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The adverse selection component of exchange traded funds

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ABSTRACT

The aim of our paper is to examine whether Exchange Traded Funds (ETFs) diversify away the private information of informed traders. We apply the spread decomposition models of Glosten and Harris (1998) and Madhavan, Richardson and Roomans (1997) to a sample of ETFs and their control securities. Our results indicate that ETFs have significantly lower adverse selection costs than their control securities. This suggests that private information is diversified away for these securities. Our results therefore offer one explanation for the rapid growth in the ETF market.

1. Introduction

Adverse selection losses arise when uninformed traders, such as market makers or liquidity traders, trade with the informed. The market maker recoups these losses by including in the spread a component to compensate for adverse selection losses (see for example, Copeland & Gali, 1983). In this paper we use the magnitude of the adverse selection component of the spread to measure adverse selection losses and information asymmetry.[1] We show that these costs are lower for exchange traded funds than for individual securities suggesting that there is less information asymmetry between traders in ETF markets than in markets for individual securities.

Since their introduction in 1993, the market for Exchange Traded Funds (ETFs) has grown rapidly. Ackert and Tian (2001) note that the most actively traded ETFs (Diamonds and the NASDAQ-100 Index Tracking Stock) have become especially popular and rank consistently as the most active issues on their exchanges. Additional evidence of their importance is given by Boehmer and Boehmer (2003) who show that by 2001, the three most heavily traded ETFs generated average daily trading volume of about $5 billion.

A number of reasons have been suggested for the popularity of ETFs. Hegde and McDermott (2004a,b) attribute the growth of ETFs to the ease with which investors can obtain portfolio diversification benefits, at low transaction costs, in comparison to trading a portfolio of underlying stocks. Although each ETF reflects the collective performance of a portfolio, there is no uncertainty about their redemption value. This contrasts with the findings of Neal and Wheatley (1998) who found that closed-end funds had similar levels of information asymmetry to individual securities. Moreover, since short selling is permitted for ETFs, arbitrage between the ETF and component securities ensures that ETFs have negligible premiums/discounts eliminating this potential source of information asymmetry. For example, Pennathur, Delcoure and Anderson (2002) and Engle and Sarkar (2006) find that ETFs closely mirror their underlying index and have low tracking errors while Harper, Madura and Schnusenberg (2006) show that tracking errors associated with ETFs are lower than for matched closed-end funds. Moreover, since short selling is permitted for ETFs arbitrage between the ETF and component securities can easily be undertaken. These advantages are reinforced by the comparatively low trading costs associated with ETFs that were identified in studies by Elton, Gruber, Comer and Li (2002) and Boehmer and Boehmer (2003) that examined both quoted and effective spreads.

In this paper we draw attention to an alternative explanation for low bid-ask spreads and high levels of trading activity associated with ETFs. An ETF is an example of a basket security, the characteristics of which were outlined by Subrahmanyam (1991). One important characteristic of a basket security is that adverse selection costs are diversified away, reducing the adverse selection component of the spread relative to component securities. The effect of lower trading costs associated with the basket encourages the concentration of trading in the basket security, accentuating liquidity, and driving trading costs down further.

We test this hypotheses for the first time using the spread decomposition models of Glosten and Harris (1988) and Madhavan,

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[1] The more private information a trader has the greater are the profits he can extract from the uninformed. Higher adverse selection losses are therefore associated with higher information asymmetries between the informed and uninformed.

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Richardson and Roomans (MRR) (1997), two of the most widely used spread decomposition models. Our results indicate that ETFs have substantially lower adverse selection costs than control securities showing that ETFs diversify private information. Our results offer an explanation for why these markets have grown so rapidly since their inception. The diversification of private information in the basket leads to concentration of trades by liquidity traders in the market for the basket security so that losses with informed traders are reduced.

The remainder of this paper is set out as follows. In Section 2 we explain why ETFs diversify adverse selection costs and review the Glosten–Harris and the Madhavan–Richardson–Roomans (MRR) spread decomposition model. Section 3 discusses our data. Section 4 provides the results and Section 5 offers a summary and conclusion to the paper.

2. Measuring the adverse selection component of the spread

Subrahmanyam (1991) showed that a basket security generates lower adverse selection losses than component securities. Using the framework of Kyle (1984, 1985) and Admati and Pfleiderer (1988), Subrahmanyam (1991) models the strategic interaction of discretionary and non-discretionary liquidity traders in a market with informed traders. Both groups of liquidity traders can choose to execute their portfolio trades either in the market for the basket or trade in the underlying security markets. Subrahmanyam shows that a basket security with identical payoffs to component securities has lower adverse selection losses than individual securities. This outcome arises because the impact of security-specific private information is diversified away in a basket security.[2]

Although Subrahmanyam (1991) considered stock index futures as an example of a basket security, the diversification of adverse selection costs will arise for any basket security that has high levels of transparency if liquidation and the creation of the basket can easily be achieved. We argue that an ETF has the characteristics of a basket security outlined by Subrahmanyam (1991).

2.1. The Glosten–Harris model

The first attempt at decomposing the spread was made by Glosten and Harris (1988). This model has since been used to study a range of issues influenced by adverse selection costs. Using the Glosten–Harris model Chiyachantana, Chiraphol, Christine, Taechapiroontong and Wood (2004) showed that adverse selection costs fell after Regulation Fair Disclosure was introduced. Examinations of the relationship between block ownership and adverse selection costs undertaken by Sarin, Atulya, Shastri and Shastri (2000) and Jiang and Kim (2005) show that adverse selection costs increase with institutional ownership. Jiang, Kim and Wood (2002) show that ADR's experience lower adverse selection costs following a stock split. The Glosten–Harris model has also been used by McInish and Van Ness (2002) and Ahn, Hamao and Ho (2002) to measure the evolution of adverse selection costs during the trading day.

The Glosten–Harris model is based on the following representation of intrinsic and observed transaction prices.

$$p_t = m_t + Q_t C_t, \tag{1}$$

$$m_t = m_{t-1} + Q_t Z_t + U_t, \tag{2}$$

$$C_t = c_0 + c_1 V_t, \tag{3}$$

$$Z_t = z_0 + z_1 V_t. \tag{4}$$

where, p_t is the observed transaction price, m_t is the intrinsic value of the security and V_t is the number of shares in the transaction at time t. U_t captures the arrival of public information and any rounding error. Q_t is a trade indicator that takes the value $+1$ if the transaction is buyer initiated and -1 if the transaction is seller initiated. The adverse selection component is Z_t and the order processing component is C_t, where both are linear functions of V_t. Solving for the price change and incorporating the equations for Z_t and C_t provide the following equation that can be estimated using OLS.

$$\Delta p_t = c_0 \Delta Q_t + c_1 \Delta(Q_t V_t) + z_0 Q_t + z_1 Q_t V_t + U_t, \tag{5}$$

The bid-ask spread is then measured as the sum of the order processing and adverse selection components, $2(c_0 + c_1 V_t)$ and $2(z_0 + z_1 V_t)$ respectively. The percentage adverse selection component of the spread is $2(z_0 + z_1 V_t)/[2(c_0 + c_1 V_t) + 2(z_0 + z_1 V_t)]$.

2.2. The MRR model

The model developed by Madhavan et al. (1997) allows the estimation of the adverse selection component and a trading frictions component that captures both inventory and order processing costs. This model has been used by McInish and Van Ness (2002) to document intraday adverse selection costs on the NYSE and by Ahn et al. (2002) to measure these costs on the Tokyo exchange. Hatch and Johnson (2002) used the MRR model to examine the impact of specialist firm acquisitions on market quality. Hegde and McDermott (2004a,b) use the MRR model to examine whether the introduction of ETFs for the Dow Jones Industrial Average (Diamonds) and the NASDAQ 100 index (Q's) altered the liquidity of the underlying stocks.

In the MRR model order flow is assumed to exhibit first order autocorrelation (ρ) and trades can take place within the quotes with a probability equal to θ. MRR shows that transaction price changes can be written as

$$p_t - p_{t-1} = \alpha + (\phi + \lambda)Q_t - (\phi + \rho\lambda)Q_{t-1} + \mu_t \tag{6}$$

Q_t is the trade indicator variable that now also takes on a value of 0 if the trade is at the midpoint, α captures the constant drift in prices and u_t is a composite error term that captures the change in price due to new information and errors due to price discreteness. The parameter vector (α, θ, ϕ, λ, and ρ) is estimated using Hansen's Generalized Method of Moments (GMM). The implied spread can be computed as

$$S = 2(\theta + \phi) \tag{7}$$

When the percentage adverse selection and the percentage market friction components are computed as spread proportions, the two components, can be expressed as

$$\%\theta = \frac{2\theta}{2(\theta + \phi)} \quad \text{order processing costs} \tag{8}$$

$$\%\phi = \frac{2\phi}{2(\theta + \phi)} \quad \text{adverse selection costs} \tag{9}$$

3. Data and summary statistics

Our ETF sample is drawn from ETFs that are comprised of US registered companies. We exclude ETFs that include constituents of non-US firms to ensure that our spread measures do not reflect an information disadvantage that US investors may have in trading foreign equities.

Subrahmanyam (1991) shows theoretically that when informed traders have private information about a common factor (such as an industry or market-wide factor) adverse selection costs in the basket

[2] Subrahmanyam (1991) demonstrates this result for risk neutral traders but Gorton and Pennacchi (1993) show that the diversification of private information is robust to alternative assumptions about the risk preferences of traders.