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Guglielmo Maria Caporale, Kyriacos Kyriacou and Nicola Spagnolo

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Aggregate Insider Trading and Stock Market Volatility in the UK

Guglielmo Maria Caporale [a *], Kyriacos Kyriacou [a] and Nicola Spagnolo [a, b, c]

[a] Department of Economics and Finance, Brunel University London, UK

[b] Centre for Applied Macroeconomic Analysis (CAMA), Canberra, Australia

[c] Universita' degli Studi della Campania, Italy

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Abstract

This paper examines the relationship between aggregate insider trading (AIT) and stock market volatility using monthly data on insider transactions by UK executives in public limited companies for the period January 2002 - December 2020. More specifically, a Vector Autoregression (VAR) model is estimated and Impulse Response analysis as well as Forecast Error Variance Decomposition are carried out. The main finding is that higher AIT (more specifically, insider purchases) leads to a short-run increase in stock market volatility; this can be attributed to a combination of insiders manipulating the timing and content of the information they release and the revelation of new economy-wide information to the market. The UK being a well-regulated market, it is plausible that the main driver of the increase in stock market volatility should be the information effect. These results are shown to be robust to using alternative (direct) measures of AIT.

JEL classification: C22, G14

Keywords: aggregate insider trading; stock market volatility; VAR; impulse responses

***Corresponding author.** Department of Economics and Finance, Brunel University London, Uxbridge, UB8 3PH, UK. Email: Guglielmo-Maria.Caporale@brunel.ac.uk; https://orcid.org/0000-0002-0144-4135

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

[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 new economy-wide information, and thus, through the information effect identified in the theoretical literature, affect stock market volatility. The present study makes a threefold contribution. First, to the best of our knowledge ours is the first to construct an aggregate insider trading variable to examine the relationship between insider trading and stock market volatility rather than its information content and predictive power. Second, for this purpose it uses actual insider trading data instead of a proxy as, for example, in Du and Wei (2004). This has the advantage of avoiding systematic biases inherent in survey-based data and is a more accurate measure of the variable of interest than a perception-based one. Third, following Chowdhury et al. (1993), Lakonishok and Lee (2001) and Tavokoli et al. (2012), it calculates measures of aggregate insider trading for both insider sales and purchases and thus can distinguish between trades that are information-driven and those that may be noisy signals; this is crucial, since the impact of insider trading on volatility is likely to depend on how the signal-to-noise ratio is affected, which, in turn, depends crucially on whether purchases and sales are equally informative. This contrasts with Du and Wei (2004) who, by construction, focused on all insider transactions within a given country and thus implicitly assumed that sales and purchases are equally informative, failing to distinguish between noise and information-motivated trades. Clearly, if it is the information revealed through insider trades that is the main driver of stock price movements, failing to separate trades may lead to incorrect conclusions.

The layout of the paper is as follows. Section 2 reviews the existing empirical literature. Section 3 describes the data and the methodology. Section 4 presents the main empirical 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 results and have focused mainly on examining the impact of differences in insider trading regulation, laws, and enforcement across countries. [2] Bhattacharya and Daouk (2002) analysed the impact of the existence and enforcement of insider trading laws in 103 countries throughout the world. By comparing the volatility in the five-year period before and after the introduction of insider trading laws (without any control variables) they found a small increase but did not provide an explanation for this result. Similarly, Du and Wei (2004) investigated the extent to which insider trading explains cross-country differences in volatility in 53 countries. Initially, they examined whether each country's insider trading laws and regulations, the vigour with which they are enforced, and the penalty given explain differences in volatility. They found a weak negative relationship which, they argued, is consistent with the view that stricter laws and enforcement of insider trading reduces volatility. They supplemented this analysis by using a proxy of insider trading intensity in each country, which is derived from an insider trading index based on survey data of corporate officers who are asked how common they feel insider trading is in their respective countries. They found that countries with more prevalent insider trading have more volatile stock markets. This, they argued, is consistent with the view that, because insiders profit more from their information in more volatile markets, they have an incentive to take actions to increase volatility. It is important to recognise that their conclusions apply collectively to the panel of 53 countries they consider rather than to individual ones. For instance, the US and UK are widely regarded as well-regulated financial markets, with relatively little illegal insider trading, where outside investors have a reasonable amount of confidence in the system. In such less permissive environments, the attempts by insiders to increase volatility by, for example manipulating markets, will not be as effective and frequent as in less regulated markets (see, e.g., Du and Wei, 2004, Cumming et al., 2011, and Brochet, 2018).

[2] Gangopadhyay et al (2014) and Chiang et al (2017) examine the relationship between firm-level insider trading and idiosyncratic volatility and suggest that the channel through which the former affects the latter at firm level is firm-specific private information. Although these studies are relevant in that they provide evidence that sales are noisier signals than purchases, the focus of the present one is on the relationship between aggregate insider trading, market-wide information, and aggregate market volatility.

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 that affect their company's returns. 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), Malliouris et al. (2020), and Bushman et al. (2022), who established that, at the aggregate level, insider trades bring new information regarding economy-wide factors. Conversely, Choudhury et al. (1993) and Iqbal and Shetty (2002) found that, although aggregate insider trading has some predictive power, it is weak. In related studies, using firm-level data, Piotroski and Roulstone (2004) and Wang (2019) argued that insider trades reveal more firm-specific than macroeconomic information. [4]

[3] An excellent discussion of why insiders may have a macro-information advantage relative to other market participants can be found in Malliouris et al. (2020).
[4] Piotroski & Roulstone (2004) base this assertion on their belief that insiders with access to economy-wide information are more likely to trade index funds. However, Colin-Dufresne et al. (2021) argue that informed trading only takes place in the stock market and that informed traders rarely use derivatives. Furthermore,

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 UK corporate directors' trading 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 Fidrmuc et al. (2006), the average value of purchase transactions is £71,987, which is much smaller than the average sale transaction of £527,360.

A variety of empirical papers have examined the effects of the Economic Policy Uncertainty (EPU) index, constructed by Baker et al. (2013), on stock market volatility (see, e.g., Liu and Zhang, 2015, Mei et al., 2018, Bialkowski et al., 2022, Ma et al., 2022). This wide-ranging measure of uncertainty is based on newspaper coverage of policy-related economic uncertainty and other information such as the dispersion between individual forecasters' predictions about the future levels of various macro variables; therefore it is widely used to

Seyhun (1988) takes the view that, if insiders are not certain (or confused) about the source of the mispricing, they are more likely to trade their own firm's stock than index derivatives.

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 documented by many researchers is mainly due to the number of transactions as opposed to their size, measured by volume or value. They argue that it is the occurrence of transactions, and not their size, that generates volatility i.e., the volume, or value, of trades has no information content beyond that contained in the number of transactions. Finally, the use of 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 increases stock market volatility in the short run.

As already mentioned, the theoretical literature has identified two channels through which insider trading can potentially affect volatility – an information effect and one caused by incentives insiders have to increase volatility. While the latter may play an important role, we argue that the channels through which they occur are much less relevant in well-regulated markets such as the UK where stakeholders are relatively better protected. Similarly, the information effect predicts that volatility will initially increase once the information revealed in insiders' trades becomes public, and that this increase will not persist as prices become more informative and volatility starts to fall. Empirical studies examining the relationship between aggregate insider trades and stock market returns suggests that it is the revelation of new economy-wide information in aggregate insider trades that has the potential to affect stock market volatility through the information effect discussed in the theoretical literature. Thus, on the basis of our priors and the extant literature we investigate whether aggregate insider trading affects UK stock market volatility.

Initially, we consider the total number of buy and sell transactions in each month (AIT 1) as our measure of aggregate insider trading activity, i.e.at first, we do not differentiate between buy and sale transactions. This is done to make our results comparable to those of previous studies that have examined the impact of insider trading on stock market volatility, such as Du and Wei (2004).

Hypothesis 2. The impact of aggregate insider purchases on stock market volatility is greater than that of sales.

The literature that examines the information content of insider trades suggests that purchase decisions made by insiders tend to be more informative than sale transactions (see, e.g., Lakonishok and Lee, 2001, Tavakoli et al., 2012, Brochet, 2018, and Bushman et al., 2022). The argument is that, because the insiders' human and financial capital is tied to their firm, there is a strong incentive for them to diversify by selling their shares. Also, many sale transactions are made for liquidity (non-information) reasons – especially when a large part of total renumeration is tied to the share price. Thus, although sales have the potential to be motivated by negative information, they are also prone to being noisy signals that outsiders may find hard to interpret. In contrast, insiders are only likely to make purchase transactions (increase their holdings) when they have positive information, and this may make them 'cleaner' signals that are easier for outsiders to interpret. Thus, on the basis of the findings of this literature one might expect any information (effect) revealed by aggregate insider trades to affect stock market volatility through purchases more than sales – or at least the impact of sales and purchases on volatility to be different.

However, previous studies on the impact of insider trading on stock market volatility (Bhattacharya and Daouk, 2002, and Du and Wei, 2004) have failed to distinguish between buy and sell transactions. If the information revealed through insider trades is an important channel through which volatility is affected, then failing to differentiate between trades that are more likely to be informative from those that are more prone to be noisy will potentially bias the results and underestimate the importance of the information effect since both noisy and informative trades are considered together - because it is assumed that purchases and sales are equally informative. That is the reason why, while in hypothesis 1 we focus on an aggregate insider trading variable (AIT 1) to make our results directly comparable to those of previous studies, in hypothesis 2 we separate buy and sell transactions to better isolate any potential information effects.

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 following:

$$X_t = \alpha + Crisis\ Dummies + \sum_{k=1}^{K} \beta_k X_{t-k} + e_t \qquad (1)$$

where X_t= (FTSE All-Share Volatility, Insider Trading, EPU), X_{t-k} is a corresponding vector of lagged variables, and e_t is a residual vector following a multivariate normal distribution. Various studies (see, e.g., Schwert, 1989, Hamilton and Lin, 1996, and Brandt and Kang, 2004) have documented that the relationship between information and volatility depends on the state of the economy i.e., stock market volatility has a very pronounced business cycle pattern. More recently, Beltratti and Morana (2006) and Chinzara (2011) have shown that the relationship between macroeconomic volatility and stock market volatility is subject to structural breaks during recessions and financial crises. Also, Campbell et al. (2001) find that stock market volatility is higher during recessions. Therefore, unlike previous studies on the relationship between insider trading and stock market volatility that estimate panels (e.g., Du and Wei, 2004) we control for financial crises by constructing dummy variables taking value 1 during the turmoil periods specified below (and 0 otherwise):

(1) The stock market downturn of 2002, which is believed to be part of the larger bear market often referred to as the Internet bubble burst: July 2002 – December 2002
(2) The Global Financial Crisis (GFC): July 2007- January 2009
(3) The Covid-19 pandemic: February 2020 – April 2020.

Akaike and Bayesian information criteria have been used to select the optimal lag length, which turns out to be six in all cases. In order to test the adequacy of the models, Ljung–Box portmanteau tests have also been performed on the standardized residuals and squared residuals. These confirm that the models are data congruent.

In the context of a VAR all variables of interest are endogenously determined; therefore spillover effects can run in either direction, and thus possible reverse causality is taken into account. This is crucial, since volatility may also cause insider trading as shown, for example, by Muelbroek (1992), Du and Wei (2004), and Gider and Westheide (2017). The reason is that insiders may prefer to trade in periods of high volatility, when the impact of their trades is less visible and they are more likely to profit from their trades. Also, as noted above, Liu and Zhang (2015), Mei et al. (2018), Bialkowski et al. (2022), and Ma et al. (2022) have all found that EPU has the potential to affect stock market volatility. Similarly, Li (2020), Cai et al. (2022), and El Ghoul et al. (2022) have reported that EPU may affect insider trading if insiders trade more on the basis of their information during periods of high economic uncertainty. [5] Thus, our VAR specification formally models the interaction between stock market volatility, aggregate insider trading, and economic policy uncertainty in a multiple equation framework. We then carry out Impulse Response analysis and Forecast Error Variance Decomposition to examine the dynamic response of stock market volatility to shocks to aggregate insider trading.

4. Empirical Results

Since all variables have been found to be stationary, the VAR model is estimated in levels. Figures 2a, 2b, and 2c display the impulse responses of stock market volatility (with the corresponding 95% confidence intervals) to a one standard deviation shock to each of our measures of AIT in turn. Specifically, Figure 2a shows the results based on the total number of buy and sell transactions (AIT 1). As can be seen, a shock to total aggregate insider trading (AIT 1) has a positive and significant short-run impact on stock market volatility that peaks within the following two months before declining and then converging towards zero as one would expect in the case of a stationary system. Note that the standard errors are computed by means of 1,000 Monte Carlo simulations.

As previously mentioned, Du and Wei (2004) had found that insider trading increases stock market volatility. They suggest that the reason is that insiders have an incentive to take actions to increase volatility because they profit more from their information in more volatile markets. However, this type of activity is likely to be less prevalent in well-regulated markets such as the UK, as confirmed by the impulse responses in Figure 2a, which are consistent with an information-based explanation of the effect of insider trading on stock market volatility. Specifically, they are in line with the theoretical argument made by Leland (1992)

[5] Li (2020) argues that a higher EPU increases the information advantage of insiders relative to outsiders, and thus insider trading. Specifically, EPU affects a firm's information environment and this, in turn, affects the value of the information to insiders; as a result, insider gains (and therefore trades) increase when EPU is higher.

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 on stock market volatility that last for approximately two months, whilst a similar shock to aggregate sales has virtually no impact, which provides empirical support to hypothesis 2. At first, this finding may seem counterintuitive. However, it is not surprising that the information effect should be different for these two measures. When positive economy-wide information is revealed, there is an increase in volatility that is consistent with Leland's (1992) information-based explanation. One can expect negative economy-wide information, when revealed, to have a significantly negative impact on volatility. However, sales are a noisier signal than purchases, which results in a negative, but insignificant impact of sales on volatility. These findings are consistent with the literature (Chowdhury et al., 1993 and Lakonishok and Lee, 2001) suggesting that the information content of insider sales is smaller than that of purchases. An alternative explanation is that market manipulation by insiders occurs through their purchases rather than sales; the reason is that they are aware that in the latter case market participants would not act on the manipulation as they regard the signal emanating from sales as noisy and therefore difficult to interpret accurately.

We also perform a Forecast Error Variance Decomposition (FEVD) which confirms the IR findings, since both AIT 1 and AIT 2 account for some of the variance of volatility in the following two months whilst AIT 3 is again found not to be significant.

Insert Tables 2 and 3 about here

[6] It should not come as a surprise that markets react to the revelation of aggregate insider trading information given the media attention this has received (see, e.g., Suria, 2022, Washington Service Research Team, 2022, 2023, Wang, 2022, and Guru Focus, 2023).

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:

$$Standardised\ AIT_{i,t} = \sum_{i=1}^{I} \frac{(AIT_{i,t} - \overline{AIT_{i}})}{s(AIT_{i})}, \qquad (2)$$

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

$$\overline{AIT_i} = \sum_{t=1}^{228} AIT_{i,t}/228, \tag{3}$$

and

$$s(AIT_i) = \left[\sum_{i=1}^{228} (AIT_{i,t} - \overline{AIT_i})^2/227\right]^{1/2}. \tag{4}$$

The method outlined above is initially applied to the total number of transactions (AIT 1) and then separately to purchases (AIT 2) and sales (AIT 3).

This set of results is presented in Figures 4a. – 4c. As can be seen, they are again consistent with the previous ones in that the positive impact on volatility is mainly due to standardised aggregate insider purchases (AIT2).

Insert Figures 4a-4c about here

As further robustness checks, we repeat the analysis using weekly data and also the aggregate number of shares traded rather than total transactions (these results are not reported but are available upon request). Both sets of estimates confirm the presence of a positive and significant short-run impact of AIT on volatility.

6. Conclusions

Previous empirical studies have analysed a wide range of factors that can drive stock market volatility (see, e.g., Konrad, 2009, Baker and Wurgler, 2007, and Lee and Mauck, 2016). However, only a few of them have focused on the possible role of insider trading (see, e.g., Bhattacharya and Daouk, 2002, and Du and Wei, 2004). Whilst the theoretical literature has identified two potential channels through which this can affect stock market volatility, the relevant empirical evidence is rather mixed. This paper examines the effects of aggregate insider trading by UK company directors on stock market volatility using monthly data covering the period from January 2002 to December 2020; in particular, a VAR model is estimated and Impulse Response analysis as well as Forecast Error Variance Decomposition are carried out. Our investigation improves upon earlier ones by using direct measures of AIT (as opposed to proxies) in the specific case of a well-regulated market such as the UK as well 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 mainly reflects purchases (which supports our hypothesis 2); these findings can be attributed to a combination of insiders manipulating the timing and content of the information they release and the revelation of new economy-wide information to the market. Although we cannot distinguish between these two channels, the explanation provided is consistent with the theoretical literature. Furthermore, we suggest that in a well-regulated market such as the UK the main driver of the observed increase in volatility is likely to be the information effect.

Our finding that insider trading increases stock market volatility in the short run is consistent with those of Bhattacharya and Daouk (2002) and Du and Wei (2004); however, our analysis is more informative about any possible information effects because our aggregate insider trading variable is more suitable for detecting the possible revelation of economy-wide information than any perception-based measure. Furthermore, distinguishing between purchases and sales enables us to capture more accurately the trades that are likely to be the main drivers of volatility. Finally, our results are shown to be robust to using alternative (direct) measures of aggregate insider trading.

Future work could examine the exact channels through which aggregate insider trading drives up stock market volatility, and also investigate whether the observed increase is due to the revelation of new economy-wide information or to market manipulation by insiders. Both of these issues have important implications for policy makers as well as investors.

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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	558.22	-6.548	-4.932

Notes: S.D. stands for standard deviation. AIT 1 is the total number of insider transactions per month. AIT 2 is the total number of insider purchases per month. AIT 3 is the total number of insider sales per month. ADF and PP stand for Augmented Dickey Fuller and Phillips-Perron unit root tests. Critical values at 1%, 5% and 10% are -3.459, -2.874 and -2.573, respectively. The sample size covers the period January 2002 - December 2020, for a total of 228 observations.

Table 2: Forecast Error Variance Decomposition – AIT 1

	Volatility		AIT 1		EPU	
Volatility_{t-1}	**0.95**	(2.25)	0.01	(1.36)	0.01	(0.82)
Volatility_{t-2}	**0.95**	(2.46)	0.01	(1.33)	0.01	(0.95)
$\text{AIT } 1_{t-1}$	**0.04**	(2.01)	0.98	(1.55)	0.03	(1.01)
$\text{AIT } 1_{t-2}$	**0.03**	(1.97)	0.98	(1.65)	0.02	(1.14)
EPU_{t-1}	0.01	(1.01)	0.01	(0.78)	**0.96**	(2.87)
EPU_{t-2}	0.02	(1.54)	0.01	(1.06)	**0.97**	(2.24)

VAR Lag Length and Residual Diagnostic Tests

Log Lik.	-566.23		
AIC	26.18		
SBC	27.42		
$\text{LB}_{(5)}$	3.68	4.02	6.32
$\text{LB2}_{(5)}$	6.97	7.45	6.89

Notes: T-ratios are reported in brackets. $\text{LB}_{(5)}$ and $\text{LB2}_{(5)}$ are the Ljung and Box (1978) tests of no autocorrelations with 5 lags in the standardized residuals and squared residuals, respectively. AIT 1 is the total number of buy and sells transactions. AIC and SBC are the Akaike and Bayesian information criteria, Standard errors are computed by means of 1,000 Monte Carlo simulations. Parameters significant at the conventional 95% are reported in bold.

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

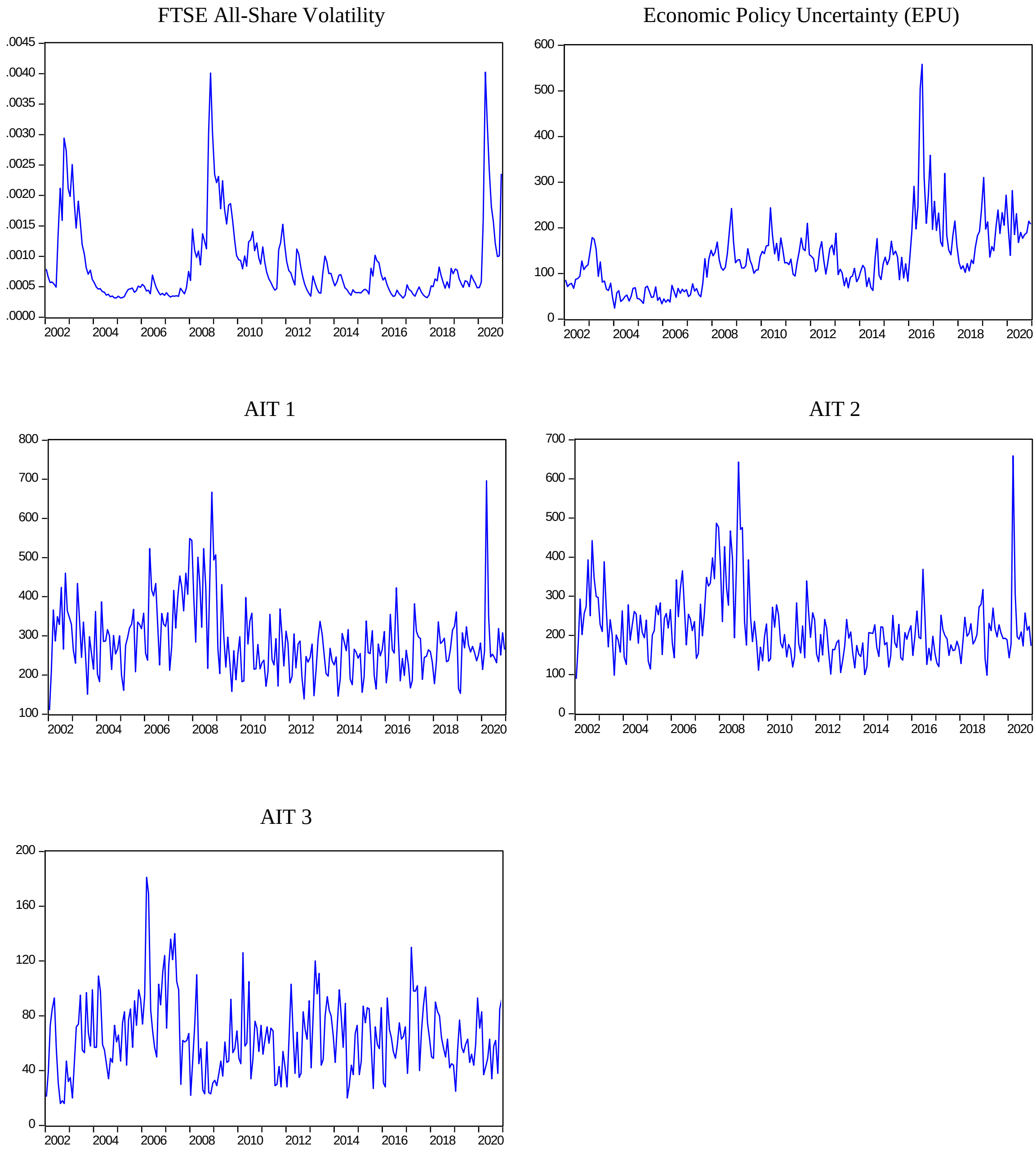
	Volatility		AIT 2		AIT 3		EPU	
Volatility_{t-1}	**0.91**	(3.06)	0.02	(1.37)	0.01	(1.11)	0.01	(1.11)
Volatility_{t-2}	**0.90**	(4.11)	0.02	(1.49)	0.01	(1.44)	0.01	(1.09)
$\text{AIT } 2_{t-1}$	**0.08**	(2.93)	**0.95**	(3.17)	0.01	(1.51)	0.01	(1.21)
$\text{AIT } 2_{t-2}$	**0.08**	(3.37)	**0.95**	(3.43)	0.05	(1.71)	0.01	(0.82)
$\text{AIT } 3_{t-1}$	0.01	(0.69)	0.01	(0.64)	**0.97**	(2.23)	0.03	(1.38)
$\text{AIT } 3_{t-2}$	0.01	(1.63)	0.01	(1.15)	**0.91**	(4.43)	0.04	(1.13)
EPU_{t-1}	0.01	(0.43)	0.01	(1.13)	0.01	(0.56)	**0.85**	(4.84)
EPU_{t-2}	0.01	(0.96)	0.01	(1.51)	0.01	(1.27)	**0.82**	(5.78)

VAR Lag Length and Residual Diagnostic Tests

Log Lik.	-557.37			
AIC	35.77			
SBC	36.38			
$\text{LB}_{(5)}$	4.35	3.56	5.34	4.02
$\text{LB2}_{(5)}$	6.11	7.23	7.25	6.98

Notes: T-ratios are reported in brackets. $\text{LB}_{(5)}$ and $\text{LB2}_{(5)}$ are the Ljung and Box (1978) tests of no autocorrelations with 5 lags in the standardized residuals and squared residuals, respectively. AIT 2 and AIT 3 are the aggregate insider purchases and sales, respectively. AIC and SBC are the Akaike and Bayesian information criteria. Standard errors are computed by means of 1,000 Monte Carlo simulations. Parameters significant at the conventional 95% are reported in bold.

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 2a: IR of Volatility to AIT 1

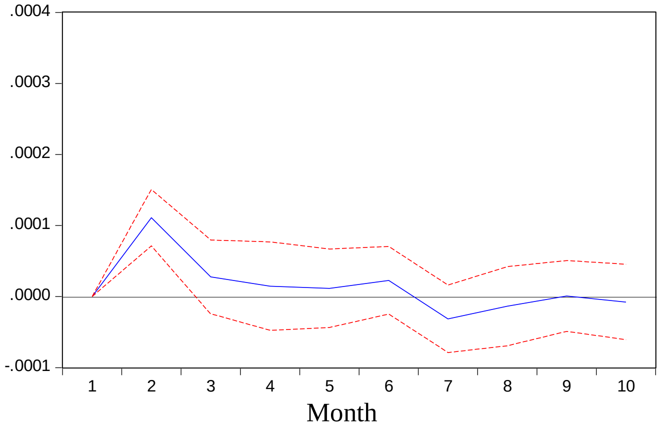


Figure 2b: IR of Volatility to AIT 2

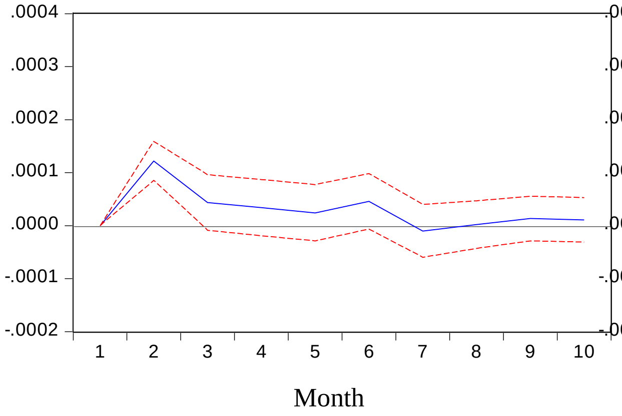
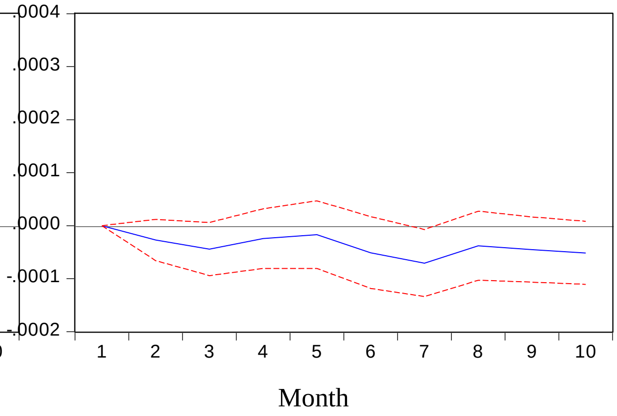


Figure 2c: IR of Volatility to AIT 3



Notes: The dotted blue line is the impulse response (IR), whilst the red dotted lines are the 95% confidence bands. AIT 1 is the total number of buy and sell transactions. AIT 2 and AIT 3 are the aggregate insider purchases and sales, respectively. Standard errors are computed by means of 1,000 Monte Carlo simulations.

Figure 3a: IR of Volatility to AIT 1

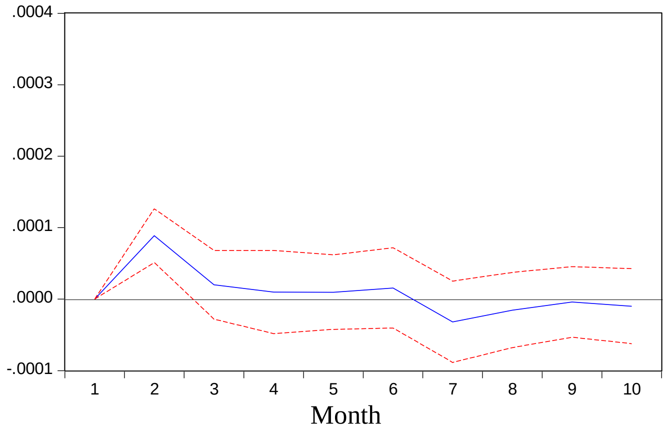


Figure 3b: IR of Volatility to AIT 2

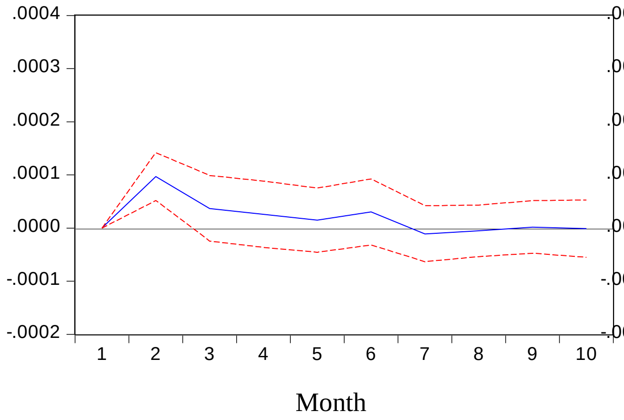
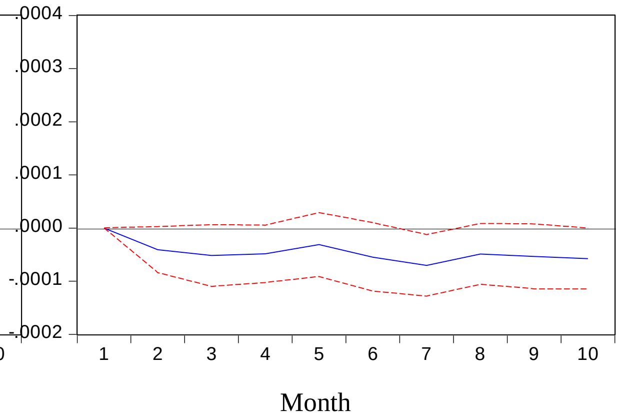


Figure 3c: IR of Volatility to AIT 3



Notes: The dotted blue line is the impulse response (IR), whilst the red dotted lines are the 95% confidence bands. AIT 1 is the log of the total number of buy and sell transactions. AIT 2 and AIT 3 are the log aggregate insider purchases and sales, respectively. Standard errors are computed by means of 1,000 Monte Carlo simulations.

Figure 4a: IR of Volatility to AIT 1

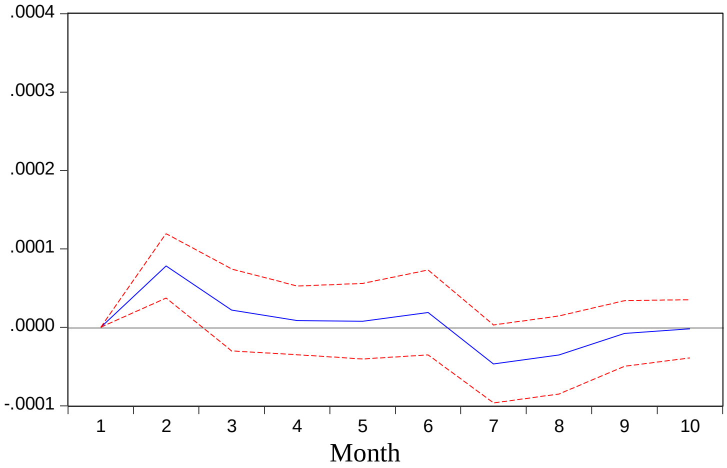


Figure 4b: IR of Volatility to AIT 2

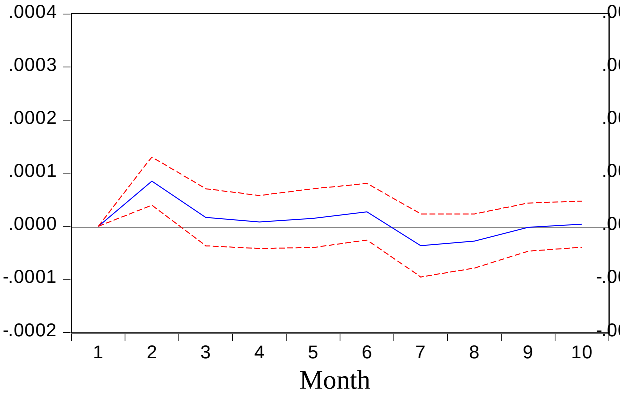
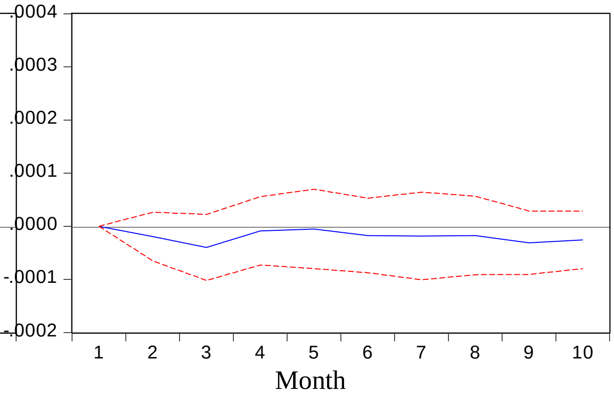


Figure 4c: IR of Volatility to AIT 3



Notes: The dotted blue line is the impulse response (IR), whilst the red dotted lines are the 95% confidence bands. AIT 1 is the standardized total number of buy and sell transactions, as per Eq. 2-4. AIT 2 and AIT 3 are the standardized aggregate insider purchases and sales, respectively. Standard errors are computed by means of 1,000 Monte Carlo simulations.