category members*
(1) Negligible price reaction	$CCAAR_{i,1,5} \leq 0.05\%$	73
(2) Medium price reaction	$0.05\% < CCAAR_{i,1,5} \leq 3\%$	69
(3) Strong price reaction	$CCAAR_{i,1,5} \geq 3\%$	64
Effect delay categories		
(1) Prompt price reaction	$\Delta t_{i,1,5} \leq 6$ min.	62
(2) Medium price reaction	6 min $< \Delta t_{i,1,5} \leq 20$ min.	66
(3) Slow price reaction	$\Delta t_{i,1,5} > 20$ min.	78

Table 3. Price effect and effect delay categorization

If the frequency of category members of the training set differs significantly there might be a bias towards the more common category resulting in poorer prediction accuracy for the rarer categories (Lawrence et al. 1999). Therefore the learning dataset contains 50 elements of each category and the remaining 56 elements were used as testing set in order to evaluate the model accuracy.

4.1 Multiple Linear Regression

The chosen explanatory variables might be correlated (e.g. there can be positive correlation between market capitalization and trading volume). Therefore, I performed stepwise multivariate ordinary least squares regressions. The regression was performed for estimating the price effect and effect delay with a tuple size of 150. Table 2 summarizes the results (*indicates significance on the 1% level).

	R^2 adj.	intercept	$CCAAR_{i,1,2}$ $\Delta t_{i,1,2}$	$ln(MCap_j)$	$ln(TradingVol_j)$	$NoAnalysts_j$	$Index_j$
I. price effect[a]	0.809	0.009	1.082*	-/-	-/-	-/-	-/-
II. effect delay[b]	0.871	46.923*	1.203*	-2.034*	-/-	-/-	-/-

[a] the price effect is measured by $CCAAR_{i,1,5}$; [b] the effect delay is measured by $\Delta t_{i,1,5}$,

Table 4. Multiple linear regression results

Table 4 illustrates that most of the effects can be explained by $CCAAR_{i,1,2}$ and $\Delta t_{i,1,2}$. Furthermore, an increasing market capitalization decreases the effect delay. This finding is intuitive as we can expect that stocks of companies with large market capitalization are traded more frequently.

The respective correlations between the dependant variables ($CCAAR_{i,1,5}$ and $\Delta t_{i,1,5}$) and the independent variables are used to forecast the values $CCAAR_{i,1,5}$ and $\Delta t_{i,1,5}$ of the testing set in order to valuate the forecast accuracy of the linear regression model. This is done by comparing the actual category membership of each testing set tuple with the category membership which is forecasted using the linear regression model. If the algorithm is not able to detect any patterns in the training set a recognition rate of 33% on average can be expected. Table 5 illustrated the recognition performance of the multiple linear regression model.

Price effect categories	*Category frequency*	*Category hits*	*Recognition rate*
(1) Negligible price reaction	12	4	33 ⅓ %
(2) Medium price reaction	16	13	81.25 %
(3) Strong price reaction	28	19	67.86 %
		Average	64.28 %
Effect delay categories			
(1) Prompt price reaction	20	11	55 %
(2) Medium price reaction	25	18	72 %
(3) Slow price reaction	11	10	90.91 %
		Average	69.64 %

Table 5. Forecast accuracy of the multiple linear regression model

The average recognition rate for price effect and effect delay is significantly above 33⅓ % which provides evidence that the used model has recognized patterns. The worst recognition rate is achieved for price effect category 1 (33⅓ %) which might be a result of a small category test sample size. Nevertheless the average recognition rates lie at a level of 64.28 % and 69.64 % which is a good result compared to other studies working with data mining techniques (Mittermayer 2004).

4.2 Artificial Neural Networks

Artificial neural networks (ANN) have been applied in many different application areas so far. They are generally used where generalization in terms of successful learning from a learning set is required. Compared to other methods they feature two important qualities. First, neural networks are able to map any nonlinear function (White 1989). Secondly, they are very robust concerning chaotic behaviour and extreme values which is beneficial when working with datasets possessing data noise (Masters 1993). In this paper ANNs are applied in order to estimate the intraday price effects and effect delays according to the multiple linear regression approach. Therefore two multi-layered perceptrons (MLPs) are designed to forecast the values of $CCAAR_{i,1,5}$ and $\Delta t_{i,1,5}$. MLP is a widely used neural network trained with the standard back-propagation algorithm with hidden layers connecting the input and output layers of the network. The back-propagation algorithm provides higher network speed but lower forecast accuracy compared to nonlinear least squares (Bishop 2004). Back-propagation is chosen because we are working with short term tick data and instantaneous processing is required for implementing a contemporary alerting service (Lo 1994). Two ANNs were designed in order to forecast the price effect and the effect delay. The network architectures are illustrated in figure 1.

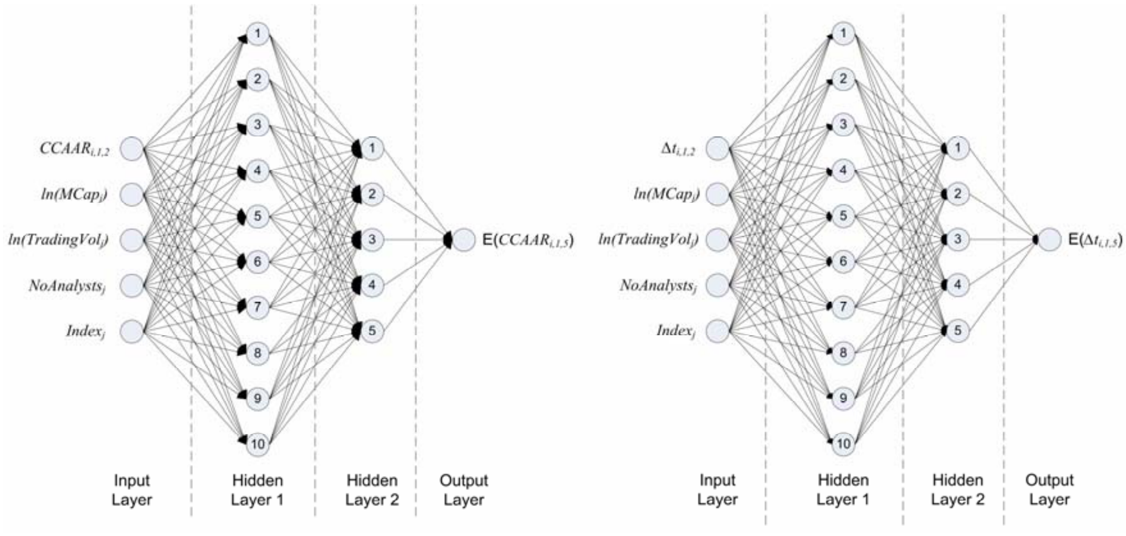

Figure 1. Artificial Neural Network Architectures

Several network architectures were tested during the network setup and the 5-10-5-1 configuration was found to be stable with good generalization performance. Furthermore, an incremental learning technique is used, dividing the learning process into four stages. First, a subsample of the training set is used to train the network for a defined number of iterations with the gradient descent algorithm. At each iteration, the weights connecting the layers are adjusted proportionally to its impact on the estimation error. After this (first 100 iterations), the parameters linked with the lowest training error are passed to the next stage. The applied four stages (100,100,100 and 400 iterations) vary in different values for the learning parameters momentum (0.1; 0.4; 0.5; 0.6) and learning rate (0.9; 0.7; 0.5; 0.4). An increasing momentum is used to smooth out the training process (Van Eyden 1996). The decreasing learning rate is applied to bypass local minima at the beginning and to optimize towards the last found minima in the end (Beale and Jackson T. 1990). The four stages with different learning parameters were applied in order to prevent network overtraining resulting in local minima optimization with poor generalization performance. Table 6 illustrates the recognition performance of the neural network approach.

Price effect categories	*Category frequency*	*Category hits*	*Recognition rate*
(1) Negligible price reaction	12	7	58.33 %
(2) Medium price reaction	16	12	75 %
(3) Strong price reaction	28	24	85.71 %
		Average	76.79 %
Effect delay categories			
(1) Prompt price reaction	20	16	80 %
(2) Medium price reaction	25	13	52 %
(3) Slow price reaction	11	9	81.82 %
		Average	67.86 %

Table 6. Forecast accuracy of the Artificial Neural Network

The neural networks achieve promising recognition rates lying significantly above the random selection rate of 33⅓%. All categories were successfully identified with at least 50% and most of them (except one) with at least 75%. The results provide evidence that the neural network approach and the multiple linear regression model are suitable price estimation models. The average recognition rate of the regression approach for the effect delay is slightly higher (69.64% compared to 67.86%) but is significantly lower for the price effect (64.28% compared to 76.79%).

5 SUITABLE MOBILE ALERTING SERVICES

Dewan and Meldenson (1998) found that institutional traders with longer information processing realize lower profits per trade and that superior IT infrastructure can confer competitive advantages. As these institutional traders observe the market development all the time, mobile alerting services could move private investors on a level playing field with the information supplied. To take into account that the mobile channel can be overloaded easily by a high quantity of alerting notifications it is required to make sure that only relevant events raise an alert. This requirement can be realized by the effect estimation proposed in the former sections. Only if a significant price effect and enough available reaction time (measured by effect delay) is estimated, the investor will be notified by an alerting notification on the mobile device.

Figure 2 illustrates how an appropriate Mobile Alerting System would notify an investor about the publication of a relevant company announcement.

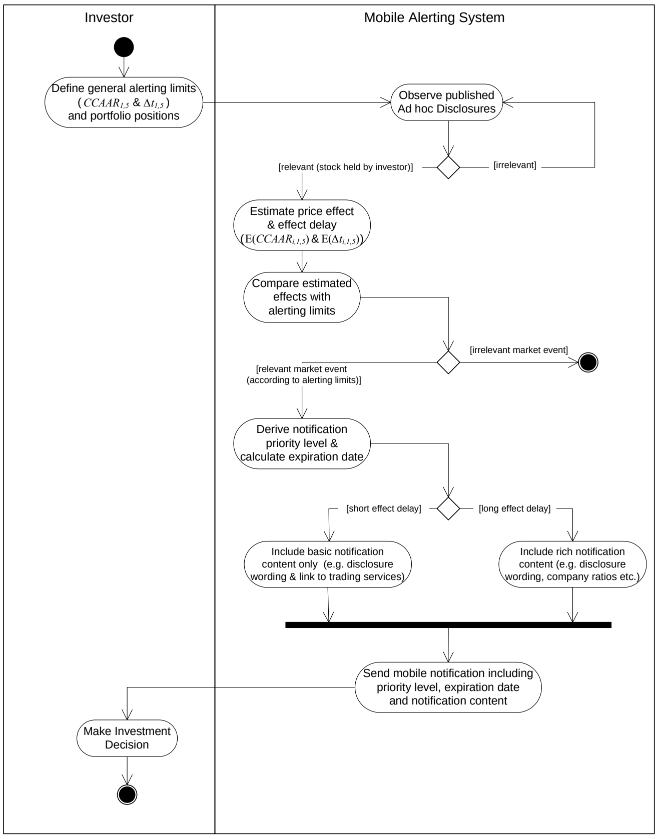

Figure 2. UML Activity Diagram of the Mobile Alerting Service

First, the investor has to define general alerting limits in order to specify which effects are relevant for the personal investment decisions.

Furthermore, relevant portfolio positions have to be provided in order to identify potential relevant ad hoc disclosures. Only disclosures published by companies which have issued these stocks are taken into account for further processing.

The most relevant activity performed by the mobile alerting system is the estimation of expected price effect and effect delay. This estimation can be done by using the neural network approach or by applying the multiple linear regression model proposed in section four. Before applying a neural network it is necessary to have prior network training enabling the system to estimate the price effect and effect delay promptly.

If these effect estimations comply with the alerting limits defined by the investor, a notification priority and expiration date (publication date + E($\Delta t_{i,1,5}$)) will be derived. If the derived priority level is appraised as negligible or the expiration date is too soon the publication is identified as an irrelevant market event and no notification will be send. If there is a strong market reaction estimated the notification priority will be set to 'high'. Furthermore, the content of the alerting notification depends on the estimated effect delay. If there are only few minutes available, the alerting notification is limited to basic notification content (including the ad hoc disclosure wording, the estimated price effect). These notification rules are summarized in the following table 6.

Estimated price effect category	*Category definition*	*Derived notification relevance*
(1) Negligible price reaction	$CCAAR_{i,1,5} \leq 0.05\%$	irrelevant
(2) Medium price reaction	$0.05\% < CCAAR_{i,1,5} \leq 3\%$	Low
(3) Strong price reaction	$CCAAR_{i,1,5} > 3\%$	High
Estimated effect delay category		*Derived notification content*
(1) Prompt price reaction	$\Delta t_{i,1,5} \leq 6$ min.	None (irrelevant)
(2) Medium price reaction	6 min $< \Delta t_{i,1,5} \leq 20$ min.	Basic notification content
(3) Slow price reaction	$\Delta t_{i,1,5} > 20$ min.	Rich notification content

Table 7. Price effect and effect delay categorization

Muntermann and Güttler (2004) evaluated several mobile push services which can be used for financial mobile push services. Their results show that the WAP Push Service Indication (SI) is most suitable as it provides most of the required service characteristics including priority level, expiration date and links to external web services (e.g. trading services to sell the affected portfolio position).

6 SUMMARY AND CONCLUSION

Automated alerting services can provide new functionality to private investors. In recent years, mobile alerting services were mainly introduced in order to prevent customers from calling the cost-intensive customer call centers. Whereas these approaches focus on the reduction of cost at the bank side, this paper proposes the application of automated mobile alerting services notifying investors about relevant market events (the paper focuses on published ad hoc disclosures) in time.

Therefore, this paper provide evidence that significant short-term intraday price effects can be observed after the publication of ad hoc disclosures and that these price effects can be successfully estimated by a set of describing variables and appropriate forecast methodologies. The evaluation of these forecast methodologies shows that artificial neural networks (ANNs) achieve a forecast accuracy comparable with a linear regression approach. Compared to prior research, this can be shown for intraday price effect estimation. Using the described neural network architecture we can estimate more than ¾ of the price effect categories and more than ⅔ of the effect delay categories correctly.

By applying these forecast methodologies we can design a mobile notification architecture which will use automated alerting services in case of relevant price effects being forecasted. Whereas most of the existing alerting approaches focus on cost savings on the banks' side, this approach provides added value to customers as e.g. potential losses can be anticipated due to contemporary information supply.

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