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Investment Market (AIM)

By

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Contents

Abstract

This paper studies liquidity provision in the Alternative Investment Market (AIM) of the London Stock Exchange. Our analysis shows that it is *possible* to generate sufficient liquidity in a small company market. Indeed, a small group of AIM stocks are found to trade frequently, exposing the investor to minimal execution risk. At the same time, we find that the majority of AIM stocks trade infrequently, with trades often clustered around a few days. We find the latter group to be further characterised by higher price volatility and wider spreads, indicating that for the majority of AIM stocks, immediacy risk is an issue of concern.

When studying AIM stocks that were transferred from the Rule 4.2. market, we report a significant increase in trading activity, but surprisingly little change in liquidity as measured by either price volatility or trading costs.

Finally, we develop a statistical model to identify the main determinants of liquidity. We find that a higher market capitalisation and a higher free float both contribute to a larger number of trades, lower trade concentration, lower price volatility and lower effective spreads. There also seems to be a technology effect, in that technology firms are more actively traded and enjoy lower trading costs, in the form of lower average effective spreads. At the same time, our empirical evidence seems to indicate that there is no “average” AIM stock, and that liquidity is therefore difficult to predict.

1. Introduction

This paper studies liquidity provision in the Alternative Investment Market (AIM) of the London Stock Exchange. AIM was created in June 1995 as a separate market place for small or start-up companies. It was a successor to the Third Market, the Unlisted Securities Market (USM) and Rule 4.2. all of which proved unsuccessful in establishing and/or maintaining a liquid trading environment.[1]

Our analysis centres on whether it is possible to have a liquid market for small company stocks.

Liquidity is commonly defined as the ability of a market to accommodate incoming public orders with minimal price impact. This definition contains two key elements: Immediacy and trading costs. Immediacy refers to the probability of finding a counterpart in a "reasonable" time span. As such, trading frequency is an important indicator of immediacy. Trading costs measure the discrepancy between a security's fundamental value and the actual value at which the trade is executed. A market is considered liquid if immediacy can be achieved at minimal trading costs.

But what does liquidity mean in a market for small company stocks, where market capitalisation can be as low as £0.5 million? Surely, it does not mean 100 trades per day, but does it mean two trades per day, or maybe two trades per week? Furthermore, what range of trading costs can be considered reasonable? It is clearly unrealistic to use the well-studied FTSE-100 stocks as a benchmark. We will argue in this paper that liquidity needs to be seen as a relative concept: Is stock A, given its features, more liquid than stock B, given its features?

The present analysis of liquidity uses a sample comprising six months of transaction data for 111 AIM stocks. We also examine 67 AIM stocks that were previously trading as rule 4.2. stocks, and compare their liquidity characteristics in the two market settings. A companion paper addresses a second, critical issue: The optimal market structure for small company stocks.

The paper is organised as follows: In section 2, we describe the institutional features of the AIM market, and its overall performance during our sample period. We also contrast AIM with other small company markets. Section 3 describes the data and our methodology. In section 4, we have a close look at three proto-typical AIM stocks. Section 5 contains the main results of our study, first for the entire AIM sample, and then for 57 stocks that transferred from rule 4.2. to AIM. Finally, in section 6, we seek to identify the main determinants of liquidity.

2. Institutional background

2.1. Market structure

In any market, investors face a trade-off between cost and immediacy. Those willing to wait can profit at the expense of more impatient traders. In quote driven markets such as London, immediacy is provided by dealers who act as principals. Traders pay a cost for immediate execution in the form of the bid-ask spread charged by the dealer. This spread compensates the dealer for the risk he incurs, which includes both his exposure to better informed counterparties and to unwanted inventory movements. The spread is a variable cost and depends, among other things, on the dealer's judgement of the probability that the investor possesses superior information. This judgement is

[1] The USM was created in 1980 as a market for small firms, that did not meet the listing requirements of the Official List. In spite of early successes, the market eventually suffered from insufficient liquidity, insufficient market maker capital commitment, and systematically underperformed the Official List. It was closed in 1996. Rule 4.2. was an off-market trading facility, with trading done on a matched bargain basis through brokers. Trading was done on a continuous basis, but market makers were not required to provide firm quotes. The market was closed in 1995. The Third Market existed from 1987 to 1990, and was meant to attract small, start-up companies with high risk profiles, that did not meet the USM requirements. Upon closing, its companies were transferred to either the USM or rule 4.2.

based upon the current negotiation and, more importantly, a long running relationship between dealers and brokers or investors. In contrast, investors who wish to avoid spread costs can do so by seeking out counterparties themselves and engaging in so called direct cross trades. The resulting search costs can be reduced by if a mechanism for congregating orders, such as an order book, is provided.

In a small company market, this trade-off between costs and immediacy is even more pronounced : First, the chance of informed trading is high. This is the result of both significant holdings by insiders and the relatively low level of public research.[2] Second, infrequent trading pushes up inventory risk for dealers. Trades are relatively rare -often clustered around a few dates such as those close to earnings announcements- and the number of interested parties is small. For these reasons, we anticipate spreads to be higher in small company markets. At the same time, the limited number of participants strengthens the relationship between dealers and their counterparties. The market becomes more like a repeated game where cheating behaviour leads to a loss of reputation and goodwill. This discipline reduces the probability that investors will use information to the detriment of market makers, and may keep spreads lower.

Nonetheless, small stock investors may be more inclined to compromise on immediacy and take out time to find a counterparty. In London, this can be done through the company's broker who knows where the interest is in the stock. But the increased use of such agency crosses puts the dealer in a more difficult position: First, he now observes less of the order flow. Second, he is more likely to face traders who have a high demand for immediacy because they posses private information. This further increases the dealer's exposure to adverse selection risk.

AIM has chosen to provide a dual trading mechanism: Trading is done either via market makers, who provide continuous, two-way, firm quotes displayed on SEAQ, or on a matched bargain basis via the exchange's old (i.e. pre-SETS) electronic order book SEAT PLUS.[3] It is also possible to arrange direct agency crosses via brokers. It is common practice, however, for brokers involved in such crosses to inform the main dealers, and even allow them to participate in the cross.

Furthermore, if it is not possible for AIM market makers to display up-to-date prices on SEAQ, then the exchange may declare an indicative market in the AIM security. This means that quotes displayed on the SEAQ screen become indicative. Any price provided over the telephone, however, must be firm.

Finally, as on the main market, all AIM trades have to be reported to the exchange within three minutes. Post-trade transparency is lower though: Publication of so called "risk trades", namely trades that involve a market maker, is delayed for three business days, irrespective of the size of the trade.

2.2. Market performance

In order to provide easy access, the LSE sets no minimum trading record, assets, profits levels, market capitalisation, or free float for admission to AIM. AIM companies are further dispensed from the LSE requirement to seek shareholder consent prior to a substantial share transaction. An announcement to the Exchange is sufficient.[4] Central to the AIM admission procedure is the

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[2] Estimates of the investor base are: 38% directors and founders; 38% private investors; 22% institutional investors and 6% venture capitalists (The London financial News, 15-21 Sept. 97, p.22).

[3] SEAT PLUS was originally created for the less liquid stocks of the Official List that have at most one market maker and was later opened up to all AIM stocks. Market practitioners claim, however, that very few investors make use of the SEAT PLUS order book.

[4] By contrast, companies on the Official List are required to have a minimum capitalisation of £700K, a trading history of three years or more, and a minimum free float of 25%. Free float is defined as the proportion of shares held in public hands, i.e. not held by a director or connected party, or in share holdings of more than 5% of the company. Admission costs are estimated to be similar to those for the Official List, but the cost of information disclosure is lower.

nomination and retention of a nominated adviser (NOMAD), who supervises the flotation and advises the company thereafter, and a nominated broker, who organises the actual flotation.[5] A company that loses its NOMAD has its trading suspended, and if it does not find a replacement within a month its quotation cancelled. Finally, AIM securities are treated as unquoted for tax purposes, offering investors several possibilities for tax relief.

The AIM market has been growing rapidly, from 14 companies at its inception in June 1995, to 173 at the end of our sample period (see table 1). Total market capitalisation increased from £82 million to £3,652 million. Monthly turnover in the same period rose from 194 trades, worth a total of £917,332 to 15,342 trades worth over £187 million. Market maker commitment is viewed by the Exchange as an alternative measure of success. At the end of June 1996, 39% of all AIM companies had one market maker, 42% had two, a further 16% had three market makers, and the remaining 3% had 4 or 5 market makers.[6]

Insert table 1

Daily returns based on the AIM index show that the AIM market slightly outperformed the FTSE-All Share index during the first six months of 1996 (mean of 0.03% vs. 0.01%), but underperformed the Small Cap index (0.04%).[7] At the same time, the AIM index wss the most volatile of the three, with a standard deviation of 0.32%, compared with 0.20% and 0.11% for the All Share and the Small Cap indices, respectively. The distinctness of the AIM market is further illustrated by the correlation matrix of the index returns: The correlations between the AIM index and both the All-Share index (0.19) and the Small Cap index (0.33) were considerably lower than the one between the All-Share and the Small Cap indices themselves (0.56).

2.3. A comparison with other second-tier markets[8]

Several other second-tier markets have seen the light in Europe following the creation of AIM. In the U.K., OFEX was created in September 1995 as an off-market trading facility. OFEX has one market maker who quotes indicative prices only. Actual trade prices are negotiated over the phone. In case of insufficient liquidity and/or excessive price swings, the market maker can limit his role to matching incoming trades. All trades on OFEX are published immediately.

The Nouveau Marche was created in March 1996 by the Paris Bourse to attract high-growth companies. The Paris Nouveau Marche, is a dual structure, where an electronic limit order book and one or two daily call auctions operate successfully side by side. Dealers participate in both the order book and the call auctions. Institutional traders are reported to prefer to trade through market makers (and account for 60% of the value of trading), whereas smaller investors typically place their orders in the book. Boussema and Hazart (1996) study six months of transaction data and report frequent interaction between the two trading mechanisms.

Several other European countries established small company markets late 1996 and early 1997: Euro.N.M.Belgium (November 1996); the Amsterdam NMAX (February 1997) and the German Neuer Market (March 1997). All have opted for electronic order book trading, combined with call auctions (mostly for retail trades) and the intermediation of market makers (for institutional trades).

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[5] One firm can carry out both functions. The Nomad must be chosen from a list maintained by the Exchange, that includes brokers, lawyers, accountants, banks and securities houses.

[6] Source: AIM Market Statistics, June 1995 - June 1996. As of May 1998, AIM had further grown to 306 companies with a combined market capitalisation of £6,864 mln. Total turnover in May 1998 was £250 mln, or 29,758 bargains (AIM Market Statistics, May 1998).

[7] The AIM index was first constructed on 2.1.96, comprising all AIM companies admitted as of 29.12.95 (See: Stock Exchange: Smaller Companies Analysis, July 1996).

[8] This section draws heavily on Bank of England (1997), "Second-Tier Equity markets in Europe and USA."

The pan-European EASDAQ was launched late September 1996, modelled after the NASDAQ. As such it is a screen-based, quote driven market, with competing market makers. There is full post-trade transparency. EASDAQ's objective is to attract medium sized companies (market capitalisation of $100 mln. or more), and as such sets minimum requirements for total assets and capital reserves. Furthermore, the listing company must have one sponsor and at least two market makers.

Finally, it is worthwhile looking at the American experience. Small and high-growth companies are listed either on NASDAQ's Small-Cap Market or the over-the-counter market. The minimum listing requirements on the Small-Cap market are $4 mln in total assets and $2 mln in equity. The OTC market comprises the OTC Bulletin Board, which is an electronic quote service, and the "Pink Sheets" which are daily bulletins in which participating market makers post indicative quotes together with their phone numbers.

The American Stock Exchange (AMEX) set up the Emerging Company Marketplace (ECM) in 1992 as an auction market. Aggarwal and Angel (1995) study 17 stocks that were moved in 1992 from the NASD to the ECM. They find that initially bid-ask spreads fell significantly, with volume increasing for some, but not all companies. Nonetheless, the ECM failed, primarily as a result of poor quality of some of the existing firms, which in turn deterred new firms from listing. The authors further suggest that an order driven auction market may not have been the ideal market setting for these stocks, but that a critical volume needs to be present to sustain a continuous auction market.

3.1. Data and methodology

3.1. Data description

Our sample consists of transaction prices and quotes of 111 AIM stocks that span the months January to June 1996.[9] In appendix A, we describe in detail how this sample was constructed. All 111 companies had been admitted to AIM by the end of 1995. Table 2 provides some descriptive statistics for this sample, and shows great heterogeneity across the AIM companies, a theme throughout this paper.

Insert table 2

Market capitalisation at entry ranges from £0.58 million to £299 million, with a mean of £17.5 million, a median of £6.2 million and a standard deviation of £36.6 million. Market capitalisation at the end of our sample period (measured as of June 30) ranges from £0.82 million to £325 million. The sample mean has risen to £22 million, and the median to £12.9 million. Free float and free market capitalisation (free float times market capitalisation as of June 1996) vary enormously as well, reflecting the absence of a minimum requirement on AIM. In section 6, we will analyse to what extent these issuer characteristics affect liquidity.

3.2. Measures of liquidity

In this section, we discuss some common measures of liquidity, that encompass both dimensions: Immediacy and trading costs. In later sections, we will discuss how to interpret these measures in the context of infrequently traded stocks.

Immediacy is viewed from two angles: How long does it take for a buyer to find a seller and vice versa? And, if one has to wait, does it matter? In the absence of data on the time it takes for an order

[9] Unfortunately, more recent data are unavailable because of data production problems at the Stock Exchange.

to be executed, we will use trade frequency and trade concentration as proxies for the first question. Indeed, the higher the number of trades and/or the less clustering occurs, the lower is the risk of execution delays.

Price volatility

As a complementary measure to asses immediacy risk, we measure price volatility. We argue that this is an insightful measure: Even if trades occur infrequently, immediacy or execution risk will not be a serious issue, unless prices are found to change sharply from one trade to the next.

Price volatility is computed as follows: First, we calculate the percentage price change using adjacent price changes. Next, we compute volatility as the standard deviation of all such transaction returns. Overnight returns are included for two reasons: First, dropping them would result in too few observations, as some stocks trade only once a day, or less. Second, because of the large differences in trade frequency across stocks, we end up working with uneven trade intervals anyway, that can be quite large. Hence, it should be acknowledged that our measure of price volatility reflects both the length of time between subsequent price changes, and the arrival of new information. We also computed the proportion of absolute price changes that fall into different size categories, ranging from small (up to 1%) to large (between 5% and 10%) and very large (over 10%).

The quoted spread

A first measure of liquidity is the bid-ask spread, which reflects the price charged by market makers for their intermediation. Market micro structure theory models the spread as a function of three components: Order processing costs, inventory risk, and asymmetric information risk. When measuring spreads, the researcher faces two issues: First, the accurate measurement of the bid-ask spread; and second the decomposition of the spread into its three cost components. The low number of observations for many AIM companies makes statistical analysis rather difficult. Consequently, we are limited in the number of spread measures that we can calculate.

Taking into account these limitations, we are able to compute the following two statistics: First, we use quotes to compute the percentage touch as:

(1) $100*(A_t - B_t)/TM_t$,

with the touch midquote (TM_t) computed as the average of the posted yellow strip bid (B_t) and yellow strip ask quotes (A_t).

In the London context, this measure is an inaccurate reflection of transaction costs for two reasons: First, market makers are often slow in updating their quotes. As a result, outstanding quotes may be "stale" and not necessarily represent the market maker's information, nor the prices at which he is actually willing to trade. Second, it is well known that transactions on the London Stock Exchange often occur inside the quoted spreads as a result of private negotiation between the market maker and his counterparts.[10] This could be the result of the exchange of valuable information that leaves the market maker less exposed to information asymmetries and therefore more willing to improve on his quoted prices. Such price discounts could also reflect long-term relationships between a market maker and a broker, although the precise impact of so called "order preferencing" is debated.[11]

The effective spread

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[10] See Reiss and Werner (1994) and Board, Fremault Vila and Sutcliffe (1997) among others.
[11] See Naik and Yadav (1997), and Hansch, Naik and Viswanathan (1997b).

To reflect these price discounts, the so called effective spread is calculated. It is commonly defined as twice the absolute difference between the actual trade price (P_t) and the prevailing touch midquote (TM_t), expressed as a percentage of the touch midquote:

(2) $200^*|(P_t - TM_t)/TM_t|$

and as such measures the improvement offered by the market maker over the touch midquote.

The effective spread could still be affected by stale quotes. Consequently, it may be preferable to look at trading cost measures that use only trade prices. Following Glosten and Harris (1988) and Huang and Stoll (1997), we estimate a simple linear pricing model, that relates price changes to order flow and provides a model based estimate for price impact. This model was first applied to the London market by Saporta et al (1998).

A model based spread

The model, explained in appendix B, estimates effective spreads together with the individual spread components using trade data only. This is done by estimating the following equation:

(3a) $\Delta P_t = (S/2)\Delta Q_t + (\alpha+\beta)(S/2)Q_{t-1} + e_t$,

where Q_t is an indicator variable, equal to +1 (-1) for a public buy (sale), P_t is the transaction price, and t and t-1 refer to two consecutive trades. S is the (constant) effective spread, α refers to the adverse selection component and β to the inventory component.

Equation (3a) can be rewritten to give the following empirical specification:

(3b) $\Delta P_t = a_1\Delta Q_t + a_2 Q_{t-1} + e_t$,

Equation (3b) yields estimates for the combined adverse selection and inventory components (a_2/a_1), the order processing component ($1- a_2/a_1$), as well as the effective spread ($2a_1$).

The spread model implicitly assumes that trades are serially uncorrelated, i.e. a buy trade is equally likely to be followed by another buy trade as by a sell trade. This assumption can be tested by

An alternative method to measure inventory risk involves analysing the market maker's trading behaviour. Theoretical micro structure models show that market makers will actively control their inventories when risk averse, and/or when carrying excess inventories is costly. Market makers will as such avoid substantial departures of their inventories from chosen long-run target level. Note that this optimal inventory level need not be zero, as the market maker may choose to take a speculative position. Nonetheless, their inventories are expected to exhibit mean reversion towards this long-run target. Large and prolonged departures from this target level may indicate that the market is insufficiently liquid and that the market maker incurs significant inventory risk.

This inventory management hypothesis is commonly tested by estimating the following equation[12]:

(5) $\Delta I_t = \alpha + \beta I_{t-1} + \varepsilon_t$,

with $-1 < \beta < 0$. The closer β is to zero, the slower the mean reversion, and the longer it will take for the market maker to rebalance his inventory I_t. [13] This will occur either if the market maker does not care very much about inventory risk, or if trading is infrequent such that he has no other option than to keep his positions. The estimated mean reversion coefficient β from the above equation is also used to estimate the inventory half-life, defined as the time required to reduce the inventory imbalance by 50%:

(6) $h = -\text{Log}(2)/\text{Log}(1+\beta)$.

Equation (5) will be estimated for the 22 most active stocks in our sample, for a selective (active) market maker.[14] End-of-day inventories I_t are constructed by summing all signed intra day trades in which the market maker participates. The opening inventory is conventionally set equal to zero (see e.g. Hansch (1997)). This artefact affects the summary statistics, but not the time series properties of the end-of-day inventory series.

3.4. Market maker revenues

Our empirical analysis of liquidity provision in the AIM market concludes with the calculation of market maker revenues. Widespread negative revenues could indicate that liquidity provision is problematic, which may warrant wider spreads. In contrast, large positive revenues may suggest excessive spreads and lack of competition between market makers.

Following Hansch et al (1997b), we calculate market maker revenues as follows: For each stock, revenues (MR) are expressed as the sum of all cash flows over the sample period plus the net change in inventory:

(7) $MR = \Sigma_t P_t Z_t V_t + P_T I_T - P_0 I_0$,

where P_t refers to the transaction price at time t, V_t is the trading volume and Z_t a trade indicator with $Z_t = 1$ ($Z_t = -1$) indicating a market maker purchase (sale). The end-of-period and opening inventories are given by I_T and I_0, respectively. It is standard practice (see e.g. Hansch et al (1997b)) to make the following simplifying assumptions: First, as in the previous section, we set the starting inventory I_0 equal to zero. Second, the end-of-sample inventory I_T is valued at the prevailing touch midquote TM_T. Hence, (7) can be rewritten as:

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[12] Equation (5) can be modified to include a trend and/or lags of the dependent variable.

[13] The model effectively assumes a target inventory of zero. This assumption is routinely made in the absence of any reliable information on optimal inventories.

[14] This is done to ensure an adequate number of observations for estimation purposes.

(8) $MR = \Sigma_t P_t Z_t V_t + MT_T I_T$.

As in the previous section, we will calculate revenues for one (active) market maker.

4. Three case studies

We start our analysis by looking at three companies that represent typical patterns observed in the AIM data set. Their stock and liquidity characteristics are listed in table 3.

Insert table 3

Stock A is one of the most actively traded and quoted stocks. The stock has three registered market makers. With a market capitalisation of £16 million, this stock lies below the sample mean reported in table 2, but above the median, and has a very high free float (80%). Quotes are regularly updated. Trades occur almost daily. Nonetheless, 23% of all trades are executed on just five days. The average effective spread is 4.99%. Trades occur mostly at (67.33%) or inside (28.13%) the touch, with a few outside (4.54%).

The numbers in table 3 further show that the market maker manages to keep a relatively tight control over his inventory: The standard deviation of end-of day inventories measured over the six-month sample period, is 151,681 shares, which is low compared to average daily turnover (459,282 shares). The mean reversion coefficient β, reported in table 3, is -0.37 and implies a half life of 1.48 days. This suggests that the market maker rebalances his inventory in less than two business days. Finally, the market maker's revenue equals £28,307 for the six-month period.

Stock B, by contrast, is a very thinly traded stock. It is one of the smaller ones with a market capitalisation of £4.78 and a free float of 55.5%. It has one registered market maker. Only 15 trades are done throughout the six month period.

Surprisingly, the stock does not have a much higher average effective spread (5.02%) than stock A. Moreover, the majority of trades are done inside the quoted spread, which equals 10.31% on average. The infrequency of trades (only 10 trading days out of 125) is reflected in the low mean reversion (-0.04) and the relatively high average end-of-day inventory (4,579 shares) compared to the average daily volume of 4,082 shares.

Finally, C is one of the largest stocks in our sample (£61 mln market capitalisation). It trades infrequently (90 trades spread over 49 days), in spite of a high free float (79%). At the same time, it has the highest average trade value. A very high proportion of trades is done inside the touch (56.76%). The average effective spread is 6.01%. This stock has two registered market makers.

Our selected market maker displays a disciplined inventory management in stock C, in spite of its low trading frequency. This is clear from the mean reversion coefficient (-0.54) and the implied half life (just under 1 day). As a result, the standard deviation of the market maker's end-of-day inventory is relatively low (11,677 shares), whereas average daily volume stands at 229,707 shares. This indicates that his inventory must be quite flat during inactive periods. Furthermore, our market maker realises a revenue of £20,199 in this stock. Clearly, in this case, the lack of continuous trading does not seem to create substantial inventory risk.

5. Measuring liquidity on aim: results

5.1. Trading activity

Table 4 reports various measures of trading activity. They include: i) Total number of trades; ii) Number of shares traded (volume); iii) Total value of shares traded, iv) Number of days with at least one trade; v) Percentage of trades done on the (5) busiest day(s); vi) the average trade value (£) and (vii) a "liquidity ratio" that expresses the number of shares traded as a percentage of all available shares. All measures are computed for each of the 111 stocks of our AIM sample. The table reports summary statistics for the entire sample, and for selected sub samples.
Insert table 4

During the six-month period (125 trading days), a total of 53,684 trades are reported for the 111 stocks under consideration, with a total value of £564 mln. Across AIM stocks, the average number of trades is 484 for the six-month period, with half of the trading days seeing at least one trade. The cross-sectional averages for the value of all shares traded and the average trade size are £5.08 mln. and £13,709, respectively. On average, 54% of available shares are traded. Trade clustering is high, with on average 58% of all trades done on the five busiest days, and 28% on the busiest day.

The earlier mentioned heterogeneity of the AIM sample becomes more apparent when comparing some of the other summary statistics. The median number of trades (122) is about four times lower than the average, as is the median of the value of shares traded (£1.197 mln.). The range of the various statistics is considerable: The most actively traded stock registers 6,034 trades, whereas the least active one has only 2 trades. Trade concentration varies too, from a high 97% of business done on the busiest day to a low 5%, whereas the liquidity ratio lies between 0.0002% and 4.74%.

Graph 1 ranks the 111 AIM stocks by number of trades and reveals a very skewed distribution of trades, with only a small group of stocks showing substantial trading activity.
Insert graph 1

Based on this preliminary evidence, we isolated the first and second decile from the remainder of the sample.[15] In terms of trade frequency, stocks in the first two deciles trade on average 1,943 times, with an average of 122 days out of 125 seeing at least one trade. On average 97% of outstanding shares are traded during the six-month period. The least active stock in this sub sample still has over 400 trades. Not surprisingly, trading is less concentrated in this sub sample than in the whole sample, with on average 14% (34%) of all trades done on the busiest (five busiest) day(s).

By contrast, stocks in the remainder of the sample trade less frequently (123 trades on average), on fewer days (an average of 50 days) and see more clustering (32% and 64% for the busiest and five busiest days, respectively). Note also that the average trade size is higher for the less frequently traded stocks (£14,413) than for the first two deciles (£10,861), although the difference is not statistically significant.

To conclude, our first results manifest a large disparity in trading activity, with a small number of actively traded stocks, and a large group of stocks that trade only infrequently. The results suggest that the two groups will display rather different liquidity characteristics. We will further examine this in the following sections.

5.2. Price volatility

In this section, we report summary statistics for the volatility measures discussed in section 3.2.

[15] Similar results are obtained when ranking the stocks based on the £ value of trades.

Insert Table 5

The average and median price volatility for the entire AIM sample are 5.19% and 4.02%, respectively. On average 39% of all price changes are less than or equal to 1%, and are termed small. Large price changes, defined as between 5% and 10%, account on average for 14.81% of all trades, and very large price changes, i.e. price changes larger than 10%, account for 7.64%. Midquotes vary more than trade prices do: the average and the median for the entire sample are 18.45% and 6.03%, respectively. This may indicate that market makers only occasionally update their quotes to reflect new information. One would expect that price discovery would therefore occur through trade prices, rather than through publicly posted quotes. We plan to investigate this issue in further research.

We hypothesise less actively traded stocks to exhibit higher price volatility: One the one hand, the longer time between consecutive trades implies more potential information arrivals. And hence, we would expect larger price changes from one trade to the next. At the same time, trades themselves are an important source of information for market participants, and as such induce price revisions. If trades occur infrequently, then they are more likely to carry new information and give rise to large price revisions. Our results confirm the above hypothesis: Both average price volatility and the percentage of large and very large price changes are lower for the first and second deciles than for the remainder of the sample, yet only the latter results are statistically significant.

Taken together, the lower trade frequency and the higher price volatility indicate that for the majority of AIM stocks, immediacy risk is an issue.

5.3. Quotes and spreads

In this section, we present estimates for the trading cost measures discussed in section 3.2. This evidence is then used to test the following hypotheses: (i) Spreads widen as trading activity declines; and (ii) Asymmetric information and inventory risk are important components of the spread. As before, all measures were calculated for each individual stock. The tables present summary statistics for the sample.

Touch and effective spreads

Table 6 presents summary statistics for the percentage spreads. The mean and median touch are 8.18% and 6.51%, respectively. The average effective spread is 7.05%, and the sample median is 5.38%. As expected, these numbers are considerably higher than those reported for liquid SEAQ stocks.[16]
Insert table 6

Next, we analyse the relationship between trading intensity and the spread. We hypothesise the spread to be lower for actively traded stocks where the market maker faces less adverse selection risk and where he is less concerned about inventory risk as he expects a steady inflow of public buy and sell orders. This hypothesis receives some support from the data as shown in panel A of table 6: The effective spreads for the more actively traded stocks (first and second deciles) are found to be significantly lower than those of the remainder of the sample (5.35% vs, 7.46%). The differences continue to be statistically significant when considering weighted averages (see panel B). This confirms that the observed differences in spreads do not only reflect trading activity and trade size, but

[16] Board and Sutcliffe (1995) report an average touch of 0.82% for FTSE-100 stocks and 1.05% for FTSE Mid-250 stocks. Naik and Yadav (1997) find the average touch to be 0.64% for the most 102 liquid stocks in August 1994. The Stock Exchange reports an average spread for the FTSE-100 stocks of 0.62% (see: Market Analysis, London Stock Exchange, 1997).

intrinsic differences in perceived risk. Note that most of the more active stocks too are characterised by much wider spreads than SEAQ stocks.

We further document the prevalence of price discounts by looking at the distribution of trade prices. Table 6 shows the percentage of trades at, inside and outside the touch. We find that on average, slightly over half of all trades occur at the touch (58.91%), 33.04% inside and 8.04% outside the touch.[17] Table 6 further reveals that the first and second deciles stocks trade more frequently at the touch (62.31% versus 58.10%) and less often outside (7.07% versus 8.27%), but also less often inside the touch (30.62% versus 33.62%). None of these differences are significant though.

These results indicate that market makers protect themselves against adverse selection risk by quoting wide spreads, but grant price discounts to selected clients (33% on average). Notice that this behaviour is not necessarily restricted to the less liquid stocks. At the same time, the fact that on average close to 60% of all trades occur at the touch suggests that posted yellow strip prices are a reasonable guide for traders, including those interested in thinly traded stocks.

Model based spread estimates

Table 7 presents the results of the spread model developed in section 3.2. and estimated for the 22 most active stocks in our sample, for a chosen (active) market maker.
Insert table 7

They show very high order processing costs (85% of the spread on average) and relatively low adverse selection and inventory costs (15% on average). The average spread is £4.54, which is slightly lower than the earlier computed average effective spread of £5.36. While some variations are found across stocks -one stock registers an order processing costs of 59%- the standard deviations are fairly low.

Our results are consistent with Huang and Stoll (1997) and Saporta et al (1998) and indicate that market makers set wide spreads in order to cover their (high) fixed costs. We do, however, find that except for four companies, the average adverse selection and inventory component is significantly different from zero. By contrast, the estimates presented by Saporta et al (1998) for both FTSE-100 and FTSE-250 companies fail to produce significant adverse selection and inventory cost components.[18] Hence, we find some evidence that information asymmetries and inventory management costs are present on AIM, although they are smaller than one might have expected in a market for small company stocks.[19]

To conclude, from the empirical evidence presented in this section, we have learned that the majority of AIM companies are characterised by wide spreads. Spreads are somewhat narrower for more actively traded stocks. We further show that the spreads for these actively traded stocks consist largely of fixed costs. Only a small (though significant) part of the spread is explained by asymmetric information or inventory risk. We expect -but are unable to show- the latter components to be higher for less actively traded AIM stocks.

5.4. Market maker inventories and profits

[17] By comparison, Board and Sutcliffe (1995) find that for the FTSE-100 stocks in their sample, 78% of all customer trades are done at the touch, 17% inside and 4% outside the touch. For the FTSE Mid-250 stocks, the percentages are 71%, 21% and 5%, respectively. Board, Fremault Vila and Sutcliffe (1997) looking at a later sample of FTSE-100 stocks find that 58% of customer trades are done at the touch, and 33% inside.

[18] They report an average order processing costs of 99% for trades below 1 NMS, and 80% for trades above 1 NMS.

[19] Our results are close in magnitude to Huang and Stoll (1997) who report order processing costs of 88% for liquid NYSE stocks.

Table 8 reports summary statistics for our market maker's end-of-day inventories. For each AIM stock, we calculate both the average end-of-day inventory (in absolute terms) and the standard deviation of end-of-day inventories. Our main hypothesis in this section is that inventory risk is higher - and therefore mean reversion slower - for less actively traded stocks.
Insert table 8

The average end-of-day inventory equals 65,847 shares but this varies widely across stocks as indicated by the much smaller median (14,030 shares), and the range (97 shares to 1.8 mln. shares). Day-to-day movement in inventories is documented by the standard deviation: Again, we report considerable variability across AIM stocks, with a cross-sectional mean of 47,325 shares, a median of 11,677 shares and a range of 150 to 1.3 mln shares.

A somewhat surprising result is that the market maker has much lower end-of-day inventory positions and much lower variability for the less actively traded stocks. This is borne out by both the averages and the medians for the different sub samples in table 8, and rejects our earlier formulated inventory risk hypothesis. Notice that the these differences are unlikely to be due to differences in trade size, as trades in less active AIM stocks were found to be on average larger, not smaller.

The above results could indicate that the market maker is more concerned to maintain a tight inventory for the less liquid stocks in order to avoid the relatively higher cost of carrying excess inventory. The question, however, is how he manages to do so, given that trade frequency is low in the first place. One possible answer is that the market maker is able to avoid wide swings in inventory by bringing crossed or pre-arranged trades to the market.[20]

As mentioned above, mean reversion coefficients were estimated for the first and second deciles stocks only. They range from -0.05 (slow mean reversion) to -0.83 (rapid mean reversion), with an average of -0.26 and a median of -0.23. Inventory half-lives range from less than one business day to close to nine days, with a mean of 2.76 days. This means that it takes the market maker on average between 2 and 3 days to reduce his inventory by 50%. Note that this is very close to the 2.74 days reported by Hansch (1997) for a sample of active FTSE-100 companies.

Taken together, the relatively rapid mean reversion, high end-of-day inventories and the relatively low price volatility reported for the first and second decile stocks suggest that inventory risk is less of an issue than one might have expected. This in turn implies that the earlier reported combined adverse selection and inventory cost component is more likely to reflect the former risk.[21]

The final row in table 8 reports revenue figures. Our market maker realises a total revenue of £1.1 mln. Interestingly, he makes losses on only 23 out of 111 stocks. The average revenue equals £10,391, and the median is £4,123. The largest revenue on any single stock in the sample is £167,959.

The table further shows that the more actively traded stocks generate the lion share of the market maker's revenues: The total revenue for this group of 22 stocks is £1.27 mln. with an average revenue of £60,590. Still, he loses money on two stocks in this group. By contrast, the market maker loses money for the remainder 89 stocks as a group (-£160,552), with 21 stocks registering a loss. It should be noted , however, that this total is biased by the occurrence of a single large loss. His median revenue for this group is positive (£1,933).

[20] This issue will be investigated in a companion paper.
[21] Huang and Stoll (1997) present a modified spread model that allows them to decompose the adverse selection and inventory cost components. In doing so, they relax the assumption of zero serial correlation in the trade sign (π=1/2). Our estimates of the trade reversal parameter in table 7 reject this zero correlation assumption for 18 out of 22 stocks, producing an average π of 0.41. Nonetheless, our estimates of the modified model Huang and Stoll yielded very implausible results which have not been reported.

Our interpretation of these revenue results is that while market making in individual AIM stocks is not always rewarding, the commitment to do so for a wide range of stocks may pay off.

5.5. A comparison with the rule 4.2 market.

This part of the analysis uses a data set of 67 stocks that were trading on AIM between January and June 1996, and were traded as rule 4.2 stocks between January and June 1995. A total of 6,922 trades were reported for the rule 4.2. period, compared with a total of 40,754 for the AIM period.

Insert tables 4b, 5b and 6b

Table 4b shows that on average, AIM stocks have seen a significant rise in their trading activity, relative to a year earlier when still under rule 4.2 (sample average of 516 versus 103 trades, and sample median of 123 versus 20 trades). Average trade size and trade value have dropped (average trade value of £11,890 versus £14,637), but not significantly so.

Taken together, these results could be indicative of improved liquidity: Both the higher trade frequency and the use of smaller trade sizes increase the probability of swift execution. This is further confirmed by the rise in the number of trading days (66 versus 28) and the fall in trade concentration (29% on the busiest day versus 45%).

Across stocks, average price volatility on AIM is lower than under rule 4.2. (table 5b: 5.42% versus 7.31%), but not significantly so. The proportions of large and very large price changes are lower on AIM, but again not significantly so (14.25% and 8.10% versus 13.01% and 12.37%).

Finally, our limited results on trading costs show that spreads have fallen (table 6b: average effective spread of 5.22% versus 6%), but not significantly so. Likewise, the relationship between trade and quote prices has only marginally changed.

Hence, our results point to a significant increase in trading activity for those stocks that transferred to AIM, while at the same time price volatility and trading costs have changed little. As explained earlier, the relationship between trading activity and price volatility is complex. On the one hand, we would expect an increase in trading activity to lead to reduced information asymmetries in the market. This would in turn be reflected in narrower spreads and lower price volatility. An additional factor is the gain in visibility that will have followed from trading on AIM. This, together with the increased likelihood of research activity, could further reduce information asymmetries. On the other hand, the increased trading activity and the superior transparency of the AIM market compared to Rule 4.2. are likely to have resulted in better price discovery. This would, however, make prices more, rather than less volatile. The small volatility reduction that we observe suggests that the liquidity effect has dominated the price discovery effect.

Tables 4b and 5b further show summary statistics for the different sub samples as determined by the 1996 data. Out of the 22 most active stocks, 17 were also trading as rule 4.2 stocks. Interestingly, the tables show that apart from the number of trades, none of the other liquidity variables have changed significantly since joining AIM. By contrast, when we look at the 62 stocks of the third to tenth deciles that were previously listed on rule 4.2., we find that trading activity has gone up significantly, trade concentration has fallen and the percentage of large price changes has been reduced. Hence, it seems that the changes in the trading environment have had the strongest effect on liquidity for the less liquid stocks.

6. The determinants of liquidity

6.1. Data and methodology

Our final objective is to explain the observed differences in stock liquidity by looking at a range of issuer characteristics. For this part of the analysis, we have chosen four liquidity characteristics: i) Trading activity as measured by the number of trades; ii) Trade frequency as measured by the percentage of trades executed on the five busiest days; iii) intra day price volatility and iv) the effective spread.

We are interested in determining the factors that directly affect liquidity, both through their effect on information asymmetries and on inventory risk. For example, can we establish that trading activity is higher for larger firms because they are better known to the public? Are there any other issue characteristics that could predict good liquidity for a firm considering coming to the AIM market?

Unfortunately, the choice of the issuer variables was largely determined by data availability. Public information on these variables was found to be incomplete in many instances. In first instance, we use four market based variables: i) Market capitalisation at entry; ii) End-of-sample market capitalisation; iii) free float and iv) free market capitalisation. Complete data for these four variables were available for all but three firms. We also use daily closing prices to compute standard deviations as a measure of stock risk.[22]

Second, we collected a number of firm data and transformed them into dummy variables.[23] They include: i) Industry code; ii) Firm age, and iii) Information on venture capital backing.[24] The age dummy divides firms into four groups: Less than one year old; one to five years old; five to 15 years old and over 15 years. The tech dummy isolates firms in the technology or bio-technology sector, whereas the venture capital dummy indicates whether a firm was backed by venture capital prior to joining AIM. For our sample, we recorded 18 and 15 such firms, respectively. We also created a rule 4.2 dummy to distinguish those AIM companies that transferred from Rule 4.2.

To establish the determinants of liquidity, we estimate the following model:

(9) $Y_i = c_0 + c_1\ SIZE_i + c_2\ RISK_i + c_k\ X_k + e_i$,

where Y_i refers to one of the four liquidity variables, $SIZE_i$ is proxied by one of the above mentioned firm variables (our final specifications use June 1996 market capitalisation or market capitalisation at entry together with free float), $RISK_i$ is measured by the standard deviation of closing prices, X_k refers to the remaining regressors (and varies from one specification to another) and e_i is the error term. Equation (9) is estimated with OLS, using White's correction for heteroskedasticity.

6.2. Results

The regression results are reported in table 9.

Insert table 9

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[22] An alternative measure for RISK would be the firm's beta. It should be noted, however, that for infrequently traded stocks, the traditional beta measure underestimates the true market risk (see Scholes and Williams (1977)). This follows from the large number of zero-returns assigned to non-trading days that bias the covariance downwards. For this reason, we have not included beta in the current regression model. Alternative covariance measures have been developed in the literature and could be explored in a subsequent revision.

[23] Source: Stock Exchange and Datastream.

[24] Information on firm age, based on the company's date of registration, was available for only 92 stocks.

The table shows that firm size is an important determinant of all four liquidity variables: A higher market capitalisation and a higher free float are both associated with a larger number of trades, lower trade concentration, lower price volatility and a lower effective spread. All market capitalisation coefficients are statistically significant. Except for the first regression (number of trades), the free float has a weaker association.

The regression results also allow us to address a number of often-asked questions. First, the technology dummy appears to significantly affect the number of trades and the effective spread. A closer look at the data confirms that of the most actively traded firms (first and second deciles), eight out of 22 are technology firms. The dummies further indicate that they enjoy lower trading costs in the form of lower average effective spreads. The technology dummy does not significantly affect the remaining liquidity variables.

The venture capital dummy is significant, but of the “wrong” sign in two out of four regressions, indicating that venture capital backed companies trade less and have higher concentration ratios. They do experience lower price volatility and narrower spreads than the remainder of the sample, but these results are not statistically significant. At its inception, AIM was thought to provide an opportune exit route for venture capitalist, which would in turn stimulate the interest of the latter in small and growing companies. Our analysis reveals that when becoming quoted companies, venture capital backed companies do not enjoy better liquidity than companies that previously relied on other forms of financing.

No systematic patterns are found across age groups. Most of the age dummies are insignificant, except for the second age group (one to five years old), which is found to have higher trading activity and lower trade concentration. Notice that this age group is also characterised by higher price volatility and wider spreads, though the relevant coefficients are insignificant.

Our regressions further indicate that former rule 4.2. stocks are on the whole unremarkable. The last set of regressions also show that market capitalisation at entry, while an important factor in determining liquidity, is dominated by the concurrent market capitalisation (June 1996).

While insightful, the above regression results fail to isolate the necessary conditions for liquidity. For example, while market capitalisation is a significant factor in all regressions, closer inspection of the data reveals that of the most actively traded firms (1st and 2nd deciles), only 12 belong to the top two deciles by market capitalisation. Moreover, three out of 22 of these actively traded firms belong to the bottom quarter of the sample when ranked by market capitalisation. Similar results are obtained when ranking firms by free market capitalisation, or when considering other liquidity measures.[25]

Finally, we examined the role of market maker competition . All but eight of the most actively traded firms have three or more market makers. In contrast, for the remainder group of less actively traded stocks (the third to tenth deciles), we find only eight firms with three or more market makers, but 45 firms with only one market maker. Yet, it would be erroneous to attribute superior liquidity to the number of market makers and the resulting potential for competition, as one would expect market makers’ interest to be a function of a stock’s activity level. Because of this circularity problem, the number of market makers was not included in the above regression model. It therefore remains an open question as to what the optimal number of market makers is in the context of a small company market.

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[25] Formally, rank correlations between the number of trades and either market capitalisation or free market capitalisation are high, but nowhere near perfect correlation (0.60 and 0.64 respectively). Likewise, these larger companies do not systematically trade at narrower spreads, as indicated by the rankcorrelations between the average effective spread and market capitalisation and free market capitalisation, respectively (0.33 and 0.43).

7. Concluding remarks

This research shows that it is *possible* to generate sufficient liquidity in a small company market. Indeed, a small group of AIM stocks trade frequently, exposing the investor to limited execution risk. At the same time, we find that the majority of AIM stocks trade infrequently, with trades often clustered around a few days. It should further be noted that trading costs on AIM are high, even for some of the more liquid stocks. These results are in line with the recent Small Firms Report published by the Bank of England, that observes that "small or tightly held companies needed to have realistic expectations about the level of trading they could achieve."

While our analysis reveals a number of *important* factors that isolate the more liquid stocks from the remainder of the sample, it fails to produce a unique set of factors that *guarantee* liquidity. Ultimately, it is investor interest that keeps a market alive, and market structure or issuer characteristics may play a lesser role. This topic remains largely unresearched.

Appendix A: The data

The data for this study are taken from the London Stock Exchange's Transaction Data Service, which contains information on transactions and quotes as submitted to the Exchange's surveillance and quotation systems.

The transaction data are derived from transaction records submitted to the Exchange by member firms as part of the settlement process. They are the matched records for the two sides of a trade. In 1996, the matched records went to a process which led to the delivery of stock and the payment of balances. These same records are used for surveillance purposes and are supplied to researchers. The quote data are the original market maker quotes submitted to the SEAQ system. They are collected by the Exchange for surveillance purposes and are also made available to researchers.

The data set is particularly rich in that it identifies all parties in a trade (e.g. agent or principal, market maker or not). The quality of these data is good, but not perfect. Most of the imperfections stem from the fact that firms supply only the information deemed necessary for settlement purposes. Fields that are not critical for settlement (notably the time of dealing) tend to be less accurate.

A number of features of the data set need to be addressed before any meaningful analysis is possible. First, the data as supplied contain non-relevant transactions, such as e.g. stock adjustments for book keeping purposes and stock loan returns, that were simply removed. In contrast, so called shapes and contras require more complex processing.

Shapes occur when a trade executed by a broker is split into several smaller trades for settlement. Since this splitting is done after the trade, it has no economic significance. Hence, the researcher has to regroup the shapes into single trades.

As member firms are not allowed to alter matched records, errors can only corrected via a reversing transaction called a "contra." Having done this, both parties then submit a corrected version of the original trade. In order to avoid double counting, the researcher has to remove the contra and the original trade it was intended to cancel.

Specifically, one needs to separate the contras from the trades before shaping, match the contras to the original trades, group the reshapes and repeat the matching process. This process is not exact and normal transactions: First, some firms use contras as a way of adjusting, rather than cancelling transactions so that the quantities do not match. Second, sometimes contras are submitted to cancel previous contras. Third, some contras are submitted more than a month after the original bargain and where $\Sigma_i Q_i$ is the cumulative inventory of the market maker since the beginning of the sample (i=1) up to time t-1. Combining (B1) and (B2), we see that quotes are adjusted to compensate for both adverse selection and inventory risk:

(B3) $\Delta M_t = (\alpha+\beta)(S/2)Q_{t-1} + \varepsilon_t$.

For example, following a public purchase ($Q_{t-1} = + 1$), the market maker will raise his midquote by $\alpha(S/2)$ to account for the probability of trading with someone who holds private information about the stock, and by a further $\beta(S/2)$ to induce public sellers so that he can rebuild his inventory.

Finally, at time t, a trade takes place of sign Q_t and is priced as follows:

(B4) $P_t = M_t + (S/2)Q_t + \eta_t$.[27]

Equations (B3) and (B4) are used to give the market maker's pricing rule:

(B5) $\Delta P_t = (S/2)\Delta Q_t + (\alpha+\beta)(S/2)Q_{t-1} + e_t$

where $e_t = \Delta\eta_t + \varepsilon_t$.

To understand equation (B5), assume for now that the market maker participates in both trades (t-1 and t). Consider first a trade reversal ($Q_t = - Q_{t-1}$). We can see from equation (B5) that the accompanying price change ΔP_t is less than the constant spread S. Indeed, as the market maker adjusts his midquote to reflect his concerns about adverse selection and inventory risk, he effectively gives up part of his spread. Hence, the difference measures his loss against informed traders and/or the cost of inventory management. If the market maker did not care about these two risk sources ($\alpha=\beta=0$) and assuming no public information arrival ($e_t = 0$), then he would leave his midquotes unchanged and realise the full spread S. Equation (B5) further shows that trades of the same sign ($Q_t = Q_{t-1}$) induce a smaller price change ΔP_t that exactly mirrors the change in midquotes.

In order to obtain estimates for the spread S and its components, we run the following regression:

(B6) $\Delta P_t = a_1\Delta Q_t + a_2 Q_{t-1} + e_t$.

Equation (B6) yields estimates for the combined adverse selection and inventory components (a_2/a_1), the order processing component
($1- a_2/a_1$), as well as the effective spread ($2a_1$).

Finally, to test the assumption of zero serial correlation, we proceed as follows: Given a trade of sign Q_{t-1}, the following trade at t has sign $Q_t = Q_{t-1}$ with probability ($1-\pi$) and has sign $Q_t = -Q_{t-1}$ with probability π. Hence, the conditional expectation of the trade sign at t is given by:

(B7) $E[Q_t | Q_{t-1}] = (1-2\pi)Q_{t-1}$.

The empirical specification is given by:

(B8) $Q_t = b_1 Q_{t-1} + w_t$,

[27] Assuming η_t has mean zero, (B4) states that on average trades take place at the posted quotes.

where w_t is an independent and identically distributed random variable with mean zero. Zero serial correlation implies $b_1 = 0$.

B.2. Estimation Procedure

Equation (3b) is estimated using General Method of Moments (GMM) procedures. This section provides a brief explanation of the GMM method. Consider the following regression model:

(B9) $y_i = h(x_i\beta) + e_i$.

GMM involves choosing a set of instruments z_i that are uncorrelated with the error term e_i:

(B10) $E[z_i e_i] = 0$.

Furthermore, minimal restrictions are imposed on the residuals:

(B11) $E[e_i] = 0$ and $E[e_i e_j] = \Omega$ for all i and all j.

allowing both heteroskedasticity and serial correlation in the residuals.

The GMM estimator minimises the following criterion function:

(B12) $m(\beta)'W^{-1}\, m(\beta)$,

where $m(\beta)$ is the sample moment:

(B13) $m(\beta) = (1/n)\Sigma_i z_i e_i = (1/n)\Sigma_i z_i(y_i - h(x_i\beta))$.

The choice of the weighting matrix W depends on the problem at hand. As we use time series observations where both heteroskedasticity and serial correlation may be present, the Newey-West estimator is used for W.[28]

[28] More details are found in Greene (1990).

References

AGGARWAL, R. and ANGEL, J. (1995), “The Rise and Fall of the AMEX Emerging Company Marketplace, mimeo Georgetown university.

BOARD and SUTCLIFFE (1995), “The Effects of Trade Transparency in the London Stock Exchange: A Summary,“ LSE Financial Markets Group, special paper no. 67.

BOARD, FREMAULT VILA and SUTCLIFFE(1997), “Market Maker Heterogeneity Evidence from the London Stock Exchange,” mimeo, London School of Economics.

BOUSSEMA, M. and HAZART, P. (1996), “Le Nouveau Marche: Interaction entre Deux Modes de Cotation,” mimeo, SBF-Bourse de Paris.

“Finance for Small Firms,” fifth report, Bank of England, January 1998.

GLOSTEN, L. and HARRIS, L. (1988), “Estimating the Components of the Bid-Ask Spread,” Journal of Financial Economics, 21, pp.123-142.

GREENE, W. (1990), “Econometric Analysis,” Prentice Hall.

HANSCH, O. (1997), “Cross-Listing Effects: Evidence from the Time Series Behaviour of Dealer Inventories,” mimeo, Birkbeck College.

HANSCH, O., N. NAIK and S. VISWANATHAN (1997a), “Do Inventories Matter in Dealership Markets? Evidence from the London Stock Exchange,” IFA working paper 225-1997, LBS.

HANSCH, O., N. NAIK and S. VISWANATHAN (1997b), “Preferencing, Internalization, Best Execution and Dealer Profits,” IFA working paper 254-1997, LBS.

HUANG, R. and H. STOLL (1997), “The Components of the Bid-Ask Spread: A General Approach,” Review of Financial Studies, 10, pp. 995-1034.

NAIK and YADAV (1997) “Execution Costs and Order Flow characteristics in Dealership Markets: Evidence from the London Stock Exchange,” working paper, London Business School.

REISS and WERNER (1994), “Transaction Costs in Dealer Markets: Evidence from the London Stock Exchange, NBER working paper 4727.

“Second Tier Equity markets in Europe and USA,” mimeo Bank of England, June 1997.

SAPORTA, V., G. TREBESCHI and A. VILA (1998), “Price formation and transparency on the London Stock Exchange,” in progress.

SCHOLES, M. and J. WILLIAMS (1977), “Estimating Betas from Non-Synchronous Data,” Journal of Financial Economics, 5, pp. 309-327.