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Aggregate Insider Trading and Stock Market Volatility in the UK

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Abstract

This paper examines the relationship between aggregate insider trading (AIT) and stock markin

1. Introduction

Understanding the sources of stock market volatility is crucial for risk-taking investment decisions, the efficient allocation of resources and macro prudential policy. Therefore it is not surprising that there should be an extensive literature considering various factors which can drive volatility. These include behavioural (non-fundamental) determinants (such as herding behaviour, loss aversion etc.), macro fundamentals (such as GDP, inflation, money supply, interest, and exchange rates etc.) and company-specific factors (such as earnings and dividend payments). [1] An additional relevant factor is insider trading activity; however, its impact has only been investigated in a relatively small number of papers (see, e.g., Bhattacharya and Daouk, 2002, and Du and Wei, 2004). The present study aims to shed further light on its possible role by estimating a vector autoregression (VAR) model and carrying out Impulse Response analysis as well as Forecast Error Variance Decomposition for a data set including insider transactions by UK executives in public limited companies.

The theoretical literature has identified two potential mechanisms by which insider trading can affect volatility, namely an information effect and one caused by incentives to increase volatility. Leland (1992) argues that, since insider trades reveal information to the market, one should expect to see an increase in volatility once this has happened. However, according to Manne (1966) and Leland (1992), because insiders bring price-relevant information to the market faster than if they were not allowed to trade, prices will become more informative, efficiency will improve, and volatility will fall thereafter. Another view is that, since the value of private information possessed by insiders is larger when volatility is higher (Muelbroek 1992), insiders are more likely to trade in that case. Moreover, they also have an incentive to increase volatility by, for example, selecting a more volatile production process (Bebchuk and Fershtman, 1994, Low, 2009, Gormley et al., 2013, and Bhattacharya, 2014), and to manipulate the timing and content of the information they release to the market to generate more volatility (Benabou and Laroque, 1992, and Aggarwal and Wu, 2006). Thus, theory does not provide unambiguous predictions regarding the impact of insider trading on volatility, with the net effect depending on the interaction between the information effect and the one caused by incentives to increase volatility. However, as argued by, amongst other, Du and Wei (2004), Cumming et al. (2011), and Brochet (2018), in well-regulated, transparent

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[1] See, for example, Konrad (2009), Gospodinov and Jamali (2012), and Mittnik et al. (2015) for macro fundamental factors; Baker and Wurgler (2007), Pati et al. (2017) and Audrino et al. (2020) for behavioural factors; Lee and Mauck (2016) and Sadka (2007) for company-specific factors.

markets such as the UK, where investors are better protected, the information effect is likely to dominate as the ability of insiders to take on more risky projects and manipulate markets are likely to be less relevant.

The available empirical evidence is limited and rather mixed, with the results depending on the country examined, the level of regulation and vigour of enforcement, the measure of insider trading used, and the empirical methodology employed (see, for example, Bhattacharya and Daouk, 2002, Du and Wei (2004, and Cumming et al., 2011). The present study focuses specifically on whether aggregate insider trading (AIT) affects aggregate stock market volatility rather than market returns as in previous papers by Seyhun (1988, 1992), Lakonishok and Lee (2001), Jiang and Zaman (2010), Brochet (2017), Malliouris et al. (2020), and Bushman et al. (2022). This literature provides evidence suggesting that aggregate insider trades may reveal results. Section 5 reports some robustness checks. Finally, Section 6 summarises the main findings and discusses their implications.

2. Literature Review

Empirical studies of the impact of insider trading on stock market volatility have produced mixed result

Therefore, countries which are better regulated and enforce their laws and regulations with vigour tend to exhibit less volatility. This finding, albeit at the firm level, is confirmed by Gilbert et al. (2007), who reported that firm-level volatility fell after the introduction of the Securities Market Amendment Act in New Zealand in 2002. Similarly, Cumming et al. (2011) examined whether differences in regulations in 42 exchanges throughout the world affect a series of liquidity measures that includes firm-level volatility. They concluded that regulations significantly reduce volatility and that this may be due to a reduction in market manipulation activities by insiders. Finally, using laboratory markets, Palan and Stockl (2017) investigated the effects of insider trading on various aspects of market quality such as liquidity, informational efficiency, and volatility. Despite obtaining evidence that legislation reduces liquidity and informational efficiency, they could not find any impact on volatility.

To date, the literature on aggregate insider trading has focused mainly on its relationship with stock market returns. Seyhun (1988) argues that insiders trade owing to both firm-specific and economy-wide factors Aggregating insider trading cancels out the idiosyncratic component of their trade and re-enforces the common response to economy-wide factors. Therefore, if trades are only based on firm-specific information, one would not expect to find a relationship between aggregate insider trades and aggregate market returns. Conversely, if trades are even partly based on economy-wide information, in advance of it being made public, then one would expect to see a positive relationship. Seyhun (1988) identified a positive linkage between aggregate insider trades and subsequent stock market returns, which is evidence that publicly available information on aggregate insider trades can be used to predict subsequent changes in stock market returns.[3] This finding was confirmed by Seyhun (1992), Lakonishok and Lee (2001), Jiang and Zaman (2010), Brochet (2017), To sum up, the previous literature has generally used proxies for aggregate insider trading and either focused on its effects on stock market returns rather than volatility, or only examined the impact on volatility of institutional and regulation differences between countries. By contrast, the analysis below is based on a direct, aggregate measure of AIT and provides evidence on how this affects stock market volatility in the case of a specific country (namely the UK) with well-regulated financial markets.

3. Data and Empirical Methodology

Monthly data on over the period from January 2002 to December 2020 (a total of 228 months) have been obtained from the Smart Insider Quantitative Data Delivery file. This database reports all transactions by UK executives in public limited companies. Since the aim is to identify those trades that are informative, we focus only on discretionary transactions that involved the purchase or sale of ordinary shares through open market operations. Therefore, non-discretionary trades (awards, contract buys, transfers in or out, dividend re-investments, exercise of options with associated sales post-exercise and subscriptions to new issues) are not included. We use similar filters and exclusion criteria to Lakonishok and Lee (2001) to clean up the data. For example, transactions with less than 100 shares, duplicated and suspicious transactions as well as transactions for which price information was not available, were excluded. As a result, our sample includes 65,484 transactions across 3427 firms made up of 50,712 buys and 14,752 sales. Consistently with capture investor sentiment reflecting the main factors that could affect stock market volatility; for this reason, it is included in our VAR model, as an endogenous variable, to investigate whether aggregate insider trading has an impact even when allowing for other possible drivers of stock market volatility. Note that Du and Wei (2004) use a simple measure (the standard deviation) of the volatility of various economic fundamentals and policy variables rather than the more comprehensive EPU index chosen here; they also consider liquidity and maturity of market variables, which would not be appropriate in our case as we are not examining the relationship of interest across countries. The data on the FTSE All-Share index and the EPU index come from Datastream. FTSE All-Share monthly returns are calculated as the log difference of consecutive end of the month prices, whereas their volatility is modelled as a standard GARCH (1,1) process.

The empirical literature that examines the relationship between aggregate insider trading and returns uses the net purchase ratio to measure aggregate insider trading, with the aim of obtaining an indicator of insider trading sentiment (see, for example, Lakonishok and Lee, 2001, Iqbal and Shetty, 2002, Jiang and Zaman, 2010, Tavakoli et al., 2012, and Malliouris et al., 2020). The monthly net purchase is defined as the ratio of net purchases (P-S) to total insider trading activity (P+S) in any given month. Net purchases are defined as either the number, volume, or value of net purchases in each calendar month. Apart from Malliouris et al. (2020), all the beforementioned papers only report results for the number of trade transactions and only volume and value of transactions in robustness tests. Seyhun (1992) argues that using the latter puts an equal weight on each share traded and is therefore likely to favour large transactions proportionately. Furthermore, since the focus of the present study is to examine whether aggregate insider trading affects volatility, and not whether insider sentiment is able to predict stock market returns, we do not employ the net purchase ratio but use instead the total number of transactions per month as our measure of aggregate insider trading activity. Specifically, we define total insider trading activity in each month (AIT1) as the sum of all purchase transactions (AIT 2) and sale transactions (AIT 3) made by UK directors within any given month. A further justification for the use of transactions is provided by Jones et al. (1994), who found that the positive volume-volatility relationship the total number of transactions as our measure of insider trading intensity, as opposed to the net purchase ratio, makes our results directly comparable to other studies that have examined the impact of insider trading activity on stock market volatility, such as Du and Wei (2004).

Insert Table 1 and Figure 1 about here

Table 1 provides descriptive statistics for the variables used. The monthly mean (median) is 287 (269) for total transactions, 222 (202) for purchases, and 65 (62) for sales. AIT1 and AIT2 have similar standard deviations, whilst AIT3 is much less volatile. Finally, all variables are stationary, as implied by the reported Augmented Dickey-Fuller and Phillips-Perron test statistics. Figure 1 shows plots of the data. Visual inspection reveals similar patterns for the volatility and the number of buy transactions. These observations, together with the evidence discussed in the literature review, lead us to formulate the following two hypotheses:

Hypothesis 1. Aggregate insider trading

More specifically, to test for the impact of aggregate insider trading on stock market volatility we estimate a Vector Autoregression (VAR) model and carry out Impulse Response analysis as well as Forecast Error Variance Decomposition. The baseline specification is the

that volatility increases when information is released, but this effect does not persist and starts to fall as prices become more informative. Our findings are also consistent with the conclusions of much of the literature that has examined the relationship between aggregate insider trading and stock market returns - namely, that aggregate insider trading brings forward the revelation of economy-wide information. [6] Thus, when this information is revealed to market participants, there is an increase in volatility that does not persist. In other words, the validity of hypothesis 1 is confirmed.

Figures 2a and 2b show the impact of aggregate insider purchases (AIT 2) and sales (AIT 3) on volatility. It can be seen that a shock to aggregate insider purchases has a positive and significant effect

5. Robustness Analysis

As a robustness check, we also estimate the impulse responses for two further measures of aggregate insider trading that have previously been used in the literature. Figures 3a, 3b, and 3c show the results when using the logarithm of AIT 1, AIT 2 and AIT 3, which has the advantage of smoothing out the impact of any outliers. For example, when examining the relationship between aggregate insider trading transaction and stock market returns, Chowdhury et al. (1992) take the log of aggregate insider trading transactions, arguing that this compresses the scale and it handles better extreme values.

Insert Figures 3a-3c about here

Figure 3a displays the results based on the log of the total number of buy and sale transactions (log AIT 1); these are consistent with the previous ones for AIT 1, i.e. there is a positive and significant effect on stock market volatility that lasts for approximately two months. Figures 3a and 3b present the impulse responses of the logarithm of aggregate insider purchase transactions and sale transactions respectively. It can be seen that again the positive and significant impact of aggregate insider trading on stock market volatility essentially comes from aggregate insider purchases.

Seyhun (1988) argues that the AIT variable should be standardised to ensure that each firm is given approximately the same weight. Therefore, we use the same method as Seyhun (1988, 1992), He et al. (2018), and Malliouris et al. (2020) to calculate the standardised number of transactions for each firm i in month t. This is calculated by subtracting the mean and dividing by the sample standard deviation of the total number of transactions over the 228 calendar months between January 2002 and December 2020, then summing across all firms in month t. Specifically:

$$_{,} = \sum_{=1} \frac{\left(\quad _{,} - \overline{\qquad} \right)}{\left(\qquad \right)}, \qquad (2)$$

where t = 1,228, from January 2002 to December 2020 and *I* is equal to the total number of firms,

$$\overline{\quad} = \sum_{=1}^{228} \quad _{,} \; /228, \qquad (3)$$

and

$$(\quad) = [\sum (\quad _{,} - \overline{\quad})^2 / 227 \qquad -$$

as distinguishing between sales and purchases. Our results provide empirical support to the two hypotheses we specify. More precisely, it appears that higher AIT leads to a short-run increase in stock market volatility (which supports our hypothesis 1), and that this effect

Chowdhury, M., Howe, J., Lin, J. (1993). The relation between aggregate insider transactions

Konrad, E. (2009). The impact of monetary policy surprises on asset return volatility: the case of Germany. Financial Markets and Portfolio Management 23, 111-135.

Lakonishok, J., Lee, I. (2001). Are insider trades informative? Review of Financial Studies 14(1),79 111.

Pati, C., Rajib, P., and Barai, P. (2017). A behavioural explanation to the asymmetric

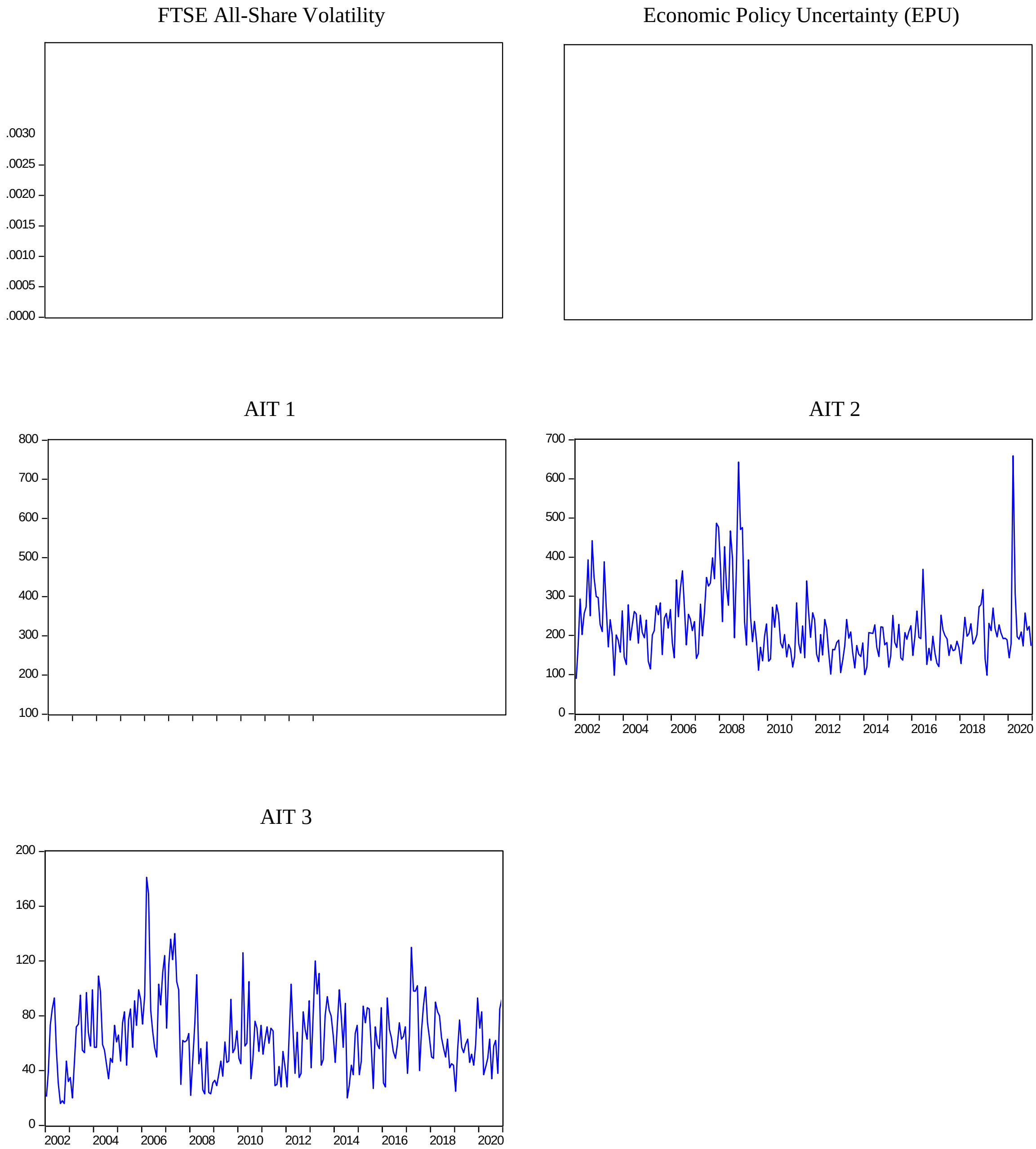
Table 1: Descriptive Statistics

Variables	Mean	Median	S.D.	Min	Max	ADF	PP
Volatility	0.008	0.005	0.006	0.003	0.004	-4.198	-3.941
AIT 1	287	269	90.43	110	696	-3.667	-4.935
AIT 2	222	202	87.49	89	659	-3.998	-9.028
AIT 3	65	62	27.34	16	181	-3.813	-11.02
EPU	131.76	123.32	72.53	24.03			

Table 3: Forecast Error Variance Decomposition – AIT 2 and AIT 3

	Volatility		AIT 2		AIT 3		EPU	
$Volatility_{t-1}$	**0.91**	(3.06)	0.02	(1.37)	0.01	(1.11)	0.01	(1.11)
$Volatility_{t-2}$	**0.90**	(4.11)	0.02	(1.49)	0.01	(1.44)	0.01	(1.09)
$AIT\ 2_{t-1}$	**0.08**	(2.93)						

Figure 1. FTSE Volatility, Aggregate Insider Trading and EPU



Notes: FTSE All-Share monthly returns are calculated as the log difference of consecutive end of the month prices, whereas their volatility is modelled as a standard GARCH (1,1) process. AIT 1 is the total number of buy and sell transactions. AIT 2 and AIT 3 are the aggregate insider purchases and sales, respectively.

Figure 4