Forecasting Market Impact Costs and Identifying Expensive Trades
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* Views expressed are those of the individual authors and do not necessarily reflect official positions of De Nederlandsche Bank.
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Abstract

Often, a relatively small group of trades causes the major part of the trading costs on an investment portfolio. For the equity trades studied in this paper, executed by the world’s second largest pension fund, we find that only 10% of the trades determines 75% of total market impact costs. Consequently, reducing the trading costs of comparatively few expensive trades would already result in substantial savings on total trading costs. Since trading costs depend to some extent on controllable variables, investors can try to lower trading costs by carefully controlling these factors. As a first step in this direction, this paper focuses on the identification of expensive trades before actual trading takes place. However, forecasting market impact costs appears notoriously difficult and traditional methods fail. Therefore, we propose two alternative methods to form expectations about future trading costs. The first method uses five ‘buckets’ to classify trades, where the buckets represent increasing levels of market impact costs. Each trade is assigned to a bucket depending on the probability that the trade will incur high market impact costs. The second method identifies expensive trades by considering the probability that market impact costs will exceed a critical level. When this probability is high, a trade is classified as potentially expensive. Applied to the pension fund data, both methods succeed in filtering out a considerable number of trades with high trading costs and substantially outperform no-skill prediction methods. The results underline the productive role that model-based forecasts can play in trading cost management.

Keywords: market impact costs, forecasting, institutional trading, trading cost management

JEL classification: G11, G23, C53
It is a well-known phenomenon that trading costs can substantially reduce portfolio performance. A stock with a high gross return may end up with a relatively low net return when trading costs are high. Therefore, trading costs are an important factor to consider when portfolio decisions are made.

There is a vast literature on trading costs and their determinants; see Keim and Madhavan [1998] for an excellent survey. Usually, the literature distinguishes explicit and implicit trading costs. The explicit part consists of fixed costs, such as commissions, taxes, and fees. Implicit costs are built up of market impact costs (price impact), bid-ask spread, delay costs (the costs of adverse price movements that may occur when trading is postponed), and opportunity costs (the costs of not trading). Market impact costs are usually found to be the most important component of trading costs and occur when price effects cause execution prices to be less favorable than benchmark prices.

Often, a comparatively small group of trades causes the major part of market impact costs. For the equity trades studied in this paper, executed by the world’s second largest pension fund ABP, we find that only 10% of the trades determines 75% of total market impact costs. Consequently, reducing the trading costs of relatively expensive trades would already lead to substantial savings on total trading costs. Since trading costs depend to some extent on controllable factors such as broker intermediation, investment style, trade timing, and trading venue (see e.g. Bikker, Spierdijk, and Van der Sluis [2007]), investors can try to reduce trading costs by carefully controlling these factors.

Since model-based forecasts of market impact costs can contribute to identifying potentially expensive trades, they play a crucial role in transaction costs.
management. Although the importance of forecasting trading costs has been widely recognized (see e.g. Cheng [2003] and Konstance [2003]), the literature has paid surprisingly little attention to this issue. To fill the gap, this paper proposes two alternative methods to identify expensive trades before actual trading takes place. Furthermore, we also discuss how to incorporate the proposed forecasting methods in trading cost management. We illustrate the approach with a unique data set containing the global equity trades in the first quarter of 2002 executed by the world’s second largest pension fund.

DATA AND DEFINITION

The ‘Algemeen Burgerlijk Pensioenfonds’ (ABP) is the largest Dutch pension fund and second largest of the world. It has about 2.6 million clients and an invested capital of approximately 190 billion Euro\(^1\), corresponding to one third of total Dutch pension fund assets. The data set contains detailed information on all 3,721 worldwide equity trades of ten different funds at ABP during the first quarter of 2002, with a total transaction value of 5.7 billion Euro. Of these trades, 1,962 are buys and 1,759 are sells executed in Europe, the United States, Canada, and Japan. The trades in this sample consist of transactions for risk control and rebalancing of index trackers, as well as informed ones for active management. The internally managed equity portfolios in our sample have a total value of about 20 billion Euro.

For each transaction the data set provides the execution price and the price of the stock just before the trade was passed to the broker. Moreover, the data also specify when the trade was submitted to the broker and when it was executed. Additionally, the data include detailed information on several trade, exchange, and stock specific characteristics, including volatility, momentum, relative trade size,

\(^{1}\)This is the total invested capital at the end of 2005.
market capitalization, type of broker intermediation, investment style, trade timing, industry sector, and trading venue. The first two columns of Exhibit 3 provide a complete list of the variable names and their definitions.

We constructed the data set on the basis of the post-trade analysis provided by ABP; the remaining data come from Factset and Reuters. For more details on the data, we refer to Bikker, Spierdijk and Van der Sluis [2007].

**PRELIMINARY DATA ANALYSIS**

Market impact costs occur when the execution price of a trade is worse than the benchmark price. Hence, in order to forecasts these costs, a benchmark price has to be chosen. We opt for the pre-execution benchmark, in line with e.g. Wagner and Edwards [1993]. More precisely, we take as the benchmark the price at the moment that the order was passed to the broker. Furthermore, we correct for market-wide price movements during trade execution, as in Chan and Lakonishok [1995, 1997]. The MSCI World industry group indices are used as a proxy for these market movements. Thus, for a buy transaction in stock $i$ at time $t$ market impact costs ($C^B_{it}$) are defined as

$$C^B_{it} = \log(\frac{P^{exe}_{it}}{P^{pt}_{it}}) - \log(\frac{M^{exe}_{it}}{M^{pt}_{it}}),$$

price impact market wide price movements

where $P^{exe}_{it}$ and $P^{pt}_{it}$ denote the execution and pre-trade price of stock $i$ at time $t$, respectively. $M^{exe}_{it}$ and $M^{pt}_{it}$ denote the value of the MSCI industry group index corresponding to stock $i$ at the time of the execution of the trade and at the pre-trade time, respectively. In a similar way we define market impact costs of sells; i.e.

$$C^S_{it} = \log(\frac{P^{pt}_{it}}{P^{exe}_{it}}) - \log(\frac{M^{pt}_{it}}{M^{exe}_{it}}).$$
For both buys and sells, positive market impact cost indicate that a trade has been executed against a price worse than at the moment of trade initiation.

To get a first impression of the magnitude of trading costs, we calculate principal-weighted average market impact costs. To obtain the principal-weighted statistics we weight each observation by the Euro value of the trade, so that larger trades contribute more than smaller ones. Average market impact costs of buys equal 20 basis points (bp) with a standard deviation of 6 bp and those of sells 30 bp with a standard deviation of 7 bp. Including commissions, these costs equal 27 bp for buys and 38 bp for sells, with respective standard deviations of 6 bp and 7 bp. These price effects are relatively moderate compared to other studies (see Bikker, Spierdijk, and Van der Sluis [2007]).

Exhibit 1 displays the contribution of each trade to total market impact costs. Starting with all trades sorted from cheap to expensive, the horizontal axis denotes the percentage of trades executed (in the range 0-100%). The vertical axis represents the total trading costs (including commission) in Euro corresponding to the trades executed. We see that the 25% cheapest trades have negative market impact costs, whereas the 35% most expensive trades incur positive trading costs. The remaining 40% of medium-expensive trades have market impact costs close to zero. Together, they yield a convex and asymmetric ‘market impact costs smile’. The convexity in Exhibit 1 implies that the 10% most expensive trades cause about 75% of total market impact costs. Consequently, the investor could already realize substantial savings on total trading costs if he or she would be able to (1) identify a few expensive trades before actual trading and (2) reduce the trading costs of these trades, e.g. by more careful monitoring.

We make this more explicit by means of simulation. For this purpose, we consider an investor that has a certain skill (in the range 0-100%) to identify expensive
trades correctly before actual trading takes place. With a skill of 100%, he or she
is able to rank all trades correctly according to future trading costs (‘perfect fore-
sight’). With a 0% skill, the investor’s ranking of the stocks is completely random.\(^2\)
At the same time we consider a cost reduction percentage that applies to the selected
trades as a result of more careful treatment of the trade. For all skill levels and each
percentage of cost reduction per trade, we simulate the corresponding total realized
savings on trading costs.\(^3\) The resulting 3-dimensional graph in Exhibit 2 (a) dis-
plays the relation between investor skill \((x\text{-axis})\), cost reduction per trade \((y\text{-axis})\),
and total expected savings \((z\text{-axis})\). For instance, an investor skill of 20% in combi-
nation with the same cost reduction percentage per trade results in total expected
savings of almost 1.4 million Euro.

Although the extremes of no skills and perfect foresight are quite trivial, the
simulation reveals various nontrivial patterns in Exhibit 2 (a). The contour plot in
Exhibit 2 (b) (where each contour line represents an additional saving of 5 million
Euro) highlights the nonlinear relation between trading costs and cost reduction.
Moving from south-west to north-east in Exhibit 2 (b), the distances between the
contour lines get smaller. Saving an additional 5 million Euro requires a compar-
atively large improvement in either skill or cost reduction whenever these are low.
By contrast, saving another 5 million needs to be combined with a much smaller
improvement once these are already high. Also, when investor skills are low and the
percentage of cost reduction is high (point A), relatively more cost reduction than
skill improvement is needed to arrive at lower market impact costs. Similarly, with
high investor skills and low cost reduction (point B), relatively more skill improve-
ment than reduction is required to reduce market impact costs. Also, the contour
\(^2\)For any skill of \(p\%\) with \(0 < p < 1\), \(p\%\) of all trades is ranked correctly and the other \((1 − p)\%)\nis ranked randomly over the remaining positions.
\(^3\)We repeat this 1,000 times and average the realized savings over the simulation runs to obtain
the expected savings for each skill level and cost reduction percentage.
lines show that relatively low skill values in combination with a substantial cost reduction per trade result in the same savings on total trading costs as relatively high skill values and low cost reduction percentages.

**DETERMINANTS OF MARKET IMPACT COSTS**

Market impact costs usually depend on various trade, exchange, and stock specific characteristics. To formalize this, we assume that the market impact costs of a buy trade are determined by $N$ factors (say $X_1, \ldots, X_N$) and a random noise term $\varepsilon$. Since trading costs of buys and sells usually show different behavior, we follow the literature and consider separate models for them. Without loss of generality, we confine ourselves here and in the sequel to buy trades. We deal in exactly the same way with sell trades, using similar notation. Thus, we assume that market impact costs of buy trades ($C^B$) satisfy

$$C^B = \beta_0^B + \sum_{j=1}^{N} \beta_j^B X_j + \varepsilon^B.$$  \hspace{1cm} (3)

For the $N$ factors we take the variables in Exhibit 3. We estimate the resulting linear regression model using ordinary least squares. Exhibit 3 displays the corresponding estimated coefficients and $R^2$'s. For a detailed interpretation of the model coefficients, we refer to Bikker, Spierdijk, Van der Sluis [2007].

**FORECASTING MARKET IMPACT COSTS**

The model in equation (3) explains market impact costs of buy and sell trades from various, to some extent controllable factors. In this section we go one step further and use the model to forecast future market impact costs.

Forecasts of market impact costs can be used to identify expensive trades before actual trading takes place. When forecasted trading costs exceed a certain critical level, the investor may decide to change the type of broker intermediation, trade
timing or trading venue, or to monitor the trade more carefully during execution.

Only accurate forecasts will contribute to effective trading cost management. When forecasted market impact costs appear to be underestimated, the respective trade may not have been given the additional monitoring that could have avoided (part of) these high trading costs. Hence, inaccurate forecasts may lead to a costly ‘missed detection’. On the other hand, when forecasted market impact costs appear to be overestimated, the trade may have been given unnecessary attention during the trading process resulting in wasted costs. Hence, inaccurate forecasts can also result in a costly ‘false alarm’. Therefore, ‘good’ forecasts strike a balance between missed detection and false alarm. Obviously, the optimal balance between these two rates will depend on individual investor preferences.

Throughout, we evaluate the forecasting power of the model both in-sample and out-of-sample. To do so, we divide the data sample into an in-sample part (the first two months of trades, about 75% of the total sample, say trades \( t = 1, \ldots, n \)) and an out-of-sample part (the final month of trades corresponding to 25% of the sample, say trades \( t = n + 1, \ldots, n + m \)). Subsequently, we estimate the models for buy and sell trades using only the in-sample data. The in-sample forecasts correspond to the predicted trading costs for the in-sample trades. For the out-of-sample forecasts we proceed in a different way. We start with estimating the model using trades \( t = 1, \ldots, n \). Next, we obtain a forecast for trade \( t = n + 1 \). In the subsequent steps we add one trade at a time and use an expanding window estimator to re-estimate the models using all trades available up to the day preceding trade \( t \). Subsequently, we calculate forecasts for one trade ahead, i.e. for trade \( t + 1 \). We repeat this step-wise for each trade \( t = n + 1, \ldots, n + m \).
Numeric forecasts of market impact costs

There are several ways to forecast future market impact costs. For the moment we assume that the investor’s goal is to predict the trading costs of every trade to be executed. The usual way to forecast market impact costs is by means of expected market impact costs. Assuming that the noise term in specification (3) has mean zero, expected trading costs of buys equal

$$E(C_B) = \beta_0^B + \sum_{j=1}^{N} \beta_j^B X_j.$$ (4)

Given estimates of the coefficients $\beta_j^B$ based on historical data, we easily calculate expected trading costs conditional on factors $X_1, \ldots, X_N$ by means of formula (4).

Exhibits 4 (a)-(d) display scatter diagrams of realized and forecasted trading costs, together with regression lines that capture the relation between forecasts and realizations. Clearly, predicted trading costs differ considerably from realized costs. This is confirmed by formal error measures, such as Theil’s U. This measure takes the value one in the no-skill case, while it equals zero with perfect foresight. In-sample, it takes the value 0.89 for buys and 0.86 for sells. Out-of-sample it equals 1.05 and 1.11, respectively. In all cases its values are relatively close to the no-skill case.

Since market impact costs reflect the price movements of a stock during trade execution, the difficulty of forecasting these costs does not come as a complete surprise. Moreover, the out-of-sample month differs substantially from the in-sample period, which also complicates forecasting.\(^4\) Nevertheless, even for the turbulent out-of-sample month the upward slopes of the regression lines in Exhibit 4 reflect fairly positive correlations between realized and forecasted trading costs. In-sample, the correlations equal 0.44 for buys and 0.50 for sells. Out-of-sample they take the values

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\(^4\)In the year 2002, January was bearish and February was quite flat. However, the out-of-sample month of March was bullish.
0.21 and 0.19, respectively. All correlations are significant at a 5% significant level. Hence, although forecasted trading costs deviate substantially from realized costs, the model at least succeeds in forecasting higher trading costs for stocks that actually experienced higher trading costs.\textsuperscript{5}

**Bucket classification approach**

Although the forecast quality of the model in equation (3) is limited, the model indeed forecasts higher trading costs for stocks that experienced higher costs of trading. Therefore, rather than providing numeric forecasts of market impact costs, we expect to be more successful in the classification of market impact costs in terms of ‘high’ or ‘low’. Moreover, we have seen that only 10% of all trades determines 75% of total market impact costs. This emphasizes that, from the perspective of cost reduction, the focus should be on detecting the most expensive trades.

To predict trading costs in terms of ‘high’ or ‘low’, we distinguish five buckets with predefined boundaries. We use the probability to encounter a certain level of market impact costs on a trade to predict the bucket in which market impact costs will fall. The higher the probability that a trade will cause high trading costs, the higher the bucket we will predict for that trade. We take the same buckets for buys and sells and define them in such a way that we have five buckets with increasing levels of market impact costs: bucket 1 (no costs, $(-\infty, 0]$ bp), bucket 2 (‘low costs’, $(0, 20]$ bp), bucket 3 (‘average costs’, $(20, 50]$ bp), bucket 4 (‘high costs’, $(50, 80]$ bp), bucket 5 (‘severe costs’, $(80, \infty)$ bp). Given $p_0 = 0$ and $p_5 = 1$, we set four critical ‘cut-off probabilities’ $p_1, p_2, p_3$, and $p_4$ to assign the trades to one of the five buckets. If the ‘excess probability’ $\mathbb{P}(C_B > T \mid X_1, \ldots, X_N)$ for a certain critical level $T$ satisfies $p_i < \mathbb{P}(C_B > T \mid X_1, \ldots, X_N) < p_{i+1}$, we predict that a buy will

\textsuperscript{5}We notice that a correlation between realized and forecasted trading costs of $x\%$ corresponds to an investor skill of approximately $x\%$ as well.
fall in bucket $i + 1$.\(^6\)

We can easily calculate the excess probability corresponding to the regression model in equation (3), provided that we know the distribution of the error term. If we denote the distribution function of the noise term by $F(x) = P(\varepsilon \leq x)$, the excess probability for buys according to model 3 writes as

$$\mathbb{P}(C^B > T \mid X_1, \ldots, X_N) = 1 - F(T - \beta_0^B + \sum_{j=1}^{N} \beta_j^B X_j).$$

(5)

The distribution of the noise term has to be known in advance to calculate this probability. As usual, the assumption of normality seems obvious and convenient, but is nevertheless likely to be restrictive. Therefore, we take the empirical distribution of the noise term based on the in-sample period, which avoids any parametric assumptions. This means that we calculate the excess probability in expression (5) as the fraction of trades in the in-sample period for which the residuals\(^7\) exceed the value in the parentheses of $F(\cdot)$ in expression (5).

In practice, the choice of the critical level and cut-off probabilities will depend on the investor’s preference regarding the balance between the false alarm and the missed detection rate. Here we use the in-sample period to determine appropriate values of the critical level $T$ and the cut-off probabilities $p_1, \ldots, p_4$. We set $T = 80$ and $p_1 = 0.15$, $p_2 = 0.25$, $p_3 = 0.375$, and $p_4 = 0.55$. For sells we proceed in a similar way and set $T = 80$ and $p_1 = 0.09$, $p_2 = 0.15$, $p_3 = 0.25$, and $p_4 = 0.40$.

Again we use an expanding estimator and evaluate the quality of the bucket forecasting approach. The upper panel of Exhibit 5 displays the classification results, both in absolute numbers and in percentages. Ideally, the percentages on the diagonals of the second and fourth panel at the right-hand-side of Exhibit 5 should be as

\(^6\)Alternatively, we could use linear discriminant analysis or an ordered probit model for this classification problem. However, we obtain better results with the current method.

\(^7\)The residuals are defined as $e^B = C^B - \hat{\beta}_0^B - \sum_{j=1}^{N} \hat{\beta}_j^B X_j$. 

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close as possible to 100%. The higher they are, the more trades are classified in the correct buckets. Misclassification occurs when off-diagonal elements in Exhibit 5 are not equal to zero. The lower panel of Exhibit 5 displays several measures related to the overall classification quality. We consider the percentage of (1) correctly classified trades, (2) trades with no or low market impact costs that are predicted to have high or severe trading costs, (3) trades with high or severe market impact costs that are predicted to have no or low trading costs, (4) seriously misclassified trades, which are defined as trades with no or low costs classified as high or severe or vice versa, and (5) trades misclassified two or more buckets away from the correct bucket. We compare the resulting percentages to the ‘no-skill’ or ‘naive’ model assigning a trade to bucket $i = 1, \ldots, 5$ with probability $1/5$. In-sample, the bucket approach applied to buy trades strongly outperforms the no-skill model on four out of five criteria. Out-of-sample, the bucket approach outperforms on all five criteria. In particular, the important category of trades with high or severe trading costs that are wrongly classified as having no or low costs is only 18% (versus 40% in the no-skill model). For sells, the bucket approach again outperforms the naive model on all criteria. In line with expectations, the performance of the bucket approach relative to the naive model is in-sample more convincing than out-of-sample. But still the percentage of trades with no or low trading costs that are erroneously predicted to have high or severe costs is substantially lower than in the no-skill model (23% versus 40%). The same holds for the percentage of seriously misclassified sells.

**Identifying expensive trades: probability method**

Another way of dealing with future market impact costs is to identify trades that have a high chance of being (too) expensive. That is, we assume that a trade is identified as expensive when the excess probability exceeds a certain critical level;
i.e. when $\mathbb{P}(C^B > T \mid X_1, \ldots, X_N) \geq p$, for certain investor-specific values of the critical level $T$ and cut-off probability $0 \leq p \leq 1$. The difference between this ‘probability method’ and the previous two approaches is that we do not longer forecast a level or range of market impact costs for each trade, but only identify those that are likely to be expensive. Again we use the empirical distribution to calculate the excess probability.

To assess how well the probability method discriminates between cheap and expensive trades, we set the critical level at $T = 50$ bp. For cut-off probabilities $p = 0.1, 0.2, \ldots, 0.9$, and 1, we plot the corresponding false alarm rate against the detection rate. The solid curves in Exhibits 6 (a)-(d) highlight several relevant quantities for buys and sells, both in-sample and out-of-sample. The distances below (respectively, to the left of) the solid curves reflect the detection (and false alarm) rate. Moreover, the distances above (respectively, to the right of) the curves correspond to the missed detection (and correct no-detection) rate. For example, for $p = 0.25$ we find false alarm and detection rates of, respectively, 54% and 83% (in-sample) and 68% and 91% (out-of-sample) for buys. For sells these rates equal 43% and 75% (in-sample) and 22% and 33% (out-of-sample). The dashed 45°-lines in Exhibit 6 reflect the no-skill forecasts that are obtained by randomly assigning $p\%$ of all trades to the group of trades with costs higher than $T = 50$ bp. For $0 \leq p \leq 1$, this results in false alarm and detection rates of $p\%$. The dashed 45°-lines are obtained by considering the entire range of possible values for the cut-off probability $p$. From Exhibit 6 we see that at each level of the false alarm rate, the probability method has a higher detection rate than the no-skill method.

The surface of the area below the solid curve can be viewed as the proportion of correct forecasts across all possible thresholds. This area ranges from $0 - 100\%$, where the value 50\% corresponds to the no-skill value (which equals the areas under
the dashed 45°-line) and 100% to perfect forecasting. It serves as a summary statistic of the discrimination power of the model. For buys, its value equals 76% for the in-sample period and 78% for the out-of-sample period. For sells, it takes the values 74% and 64%, respectively. Hence, the probability method substantially outperforms the naive forecasting approach across all values of the cut-of probability.

In practice, the investor will choose a probability level on the basis of his or her preferences regarding the balance between the false alarm and the missed detection rate. However, the above analysis of forecast quality provides a convenient measure of discrimination that does not depend on arbitrary threshold levels.

CONCLUSIONS

When a relatively small group of trades causes the major part of the market impact costs of an investment portfolio, a reduction of the trading costs of comparatively few expensive trades would already result in substantial savings on total trading costs. For the equity trades analyzed in this paper, executed by the world’s second largest pension fund ABP in the first quarter of 2002, we find that only 10% of the trades causes 75% of total trading costs. Simulations emphasize that there is a strong nonlinear tradeoff between trading costs and the number of trades executed.

Since trading cost depend to some extent on controllable factors such as broker intermediation, trade timing and trading venue, investors can try to reduce the costs by carefully controlling these factors. As a first step in this direction, this paper has proposed two methods to obtain forecasts of market impact costs that can help to identify potentially expensive trades: a ‘bucket’ classification approach and a method to identify expensive trades. Applied to the equity trades executed by ABP, the proposed methods succeed in identifying a considerable number of expensive trades and substantially outperform no-skill prediction methods. The results illustrate the
productive role that model-based forecasts can play in trading cost management.

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This exhibit displays total market impact costs plus commission (in Euro) as a function of the percentage of trades executed. For example, when the 3% most expensive trades are not executed, the costs of the remaining 97% cheapest trades sum to zero.
EXHIBIT 2: RELATION BETWEEN INVESTOR SKILLS, COST REDUCTION, AND SAVINGS

Exhibit (a) shows total (expected) savings on market impact costs including commission (in Euro) for each percentage of investor skills and cost reduction per trade. Exhibit (b) displays the corresponding contour plot for various levels of total savings.
<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
<th>Buys</th>
<th>Estimate</th>
<th>t-value</th>
<th>Sells</th>
<th>Estimate</th>
<th>t-value</th>
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<td>-27.09</td>
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<td>Jandum</td>
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**EXHIBIT 3: DESCRIPTION OF DETERMINANTS OF MARKET IMPACT COSTS AND CORRESPONDING ESTIMATION RESULTS**

This exhibit displays a list of determinants of market impact costs and their estimated coefficients (with corresponding t-values) based on the model of equation (3) for buys. The same model was estimated for sells. Coefficients in bold face are significant at a 5% level.
EXHIBIT 4: REALIZED AND FORECASTED MARKET IMPACT COSTS

This exhibit displays realized and forecasted market impact costs for buys and sells (both in-sample and out-of-sample), together with regression lines that express forecasted trading costs as a function of realized costs.
### Exhibit 5: Classification Results Based on Bucket Approach

This upper panel of this exhibit displays the classification results for the bucket approach. For both buys and sells it reports the amounts and percentages of trades with realized costs in bucket \(i\) and forecasted costs in bucket \(j\) \((i, j = 1, 2, 3, 4, 5)\). The lower panel reports five ‘overall’ quality measures corresponding to the bucket classification method.
EXHIBIT 6: DISCRIMINATION ABILITY OF FORECASTS FOR VARIOUS CUT-OFF PROBABILITIES

For cut-off probabilities $p = 0.1, 0.2, \ldots, 0.9$ and 1, the solid curves in this exhibit plot the false alarm rate against the detection rate for buys and sells, both in-sample and out-of-sample. The distances below (respectively, to the left of) the curve reflect the detection (and false alarm) rate. Moreover, the distances above (respectively, to the right of) the curve correspond to the missed detection (and correct no-detection) rate. The dashed $45^\circ$-lines reflect the no-skill forecasts that are obtained by randomly assigning $p\%$ of all trades to the group of trades with more than $T = 50$ bp. For $0 \leq p \leq 1$, this results in false alarm and detection rates of $p\%$. The dashed $45^\circ$-lines are obtained by considering the entire range of possible values for $p$. 
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