

An Econometric Assessment of the Change in Quality of the Irish Gilt Market Since the Introduction of Market Making

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Abstract: Hasbrouck's (1993) measure of market quality is used to assess the effect of introducing market making in Irish Gilts. The measure is based on aspects of the literature on the decomposition of time series' into stochastic trend and stationary components. The Hasbrouck approach is modified somewhat, first, to account for a trade-type indicator in a different way than before, and second, by allowing for time variation in the variance of the relevant components. A measure for comparison of different market regimes is obtained and on the basis of this measure the Irish Gilt market appears to be quite competitive at present.

I INTRODUCTION

The Irish Gilt market has changed from an "agent only" market structure to one in which there is a combination of competing market makers and broker-agents. Market making firms are permitted to provide a dual service. This took place in early December 1995. The focus of attention in this study, is a comparison of trading costs in the pre- and post-market making trading environment, when this is measured as the deviation between the implicit efficient price in period "t" and the transaction price in that period (the implicit efficient price is defined as the valuation of the security at time "t", based on all available information up to and including period "t"). Specifically, the measure of the quality of a security market proposed by Hasbrouck

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(1993) is used, with some modification. The term "quality" is used in a narrow sense by Hasbrouck to mean the expected cost of liquidity but this is obviously related to market depth. The Hasbrouck (1993) analysis, in its most general form involves a VAR representation for transaction price returns and trade type/size. While there are alternative methods for the decomposition of a time series, the Hasbrouck approach makes particular use of a generalisation of the unobserved components analyses of Beveridge and Nelson (1981) and Watson (1986).

Most theoretical microstructure models (see the review by O'Hara (1995)), lead to the conclusion that the pattern of trade flow and unexpected trade volume contain information about influential opinion and inside information. The market maker, is often modelled as setting quotes to protect himself from the adverse selection of informed trading partners (this is complicated by the fact that there is also an underlying inventory control problem). The presence of better informed traders (according to Copeland and Galai (1983) and Glosten and Milgrom (1985)), motivates the need for a bid-ask spread even in the absence of normal order processing and inventory holding costs. Since quotes react to the information in trades while, at the same time, quotes are set strategically to encourage the preferred trade-type, there is often a two-way dynamic between quotes and trade type/size. The theoretical literature leads to the conclusion that the quoted spread is not generally a reliable measure of market quality.

Section II below considers the Hasbrouck (1993) approach to measuring the quality of a security market in more detail. Section III discusses some of the special features of the data and econometric modelling. Section IV presents the main empirical results from application of the Hasbrouck measure, and Section V concludes.

II THE HASBROUCK MEASURE OF MARKET QUALITY

Consider the natural logarithm of the observed transaction price at time "t", p_t , as the sum of two components:

$$p_t = m_t + s_t \quad (1)$$

m_t is considered to be the efficient price conditional on available information at time t . s_t is the pricing error which may include a number of microstructural effects, e.g., inventory control and the non-information based component of the bid-ask spread. The standard deviation of the pricing error is a valid measure of market quality since it is the expected cost of transacting (when this is measured as the deviation of transaction price from the implicit

efficient price). It is assumed that the efficient price has a simple random walk property:

$$m_t = m_{t-1} + w_t \quad (2)$$

where $E(w_t) = 0$, $E(w_t^2) = \sigma_w^2$, and $E(w_t w_\tau) = 0$ for $t \neq \tau$.

A model for s_t which allows for the division of the stationary innovation into that which is correlated with the non-stationary innovation and that which is uncorrelated, is given as:

$$s_t = \alpha w_t + \eta_t \quad (3)$$

Two special cases can be derived as restrictions on this simple components model. In the first case, $\alpha = 0$ and $\eta_t = \pm(0.5)$ *effective spread*¹ which implies that there is random switching between the bid and ask and that the deviation of the transaction price from the implicit efficient price is not related to the non-stationary innovation. This is essentially the Roll (1984) model of the bid-ask spread. In this case the dispersion of s_t will be equal to half the effective spread and is an obvious measure of the quality of the market. The transaction returns can be modelled as an MA(1) and the estimate of the pricing error is related to the variance of the MA error and the MA(1) parameter. This approach negates the need to include a news variable in such a regression as, for example, in the analyses by Hsia, Fuller and Kao (1994) and Dunne (1994) respectively.

Given the general model for s_t the transaction returns can be written as:

$$\begin{aligned} r_t = p_t - p_{t-1} &= m_t - m_{t-1} + s_t - s_{t-1} = w_t + s_t - s_{t-1} \\ &= w_t + \alpha w_t - \alpha w_{t-1} + \eta_t - \eta_{t-1} \end{aligned} \quad (4)$$

This can be expressed as a first order moving average error process:

$$r_t = \varepsilon_t - a\varepsilon_{t-1} = w_t + \alpha w_t - \alpha w_{t-1} + \eta_t - \eta_{t-1}. \quad (5)$$

Two parameters, $\{a, \sigma_\varepsilon^2\}$, fully characterise the mean and autocovariance of the return process. The components model however, has three parameters $\{\sigma_w^2, \alpha, \sigma_\eta^2\}$, implying that the model is under-identified. Applying the

1. The effective spread is defined as the average difference between the buying and selling price when these are separated by the time gap between successive transactions. In general, the microstructure effects mentioned above imply that the effective spread differs from the quoted spread.

restriction $\eta_t = 0$ allows for a correspondence between the two representations; $r_t = \varepsilon_t - a\varepsilon_{t-1} = w_t + \alpha w_t - w_{t-1}$, such that the parameters of the unobserved components model are econometrically identifiable. The estimate of the pricing error for a particular transaction is: $\hat{s}_t = a\varepsilon_t = a(r_t + ar_{t-1} + ar_{t-2} + \dots)$. Applying the alternative restriction $\alpha \geq 0$ and $\eta_t = 0$ (this one has been analysed by Watson (1986)), gives rise to identification as follows: $\sigma_s^2 = \sigma_\eta^2 \sigma_w^2 = (1-a)^2 \sigma_\varepsilon^2$, $\sigma_s^2 = a\sigma_\varepsilon^2$.

Since the Beveridge-Nelson estimate of the stationary component is only capable of giving a lower bound estimate of the pricing error (this is assuming that the spread contains a portion which is correlated with the innovations to the non-stationary component of transaction prices), this estimate is of limited use in the current analysis. However, Hasbrouck shows that the lower bound can be strengthened substantially by making use of the information contained in variables other than the transaction prices.

The interaction between trades and quotes can be expected to contain quite complicated lag-dependency effects. In this case vector autoregression provides a framework that is general enough to capture whatever lagged dependencies exist. Consider, for example, the following specification:

$$\begin{aligned} r_t &= a_1 r_{t-1} + a_2 r_{t-2} + \dots + b_1 x_{t-1} + b_2 x_{t-2} + \dots + v_{1,t}, \\ x_t &= c_1 r_{t-1} + c_2 r_{t-2} + \dots + d_1 x_{t-1} + d_2 x_{t-2} + \dots + v_{2,t}. \end{aligned} \quad (6)$$

Where, x_t could be the trade-type indicator (-1 for a public buy and +1 for a public sell). Hasbrouck allows this variable to represent any variable which is correlated with innovations to both the non-stationary and stationary components of transaction returns. The disturbance terms are zero mean and serially uncorrelated.

The VAR has a vector moving average (VMA) representation as:

$$\begin{aligned} r_t &= a_0^* v_{1,t} + a_1^* v_{1,t-1} + a_2^* v_{1,t-1} + \dots + b_0^* v_{2,t} + b_1^* v_{2,t-1} + b_2^* v_{2,t-2} + \dots \\ x_t &= c_0^* v_{1,t} + c_1^* v_{1,t-1} + c_2^* v_{1,t-1} + \dots + d_0^* v_{2,t} + d_1^* v_{2,t-1} + d_2^* v_{2,t-2} + \dots \end{aligned} \quad (7)$$

The more general pricing error is now given by:

$$\begin{aligned} s_t &= \alpha_0 v_{1,t} + \alpha_1 v_{1,t-1} + \dots + \beta_0 v_{2,t} + \beta_1 v_{2,t-1} + \beta_2 v_{2,t-2} \\ &\quad + \dots + \eta_t + \gamma_{t-1} + \dots, \end{aligned} \quad (8)$$

where η_t is a disturbance which is uncorrelated with all components of v_t . A generalisation of the Beveridge-Nelson (BN) decomposition allows for identification of the non-stationary innovation variance as:

$$\sigma_w^2 = \left[\sum a_i^* \quad \sum b_i^* \right] \text{COV}(v) \begin{bmatrix} \sum a_i^* \\ \sum b_i^* \end{bmatrix}. \quad (9)$$

The parameters of the pricing error component, $(\alpha_i, \beta_i \ i=0, 1, 2, \dots)$, are econometrically identifiable if the BN restriction is applied (in this case $\eta_t = \gamma_i = 0 \ i=1, 2, \dots$). These are computed as:

$$\alpha_j = - \sum_{k=j+1}^{\infty} a_k^* \quad \text{and} \quad \beta_j = - \sum_{k=j+1}^{\infty} b_k^*. \quad (10)$$

The pricing error variance is now given by:

$$\sigma_s^2 = \sum_{j=1}^{\infty} \begin{bmatrix} \alpha_j & \beta_j \end{bmatrix} \text{COV}(v) \begin{bmatrix} \alpha_j \\ \beta_j \end{bmatrix}. \quad (11)$$

This provides the estimate of the pricing error which is no longer a lower bound estimate. It can be further strengthened by the inclusion of equations for the possible proxies to represent the non-stationary innovations. The reader is directed to Hasbrouck (1993) for results on simulations of the econometric approach described above in which the method performs extremely well.

In the current study a VMA of trade type and returns was attempted but did not give rise to reliable results. This was most likely due to the fact that the trade type variable is discrete. Aside from this, a preliminary analysis of the data indicated that the complex dynamics often found between returns and trade type (in stock market data), did not arise here. Trade type was not found to be predictable using its own lags and those of the returns series (although the returns series was predictable using lagged returns and trade type). This implies that a VMA representation would not produce any significant improvement over a single equation representation of the returns process.

In the single equation case, Hasbrouck's approach would involve a moving average representation arising out of an AR model of returns which also includes current and lagged trade type. An alternative strategy adopted below, treats the trade type indicator as a series of known, uncorrelated, informative, discrete shocks which can be modelled via an unrestricted moving average transfer function along with the moving average representation of returns. The alternative econometric specification is then (in general):

$$r_t = a_0^* v_t + a_1^* v_{t-1} + a_2^* v_{t-1} + \dots + b_0^* x_t + b_1^* x_{t-1} + b_2^* x_{t-2} + \dots \quad (12)$$

where, as before $\{x_t\}$ is the trade type indicator series. The expression for the pricing error is then:

$$s_t = \alpha_0 v_t + \alpha_1 v_{t-1} + \dots + \beta_0 x_t + \beta_1 x_{t-1} + \beta_2 x_{t-2} + \dots + \eta_t + \eta_{t-1} + \dots, \quad (13)$$

and, the BN identification restriction again implies that the variance of both the stationary and permanent components can be calculated using expressions (9) and (11) above. The $\text{Cov}(v)$ is then of the more simple form:

$$\text{Cov}(v) = \begin{bmatrix} \text{var}(v) & 0 \\ 0 & 1 \end{bmatrix}.$$

III DATA AND ECONOMETRIC MODELLING

Results will be presented for three gilts (these are the same three gilts in the pre- and post-market making cases). These have been numbered (1) to (3) in order of years to maturity. In all regressions below the transaction returns have been calculated using the log difference of "clean prices" (i.e., excluding accrued interest). A trade type indicator is available for the post-market making case only. The correlograms for both the pre- and post-market making returns did not provide evidence of serial dependence beyond the first couple of lags in most cases. One would have expected less evidence of negative serial correlation in the pre-market making case since trading cost was in the form of commission. This would lead to very limited fluctuation of transaction price from the implicit efficient price. This was not always found to be the case. However, the varying state of liquidity in the market might imbue returns with characteristics reminiscent of bid-ask bounce, (reflecting the presence of an implicit cost for immediate enactment of a trade).

In the pre-market making case, no trade type indicator was available and so returns were modelled as MA(1) with a constant variance. For comparison, the same model was applied to the post-market making data (see Table 1 below). The post-market making mean equation was modelled using a general-to-specific approach, with MA(3) and three lags of the trade type indicator included in the most general model considered. In the first instance, this was done under the assumption of normally distributed homoscedastic errors. The variance process was then modelled, also using a general-to-specific methodology with GARCH(2,2) as the most general specification. Various exogenous variables were included in the variance equation (i.e., a day indicator, intraday period dummies, over-night dummy and log of volume traded). Only the volume variable had a significant parameter in some cases. The eventual specification, GARCH(1,1), was chosen using t-statistics based on standard errors that were equivalent to the Bollerslev-Wooldridge (1988) standard errors.

With the variance process specified, the mean equation was re-examined and in some cases, a lagged term of the MA process or of the trade type indicator was dropped. The assumption of normality was maintained up to this point but tests on the residuals indicated non-normal kurtosis. The estimation was repeated using the t-distribution. In two of the three cases this had a significant effect, and in these cases the results are for these regressions.

IV RESULTS

Table 1 presents both the pre- and post-market making results for the MA(1) regressions with constant variance. The significant MA(1) parameter in all cases is a common result with high frequency returns in the presence of a bid-ask spread. In all cases the Ljung-Box statistics indicate that the MA(1) specification is appropriate. As discussed above, the BN pricing error estimate can only be considered a lower bound on the true pricing error and this is confirmed by the fact that it is in all cases below both the Watson and Roll measures. Regarding the comparison of pre- and post-market making results; in the cases of Gilt (1) and (2) the pricing error is largest in the pre-market making case. The opposite is true for Gilt (3).

Table 2 presents the results for the more general specification of the post market making data. In particular, it was hoped that the BN lower bound estimate of the pricing error could be strengthened by the inclusion of the trade type variable in the mean equation. In all cases the BN estimate did increase relative to the estimate in the simpler MA(1) regressions. The estimates of the variance of random walk shocks has also risen in two out of the three cases.

It is worthwhile comparing the revised BN estimates with the original Watson pricing error estimates. These are: Gilt (1) $\hat{S}_{BN}^* = 0.0757$, $\hat{S}_{Wat} = 0.091$. Gilt (2) $\hat{S}_{BN}^* = 0.0359$, $\hat{S}_{Wat} = 0.064$; Gilt (3) $\hat{S}_{BN}^* = 0.1517$, $\hat{S}_{Wat} = 0.15$. The fact that the revised pricing error estimate is virtually equal to the Watson estimate in the case of Gilt (3) indicates support for the assumption of an information uncorrelated pricing error. Although the Watson estimate is not an upper bound on the possible value of the true pricing error, the concurrence among all three measures in this case and the fact that there was no evidence of complex dynamics between trade type and lagged returns, points firmly in the direction of information uncorrelated pricing errors. The quoted spread is the likely source of the entire pricing error for Gilt (3) and represents a higher cost of trading in the post-market making regime for this gilt alone.

The expected transaction cost under the assumption of normality is

Table 1: *Pre- and Post-market Making MA(1) Regressions and Estimates of Pricing Errors*

GILT (1) PRE:	$r_t = \varepsilon_t - 0.533 \varepsilon_{t-1}$ (-12.77)	$\left\{ \begin{array}{l} \text{Obs.} = 271 \\ \overline{R}^2 = .236 \end{array} \right.$	Log L = 1403.4 Skewness = 0.276	$\hat{\sigma}_\varepsilon^2 = 0.00000186$ Kurtosis = 3.435
	L - Box (1) = 1.096 $\hat{s}_{BN} = 0.0727$	L - Box (2) = 0.140 $\hat{s}_{Watson} = 0.0995$	L - Box (3) = 2.104 $\hat{s}_{Roll} = 0.1055$	L - Box (9) = 7.174 $\hat{\sigma}_w = 0.0637$
GILT (1) POST:	$r_t = \varepsilon_t - 0.432 \varepsilon_{t-1}$ (-13.091)	$\left\{ \begin{array}{l} \text{Obs.} = 504 \\ \overline{R}^2 = 0.166 \end{array} \right.$	Log L = 2600.9 Skewness = 0.103	$\hat{\sigma}_\varepsilon^2 = 0.000001928$ Kurtosis = 1.301
	L - Box (1) = 0.1217 $\hat{s}_{BN} = 0.060$	L - Box (2) = 0.942 $\hat{s}_{Watson} = 0.091$	L - Box (3) = 1.095 $\hat{s}_{Roll} = 0.095$	L - Box (9) = 10.32 $\hat{\sigma}_w = 0.079$
GILT (2) PRE:	$r_t = \varepsilon_t - 0.349 \varepsilon_{t-1}$ (-8.245)	$\left\{ \begin{array}{l} \text{Obs.} = 235 \\ \overline{R}^2 = 0.117 \end{array} \right.$	Log L = 1223.0 Skewness = 0.103	$\hat{\sigma}_\varepsilon^2 = 0.000001767$ Kurtosis = 5.582
	L - Box (1) = 1.038 $\hat{s}_{BN} = 0.046$	L - Box (2) = 3.073 $\hat{s}_{Watson} = 0.079$	L - Box (3) = 3.189 $\hat{s}_{Roll} = 0.088$	L - Box (9) = 6.125 $\hat{\sigma}_w = 0.087$
GILT (2) POST:	$r_t = \varepsilon_t - 0.290 \varepsilon_{t-1}$ (-9.496)	$\left\{ \begin{array}{l} \text{Obs.} = 509 \\ \overline{R}^2 = 0.078 \end{array} \right.$	Log L = 2708.4 Skewness = -0.23	$\hat{\sigma}_\varepsilon^2 = 0.000001399$ Kurtosis = 3.05
	L - Box (1) = 0.010 $\hat{s}_{BN} = 0.034$	L - Box (2) = 1.230 $\hat{s}_{Watson} = 0.064$	L - Box (3) = 3.837 $\hat{s}_{Roll} = 0.062$	L - Box (9) = 15.762 $\hat{\sigma}_w = 0.084$
GILT (3) PRE:	$r_t = \varepsilon_t - 0.241 \varepsilon_{t-1}$ (-5.141)	$\left\{ \begin{array}{l} \text{Obs.} = 263 \\ \overline{R}^2 = 0.048 \end{array} \right.$	Log L = 1312.8 Skewness = 0.387	$\hat{\sigma}_\varepsilon^2 = 0.00000027$ Kurtosis = 2.73
	L - Box (1) = 0.239 $\hat{s}_{BN} = 0.040$	L - Box (2) = 0.820 $\hat{s}_{Watson} = 0.081$	L - Box (3) = 1.031 $\hat{s}_{Roll} = 0.087$	L - Box (9) = 9.717 $\hat{\sigma}_w = 0.125$
GILT (3) POST:	$r_t = \varepsilon_t - 0.389 \varepsilon_{t-1}$ (-10.012)	$\left\{ \begin{array}{l} \text{Obs.} = 435 \\ \overline{R}^2 = 0.136 \end{array} \right.$	Log L = 2004.2 Skewness = -0.44	$\hat{\sigma}_\varepsilon^2 = 0.000005829$ Kurtosis = 1.75
	L - Box (1) = 0.099 $\hat{s}_{BN} = 0.094$	L - Box (2) = 0.319 $\hat{s}_{Watson} = 0.151$	L - Box (3) = 5.920 $\hat{s}_{Roll} = 0.152$	L - Box (9) = 17.613 $\hat{\sigma}_w = 0.148$

t-statistics are shown in parentheses. L-Box is the Ljung-Box statistic applied to the residuals. The variance of the non-stationary component is $\sigma_w^2 = (1-a)^2 \sigma_\varepsilon^2$, where a is the MA(1) parameter. The pricing error based on the Beveridge-Nelson, Watson, and Roll analyses are presented as $\hat{s}_{BN}$, $\hat{s}_{Watson}$, and $\hat{s}_{Roll}$ respectively.

$E|S_t| = \sqrt{2/\pi}\sigma_s$ which in the case of Gilts (1)-(3) are, respectively, 0.6 per cent, 0.28 per cent and 1.2 per cent of the price of the gilt. The first and last of these are roughly half the quoted spread for medium and long dated gilts respectively. Similarly, $E|w_t| = \sqrt{2/\pi}\sigma_w$ represents the expected per-period permanent innovation to returns. These are 0.7 per cent, 0.8 per cent and 1.1 per cent, in the case of Gilts (1)-(3) respectively. Since this is, in two cases, a good deal greater than the pricing error, the Irish gilt market can be considered quite competitive in terms of cover for risk.

Table 2: *Post-market Making MA (transfer)-GARCH-X Results*

GILT (1)	$r_t = \varepsilon_t - 0.334 \varepsilon_{t-1} - 0.003 BS_t + 0.00025 BS_{t-1}$			
	$(-7.350) \quad (-6.770) \quad (5.741)$			
	$h_t = 0.00000396 + 0.230 h_{t-1} + 0.352 \varepsilon_{t-1}^2 - 0.0000002 VOL_t \quad Ku = 4.13$			
	$(3.495) \quad (1.849) \quad (2.556) \quad (-3.421) \quad (3.57)$			
	Obs. = 504	Log L = 2979.9	$\bar{\sigma}_\varepsilon^2 = 0.0000017$	$\bar{R}^2 = 0.255$
GILT (2)	L-Box (1) = 3.628	L-Box (2) = 4.053	L-Box (3) = 4.378	L-Box (9) = 9.205
	Skewness = 0.235	Kurtosis = 1.575	$\bar{s}_{BN}^* = 0.0757$	$\bar{\sigma}_w^* = 0.0875$
	$r_t = \varepsilon_t - 0.153 \varepsilon_{t-1} - 0.00031 BS_t$			
	$(-2.084) \quad (-1.979)$			
	$h_t = 0.00000109 - 0.153 h_{t-1} + 0.288 \varepsilon_{t-1}^2$			
GILT (3)	$(1.690) \quad (-1.432) \quad (14.151)$			
	Obs. = 509	Log L = 2755.8	$\bar{\sigma}_\varepsilon^2 = 0.00000129$	$\bar{R}^2 = 0.141$
	L-Box (1) = 2.501	L-Box (2) = 3.736	L-Box (3) = 5.788	L-Box (9) = 15.62
	Skewness = -0.299	Kurtosis = 3.339	$\bar{s}_{BN}^* = 0.0359$	$\bar{\sigma}_w^* = 0.102$
	$r_t = \varepsilon_t - 0.378 \varepsilon_{t-1} - 0.00058 BS_t + 0.000556 BS_{t-1}$			
	$(-8.956) \quad (-6.743) \quad (6.385)$			
	$h_t = 0.00000159 - 0.202 h_{t-1} + 0.239 \varepsilon_{t-1}^2 - 0.00000084 VOL_t \quad Ku = 6.134$			
	$(14.858) \quad (-4.676) \quad (2.539) \quad (-4.622) \quad (3.751)$			
	Obs. = 435	Log L = 2329.2	$\bar{\sigma}_\varepsilon^2 = 0.00000481$	$\bar{R}^2 = 0.2769$
	L-Box (1) = 0.034	L-Box (2) = 0.247	L-Box (3) = 8.818	L-Box (9) = 16.501
	Skewness = 0.428	Kurtosis = 1.881	$\bar{s}_{BN}^* = 0.1517$	$\bar{\sigma}_w^* = 0.1373$

The caption for the previous table also applies to this table. BS stands for the buy-sell indicator variable. h_t is the conditional variance and VOL is the log of absolute volume traded in period t . Ku is the "degrees of freedom" parameter estimate from estimation with the t -distribution. Since the variance is not constant, various statistics are based on the average variance. This is indicated by the presence of a bar over the usual notation used.

V CONCLUSION

A modified version of Hasbrouck's measure of market quality was applied to pre- and post-market making gilt data. The inclusion of a trade type variable in an MA-GARCH regression led to a significant increase in the BN estimate of the pricing error and in one case it was brought to virtual equality with the Watson estimate, (which assumes an information uncorrelated pricing error). The results show that, for the two shortest gilts, the pricing error in the pre-market making situation appeared to be greater than in the post-market making case. This reveals an implicit spread which resulted in quite unfavourable prices for urgent trades in the agency regime for the shorter gilts. The long gilt appears to provide the opposite result.

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