J. Int. Financ. Markets Inst. Money 89 (2023) 101861

Contents lists available at ScienceDirect

Journal of International Financial Markets, Institutions & Money

journal homepage: www.elsevier.com/locate/intfin

Aggregate insider trading and stock market volatility in the UK

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ARTICLE INFO

Keywords:
Aggregate insider trading
Stock market volatility
VAR
Impulse responses

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 is 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.

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 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), since 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.

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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.

https://doi.org/10.1016/j.intfin.2023.101861
Received 5 August 2023; Accepted 10 October 2023
Available online 11 October 2023
1042-4431/

Moreover, they also have an incentive to increase volatility by, for example, selecting a more volatile production process (Bebchuk & 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). As a result, 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 others, Du and Wei (2004), and Cumming et al. (2011), in well-regulated, transparent 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 (2019), Malliouris et al. (2020), and Bushman et al. (2022). This literature provides evidence to suggest 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 it 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

This section reviews both (a) studies that have examined the impact of insider trading on stock market volatility, and (b) studies on the relationship between aggregate insider trading and stock market returns. The final subsection sums up the two preceding ones and relates the studies of these two related areas to the central arguments of the present one. For the convenience of the reader, we have also summarised the most relevant studies in both of these areas in Table 1.

2.1. Insider trading and stock market volatility

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 countries. 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

[2] Gangopadhyay Yook and Shin (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.

Table 1
Summary of the literature.

Panel A: Summary of studies on the impact of insider trading on stock market volatility			
Authors	*Sample*	*Volatility Measure*	*Main Results*
Bhattacharya & Daouk (2002)	103 countries	Standard deviation of monthly stock index returns	Average volatility across the panel of countries examined increases slightly in the five years after the introduction of insider trading laws and the first prosecution, relative to the five years before.
Du and Wei (2004)	Cross-section of 53 countries	Standard deviation of monthly stock index returns	(1) Negative, but insignificant, relationship between stock market volatility and both (i) the time a country has had an insider trading law and (ii) time since the first prosecution. (2) Countries with more prevalent insider trading - proxied by a perception-based measure constructed from a survey of corporate officers in each country - have more volatile stock markets.
Gilbert et al. (2007)	Panel of 85 companies listed on the New Zealand Stock Exchange (1996–2004)	Variance of individual firm's monthly returns	A significant decrease in mean volatility after the introduction of the Security Market Amendment Act in New Zealand in 2002.
Cumming et al. (2011)	Panel of 42 countries (2006–2008)	Average annualised monthly variance of returns of all companies that make up each country's main index	Average volatility is significantly lower for stock exchanges with more detailed insider trading rules.
Palan & Stockl (2017)	Laboratory experiment employing 384 undergraduates and graduates at the University of Innsbruck (2013)	Standard deviation of log returns	Volatility is unaffected by insider trading legislation.
Panel B: Summary of studies of the relationship between aggregate insider trading (AIT) and the predictability of future stock market returns			
Authors	*Sample*	*Data frequency*	*Main Results*
Seyhun (1988)	US insider trades (1975–1981)	Monthly	Positive and significant relationship between current monthly AIT and market returns during the subsequent two months. Suggests this may be because insiders see the effect of unanticipated changes in economy-wide activity two months before other market participants.
Seyhun (1992)	US insider trades (1975–1989)	Monthly	Confirms Seyhun (1988) by finding a positive and significant relationship between past AIT and future stock market returns. Provides evidence to suggest that the predictive ability of AIT is partly due to its ability to forecast future economy-wide information.
Chowdhury et al. (1993)	US insider trades (1975–1986)	Weekly	Stock market returns are dependent on lagged (eight weeks) aggregate insider purchases (AIPs) but not sales (AISs). Evidence that AIPs have more information content than AISs.
Lakonishok & Lee (2001)	US insider trades (1975–1995)	Monthly	At the aggregate level, insiders are better at predicting stock market returns than simple contrarian investors i.e., AIT contains new information about future economy-wide activity. The predictive power improves for longer horizons.
Iqbal & Shetty (2002)	US insider trades (1988–1998)	Monthly	Positive, but weak, relation between AIT and subsequent stock market returns.
Jiang & Zaman (2010)	US insider trades (1975–2000)	Quarterly	Predictive ability of AIT is strong, because of their ability to predict unexpected changes in economy-wide factors, as opposed to simple contrarian investors.
Brochet (2019)	32 countries (2004–2012)	Quarterly	Insider purchases, aggregated by country and calendar quarter. are on average positively related to next country quarter's stock market return i.e., on average, across countries, insiders' trade on the expected effect of market-wide events on their firm.
Malliouris et al. (2020)	32 countries (2003–2017)	Monthly	Only insiders in the US, Asia, China, Hong Kong, and India are able predict future stock market returns, possibly because they trade based on economy-wide information. A positive, but weaker, association exists for Switzerland, Malaysia, Poland, Sweden, Philippines, and Singapore.

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, and Cumming et al., 2011). 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.

2.2. Aggregate insider trading and stock market returns

To date, the literature on aggregate insider trading has focused 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 (2019), Mallliouris 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]

2.3. Summary

Theory suggests that the net effect of insider trading on volatility depends on the interaction between an information effect and the ability of insiders to increase volatility, for example by manipulating markets. The empirical literature on the impact of insider trading on stock market volatility (summarised in Table 1, Panel A) has taken two distinct approaches and produced mixed results. First, it has examined the impact of insider trading regulations, and enforcement, on volatility before and after their introduction. The present study instead models the relationship in a time-series framework that allows these effects to change over time (see Section 3). Second, to the best of our knowledge, to date only Du and Wei (2004) examine this relationship directly by using a measure of insider trading intensity. One drawback of their approach is that it may not measure accurately the actual degree of insider trading in a country as it is perception-based, and systematic bias may be introduced into the survey question since corporate officers are simply asked how common they 'feel' insider trading is in their own country. Therefore, as Du and Wei (2004) recognise, theirs is an imperfect proxy. Furthermore, their conclusion that countries with more insider trading have higher stock market volatility applies to the entire panel of countries they examine and not to individual ones. As Du and Wei (2004) and Cumming et al. (2011) suggest, the level of regulation in a country may affect the relationship. Specifically, in less permissive environments, such as the UK, the ability of insiders to take actions that increase volatility is likely to be restricted. Therefore, differentiating between regulatory environments may be more informative about the net effect of insider trading on volatility.

The advantage of focusing on a single, well-regulated country such as the UK is that we can control for differences in regulation and therefore better isolate (or bring into prominence) any possible information effect. This is the reason why we choose to examine this relationship in the UK, where the information effect is likely to be more prominent than in less regulated countries. Furthermore, we construct a more direct measure of actual, reported, aggregate insider trading, which does not suffer from the same issues as survey-based ones, and use it to examine the relationship over time as opposed to a single point in time.

A second strand of literature that is relevant to the present study is that on aggregate insider trading and returns (summarised in Table 1, Panel B), which identifies a potential source of the information effect highlighted by the theoretical literature. The latter suggests that there should be a short-run increase in volatility resulting from the information effect of insider trading, followed by a decrease as prices become more informative. The consensus view of the studies that have examined the relationship between aggregate insider trading and stock market returns is that, at the aggregate level, insider trades are able to predict stock market returns. The explanation given is that insiders observe macro-signals – such as order flows - in advance of this information being made public. Thus, at the aggregate level, insider trades have the potential to predict economy-wide information. Therefore, in order to allow for the possibility that, at the aggregate level, insider trades may reveal market-wide information it is necessary to construct an AIT variable in a similar way to the literature on AIT and returns (see Section 3). To the best of our knowledge, ours is the first study to consider

[3] An excellent discussion of why insiders may have a macro-information advantage relative to other market participants can be found in Mal-liouris 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, 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.

directly the possibility that the revelation of economy-wide information to the market may affect stock market volatility. Examining a well-regulated country such as the UK rather than many dissimilar ones allows us to isolate more precisely this effect. Furthermore, constructing the AIT variable as we do allows us to differentiate between purchase and sale transactions, since the literature suggests that the former may be more informative (see, e.g., Lakonishok and Lee, 2001, Tavakoli et al., 2012, Brochet, 2018, and Bushman et al., 2022). This is crucial when examining any possible informational effect of aggregate insider trading on stock market volatility.

To sum up, relative to the existing literature this study sheds new light on the relationship between insider trading and stock market volatility. To date, most papers have focused on the relationship between aggregate insider trading and returns. The consensus view is that aggregate insider trading may contain information on economy-wide factors. The theoretical literature that examines the mechanisms by which insider trading may affect volatility identifies an information effect that increases volatility once it is revealed but is not persistent, since it declines as prices become more informative. We suggest that AIT may affect stock market volatility through this information effect. Specifically, the revelation of economy-wide information in aggregate insider trades is a factor potentially driving stock market volatility. To the best of our knowledge, ours is the first study to apply the aggregate insider trading variable to examining the relationship between insider trading and volatility.

Further, while Du and Wei (2004) analyse this relationship indirectly through a proxy for insider trading intensity, we are the first to use actual, reported, insider trading data to construct our AIT variable. One advantage of using such data, as opposed to an imperfect proxy, is that this avoids the systematic biases inherent in survey-based data and captures more directly the variable of interest than a perception-based measure. Moreover, unlike Du and Wei (2004), who examine this relationship at one point of time, we introduce the time dimension into the analysis and thus are able to examine changes over time.

Finally, as previously mentioned, we choose to focus on the UK market, namely a single, well-regulated, and transparent one where the ability of insiders to undertake activities that increase volatility is limited. This enables us to obtain clearer evidence on the informational impact of insider trading on volatility.

3. Data and empirical methodology

The discussion in the previous section suggests that any possible informational impact of aggregate insider trading on stock market volatility may be relatively more prominent in well-regulated markets, such as the UK and US, because activities such as market manipulation by insiders are less likely to occur since investors are better protected and penalties are higher. While both the UK and US are relatively well-regulated, Fidrmuc et al. (2006) provides evidence indicating that there are significant differences between regulations and enforcement between these two countries such that UK director's trades may be more informative. Specifically, whilst directors in the UK cannot trade in the two months prior to an earnings announcement, there are no such restrictions in the US. This leads Fidrmuc et al. (2006) to conclude that regulations are stricter in the UK. Furthermore, they find that the speed with which insider trades are reported to market participants is much faster in the UK than in the US, and thus insider trades are more informative in the former than in the latter. Finally, Conyon and Murphy (2000) and Edmans et al. (2017) report that, because CEO pay in the US is much more strongly related to performance, US CEOs are much more likely to sell shares to realise an income (liquidity need) or to diversify than their UK counterparts. Thus, UK director trades may be more informative than those in the US.

In brief, while both the US and UK can be regarded as well-regulated countries, there exist significant differences between the two implying that UK director trades may be more informative. Therefore, since one of the aims of the current study is to analyse how the information revealed in aggregate insider trades affects volatility, we focus on the UK. Furthermore, as highlighted in Table 1, Panel B. the majority of studies that have used the AIT variable to examine its relationship with stock market returns concern the US. To the best of our knowledge, the present one is the first single-country study to date to examine the impact of aggregate UK directors trading on stock market volatility.

Monthly data on UK corporate directors' trading over the period from January 2002 to December 2020 (a total of 228 months) are gathered from the Smart Insider Quantitative Data Delivery file. The 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 via 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 index 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 capture investor sentiment reflecting the main factors that could affect stock market volatility; for this reason, it is included in the 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. 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, which is the benchmark model generally used in the literature.

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 before mentioned 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).

Table 2 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. Fig. 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, leads us to examine 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 impact 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. The literature that examines 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 assumes 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 effect.

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. Our model selection reflects general practice in this literature, which makes our

Table 2
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.

results comparable to previous ones, and is guided by the parsimoniousness criterion – namely, we follow the same modelling approach as previously done for the FTSE volatility, when a benchmark GARCH (1, 1) specification was chosen. Since in both cases all the diagnostics confirm that the estimated models are data congruent, we do not consider alternative specifications. Therefore, the baseline VAR model we estimate is the following:

$$X_t = \alpha + CrisisDummies + \sum_{k=1}^{K} \beta_k X_{t-k} + e_t \tag{1}$$

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 following episodes, 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 bursting: July 2002 – December 2002
(2) The Global Financial Crisis: July 2007- January 2009
(3) The 2020 (Covid-19 pandemic) crash – February 2020 – April 2020.

Akaike and Bayesian information criteria have been employed to determine the conditional mean equations lag lengths. The number of selected lags was equal to six for all specifications. In order to test the adequacy of the models, Ljung– Box portmanteau tests were performed on standardized residuals and standardized squared residuals. The latter confirm that the model is 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 (2016). 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 in the aggregate insider trading variable.

There are numerous advantages to using our constructed AIT variable to examine the relationship between aggregate insider trading and volatility. Most previous studies in this area have examined indirectly the effect that insider trading has on volatility by measuring the latter before and after the introduction of new regulations. While this sheds light on the effect that regulating insider trading has on volatility, it is not directly informative about its relationship with actual reported insider trades. In contrast to the present study, Du and Wei (2004) construct a proxy of insider trading intensity and, in a cross-sectional study of 44 countries, examine its relationship with stock market volatility. As they acknowledge, a potential drawback of constructing their insider trading variable using survey data is that it is a perception-based measure that is susceptible to systematic biases. We overcome this limitation by employing actual, reported, insider trading data when constructing our aggregate insider trading variable rather than using an

[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.

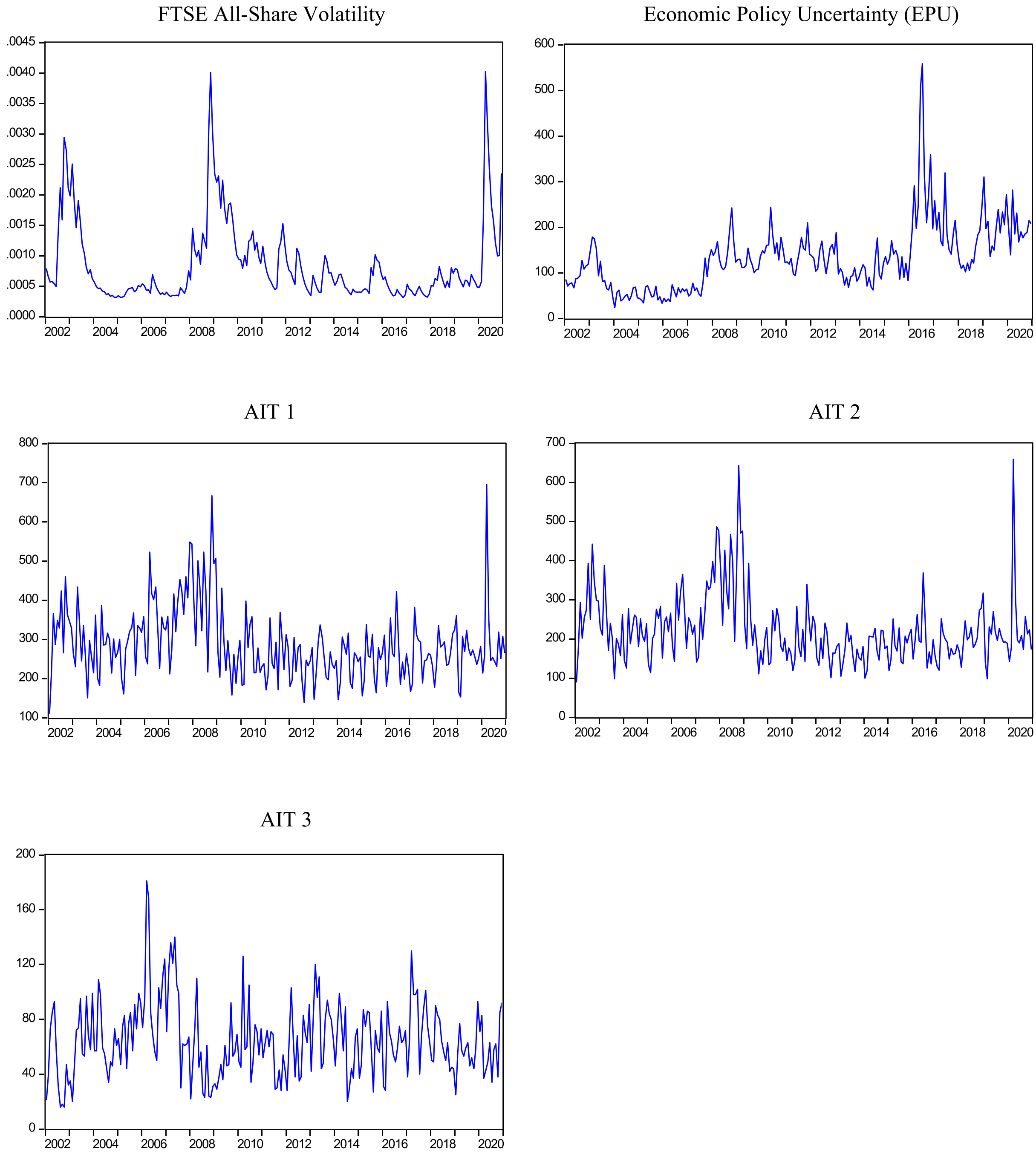

Fig. 1. FTSE volatility, aggregate insider trading and EPU. Notes: FTSE All-Share monthly returns are calculated as the log difference of consecutive end of the month prices, whereas their volatility is modelled as a standard GARCH (1,1) process. AIT 1 is the total number of buy and sells transactions.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

imperfect proxy. Thus, we are able to examine directly the relationship between actual insider trading and stock market volatility as opposed to inferring it or using a proxy to measure insider trading intensity. A further advantage of constructing our AIT variable in the way described above is that, unlike Du and Wei (2004), who examine the relationship at one point in time, we can investigate its evolution over time – specifically over the period 2002–2020. In addition, we are able to test the possibility suggested in the theoretical literature that insiders trade increases when volatility is high, i.e. that the latter can cause the former. Furthermore, as discussed below, introducing the time dimension into the analysis allows us to model the impact that business cycles may have on the relationship between information and volatility.

Another benefit associated with constructing the AIT variable by aggregating insider trades every month is that is that this cancels out firm-specific components of insider's trades, thus re-enforcing the common response to economy-wide factors. The empirical literature that has examined the relationship between aggregate insider trading and returns has established that, at the aggregate level, insider trades may bring new information regarding economy-wide factors. Thus, a further gain from constructing our insider trading variable is that we are better able to examine any potential effect the revelation of economy-wide information may have on stock market volatility. To the best of our knowledge, this is the first study to do this. Finally, using actual insider trading data to construct the AIT variable allows us to distinguish between purchase and sale transactions. We would argue that this is crucial, since purchases are likely to be more informative than sales.

4. Empirical results

Since all variables have been found to be stationary, the VAR model is estimated in levels. Figs. 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, Fig. 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. 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 Fig. 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) 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.

Figs. 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; Lakonishok and Lee, 2001)) that suggests that the information content of insider sales is smaller than that of purchases. An alternative explanation for them 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 – see Tables 3 and 4) which confirms the IR findings; in particular, AIT 1 and AIT 2 contribute to the following two months volatility prediction, whereas AIT 3 is confirmed to be not significant.

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. Figs. 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.

Fig. 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 effect on stock market volatility that lasts for approximately two months. Figs. 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 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

[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).

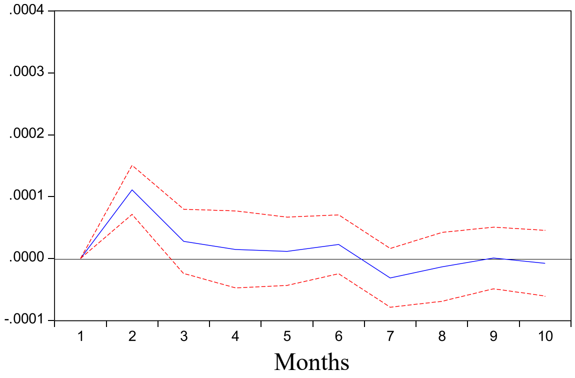

Fig. 2a. IR of volatility to AIT 1. Notes: The dotted blue line is the impulse response (IR), whilst the red dotted lines are the 95% confidence bands. AIT 1 is the total number of buy and sells transactions. AIT 2 and AIT 3 are the aggregate insider purchases and sales, respectively. Standard errors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

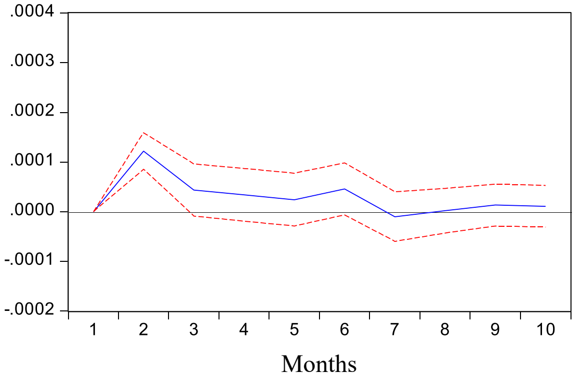

Fig. 2b. IR of volatility to AIT 2. Notes: The dotted blue line is the impulse response (IR), whilst the red dotted lines are the 95% confidence bands. AIT 1 is the total number of buy and sells transactions. AIT 2 and AIT 3 are the aggregate insider purchases and sales, respectively. Standard errors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

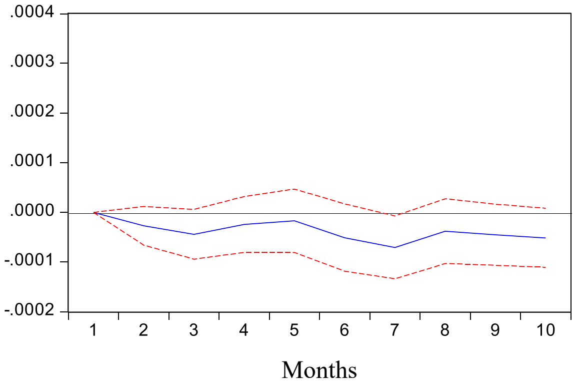

Fig. 2c. IR of volatility to AIT 3. Notes: The dotted blue line is the impulse response (IR), whilst the red dotted lines are the 95% confidence bands. AIT 1 is the total number of buy and sells transactions. AIT 2 and AIT 3 are the aggregate insider purchases and sales, respectively. Standard errors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

Table 3
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)
$AIT\ 1_{t-1}$	**0.04**	(2.01)	0.98	(1.55)	0.03	(1.01)
$AIT\ 1_{t-2}$	**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					
$LB_{(5)}$	3.68		4.02		6.32	
$LB2_{(5)}$	6.97		7.45		6.89	

Notes: T-ratios are reported in brackets. $LB_{(5)}$ and $LB2_{(5)}$ are the Ljung and Box (1978) tests of no autocorrelations of 5 lags in the standardized and standardized 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 4
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)	**0.95**	(3.17)	0.01	(1.51)	0.01	(1.21)
$AIT\ 2_{t-2}$	**0.08**	(3.37)	**0.95**	(3.43)	0.05	(1.71)	0.01	(0.82)
$AIT\ 3_{t-1}$	0.01	(0.69)	0.01	(0.64)	**0.97**	(2.23)	0.03	(1.38)
$AIT\ 3_{t-2}$	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							
$LB_{(5)}$	4.35		3.56		5.34		4.02	
$LB2_{(5)}$	6.11		7.23		7.25		6.98	

Notes: T-ratios are reported in brackets. $LB_{(5)}$ and $LB2_{(5)}$ are the Ljung and Box (1978) tests of no autocorrelations of 5 lags in the standardized and standardized 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.

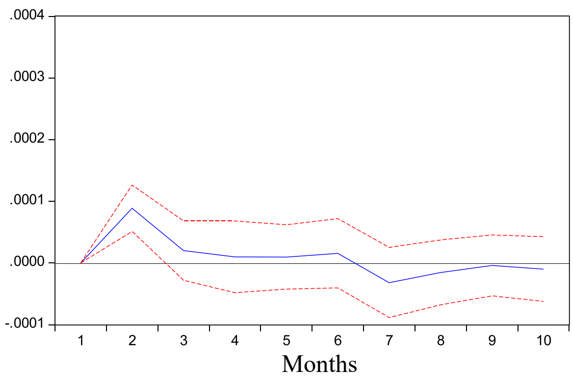

Fig. 3a. IR of volatility to AIT 1. Notes: The dotted blue line is the impulse response (IR), whilst the red dotted lines are the 95% confidence bands. AIT 1 is the log of the total number of buy and sells transactions. AIT 2 and AIT 3 are the log aggregate insider purchases and sales, respectively.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

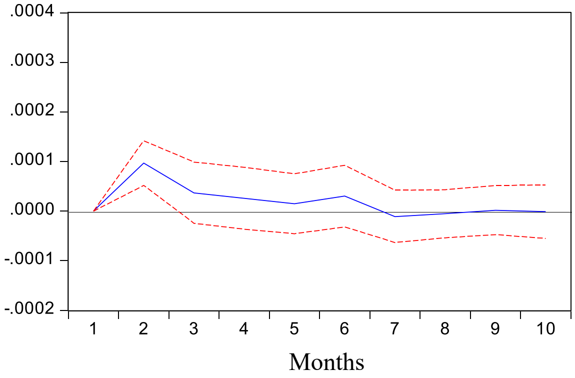

Fig. 3b. IR of volatility to AIT 2. Notes: The dotted blue line is the impulse response (IR), whilst the red dotted lines are the 95% confidence bands. AIT 1 is the log of the total number of buy and sells transactions. AIT 2 and AIT 3 are the log aggregate insider purchases and sales, respectively.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

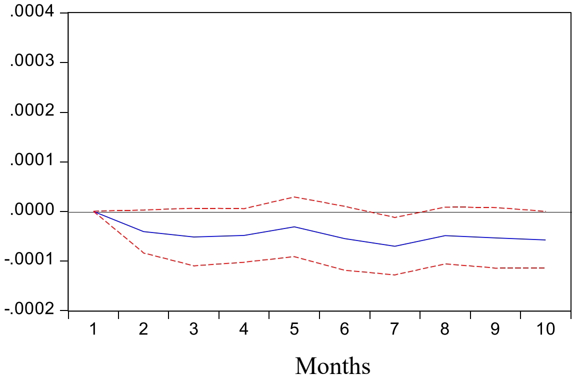

Fig. 3c. IR of volatility to AIT 3. Notes: The dotted blue line is the impulse response (IR), whilst the red dotted lines are the 95% confidence bands. AIT 1 is the log of the total number of buy and sells transactions. AIT 2 and AIT 3 are the log aggregate insider purchases and sales, respectively.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

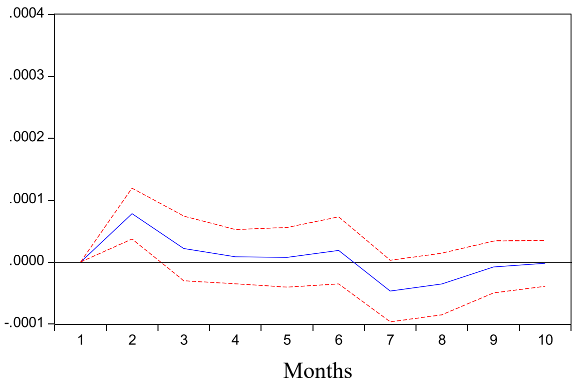

Fig. 4a. IR of volatility to AIT 1. Notes: The dotted blue line is the impulse response (IR), whilst the red dotted lines are the 95% confidence bands. AIT 1 is the standardized total number of buy and sells transactions, as per Eq. 2-4. AIT 2 and AIT 3 are the standardized aggregate insider purchases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

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:

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

where t = 1,228, from January 2002 to December 2020 and *I* equals 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 Figs. 4a – 4c. As can be seen, they are again consistent with the previous ones in that the positive impact on volatility is due mainly to standardised AIT 2, aggregate insider purchases.

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 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, relatively limited evidence is available 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 is carried out. Similarly to some previous studies in this area of the literature (e.g., Bhattacharya and Daouk, 2002, and Du and Wei, 2004), we also find that higher volatility is associated with more insider trading. However, our investigation provides additional insights and improves upon earlier studies 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. First, unlike Du and Wei (2004), by examining a single, well-regulated country we are able to minimise the potential impact of factors that may increase volatility such as market manipulation and in this way can detect any potential information effect on volatility. Second, and more importantly, the way in which we have constructed our AIT variable enables us to establish the nature of the information that may be affecting volatility – namely, the possible revelation of economy-wide information by aggregate insider trades. By choosing to use actual, reported insider trades – as opposed to the perception-based measure employed by Du and Wei (2004) – we are able to distinguish between purchase and sale transactions. This is crucial because the literature in this area suggests that those are not equally informative – since sales by insiders are more likely to be motivated, for instance, by (noise) liquidity and diversification reasons, they may not be informative as they may simply reflect the need to obtain cash from the stocks held by insiders. We find that the increase in volatility is potentially being driven by the revelation

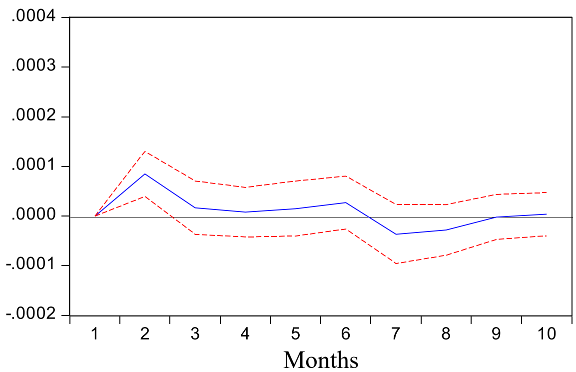

Fig. 4b. IR of volatility to AIT 2. Notes: The dotted blue line is the impulse response (IR), whilst the red dotted lines are the 95% confidence bands. AIT 1 is the standardized total number of buy and sells transactions, as per Eq. 2-4. AIT 2 and AIT 3 are the standardized aggregate insider purchases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

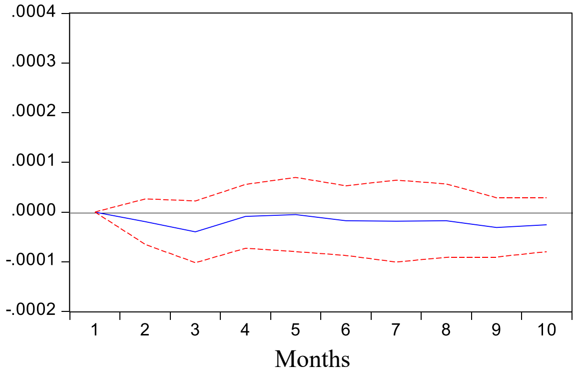

Fig. 4c. IR of volatility to AIT 3. Notes: The dotted blue line is the impulse response (IR), whilst the red dotted lines are the 95% confidence bands. AIT 1 is the standardized total number of buy and sells transactions, as per Eq. 2-4. AIT 2 and AIT 3 are the standardized aggregate insider purchases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

of economy-wide information and that this is largely driven by insider purchases. Finally, because we examine the relationship over time, we are able to establish that there is only a short-run increase in volatility, as one should expect according to the theoretical literature. The reason is that insider trades reveal economy-wide information to the market; however, this effect should not persist if they bring this price-relevant information to the market faster than if they were not allowed, thus making prices more informative.

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 hypothesis 1), and that this effect mainly reflects purchases (which supports 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. As first mentioned by Seyhun (1988), aggregating all insider transactions in a given month has the advantage of cancelling out the idiosyncratic component of insider trades, with the resulting measure re-enforcing their common response to economy-wide factors. Furthermore, distinguishing between purchases and sales enables us to capture more accurately the information motivated 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.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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