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How Do Verified Emissions Announcements Affect the Comoves between Trading Behaviors and Carbon Prices? Evidence from EU ETS

Jianfeng Guo ^{1,2}, Bin Su ³ , Guang Yang ⁴, Lianyong Feng ⁴, Yinpeng Liu ^{1,2} and Fu Gu ^{5,6,*} 

¹ Institutes of Science and Development, Chinese Academy of Sciences, Beijing 100190, China; guojf@casipm.ac.cn (J.G.); liuyinpeng@casisd.cn (Y.L.)

² School of Public Policy and Management, University of Chinese Academy of Sciences, Beijing 100049, China

³ Energy Studies Institute, National University of Singapore, Singapore 119620, Singapore; subin@nus.edu.sg

⁴ School of Business Administration, China University of Petroleum-Beijing, Beijing 102249, China; iammryang@126.com (G.Y.); fenglyenergy@163.com (L.F.)

⁵ Department of Industrial and System Engineering, Zhejiang University, Hangzhou 310027, China

⁶ National Institute of Innovation Management, Zhejiang University, Hangzhou 310027, China

* Correspondence: gufu@zju.edu.cn

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Abstract: Verified emissions announcements are the most influential events in the European Union emissions trading scheme (EU ETS); they reveal demand information and have a significant impact on the carbon market. The extant literature tends to focus on examining the impacts of these verification events on the prices of carbon allowances, while scholars barely discuss how trading behaviors react to the announcements. Moreover, most of the studies are carried out from a macroeconomic perspective. This paper fills this gap by analyzing the impacts of the verified emissions announcements on the comoves of trading behaviors and carbon prices in Phase I (2005–2007) and Phase II (2008–2012). Specifically, we construct GARCH models to investigate the events' heterogeneous influences in different periods, i.e., the complete periods, the announcement periods, the pre- and post-announcement periods. We observe that the verified emissions announcements boost the volume of compliance trading, particularly in Phase I. Furthermore, we show that the over-allocation of carbon allowances can be even more influential in disturbing the comoves than the verification events. Our microeconomic findings confirm the maturity of EU ETS in Phase II, exhibiting good agreement with the extant macroeconomic literature.

Keywords: European Union emissions trading scheme; carbon allowance; carbon price; verified emissions announcement; micro-behavior

1. Introduction

Emissions trading schemes for CO₂ have been established across the globe in response to the commitment to an 8% reduction in greenhouse gases (GHG) in the Kyoto Protocol [1,2]: the European Union Emission Trading Scheme (EU ETS) in Europe [3], the Regional Greenhouse Gas Initiative in the United States [4], the New South Wales Greenhouse Gas Abatement Scheme in Australia [5], Pilot Carbon Trading Markets in selected provinces and cities in China [6–8], and the Korean Emissions Trading Scheme in the Republic of Korea [9]. Since new emissions trading schemes are continuously being designed and implemented, such as a national-scale carbon market of China that launched at the end of 2017 [10], it is highly desirable to investigate the operations of the extant ones for providing a better understanding of this important climate change mitigation strategy. Among the existing

emissions trading schemes, EU ETS is the oldest and largest carbon market, as well as the most intensively studied one, so it should provide important lessons [11,12].

Like any market, EU ETS is under the influences of some important short-term events [13,14]. One representative example of such events is verified emissions announcements [14–16]. The verified emissions announcements reveal the demand information for European Union Allowances (EUAs), carbon emission allowances that are traded in EU ETS. EU ETS is essentially a cap-and-trade system, in which the periodical supply of EUAs is predetermined [17]. These verification events are institutional information disclosure, providing authenticated information to a market that is full of speculation [18]. The verified emissions announcements have a spectrum of strong market effects, as the efficiency of EU ETS is affected by the incorporation of this piece of official information. A close examination of the impacts of these events is highly desirable and of great importance, for the sake of analyzing the status quo and formulating future policy to manage the carbon market.

In the extant literature, efforts are concentrated on examining the impacts of these verified emissions announcements on the prices of carbon emission allowances. As argued by Jia et al. [15], the verified emissions announcements could facilitate the discovery of carbon prices, and these events have thereby imparted significant shocks to EU ETS. The first structural breakdown of the carbon prices in EU ETS occurred after the announcement of the 2005 verified emissions [19]; the 2005 announcement corrected market inefficiency [20]. The past returns on carbon prices were found to be related to the 2006 verified emissions announcements [21], which further altered the market perception of risk [18]. EU ETS was gradually adapted to the impacts of these announcements; the surprise effect of these announcements diminished between 2006 and 2010 [22]. The most significant impacts came from the two first verified emissions announcements, that is, of Phase I in 2006 and of Phase II in 2009 [23]. In essence, the carbon prices are influenced by trading behaviors, that is, buying and selling initiated by a firm participating in EU ETS, because EU ETS is a cap-and-trade market. Yet, to the best of our knowledge, there is little knowledge about how verified emissions announcements alter the influences of trading behaviors on the carbon prices, despite these events directly determining the supply and demand of carbon allowances [16]. Moreover, the aforementioned studies are carried out only from a macroeconomic perspective. Since EU ETS was originally proposed as an instrument to achieve abatements in carbon emissions of participating firms [3,24], it might be helpful to examine how firm-level trading behaviors affect the carbon prices during important events.

Firm-level trading data can be acquired from the European Commission's website (ec.europa.eu/environment/ets/), with lags of five years (for Community Independent Transaction Log, CITL) and three years (for European Union Transaction Log, EUTL), respectively [25], enabling micro-behavioral research on EU ETS. According to the trading data, the trading behaviors of firm are found to be affected by their sizes, sectors, ownership structures [26], and transaction costs [27]. One compelling observation is that the trading behaviors are driven by the compliance obligation [28,29]; firms are most likely to purchase allowances when they need to avoid financial penalties, particularly at the end of the compliance cycle [30]. Fan et al. [29] found that the mean values of carbon prices are positively correlated to the volume of trading behaviors for compliance purpose, that is, transactions to fill the gap between on-hold allowances and surrendered allowances. These empirical findings confirm that EU ETS is operating as a compliance instrument, in which the verified emissions announcements play a regulatory role that enables firms to discover the true value of carbon allowances [15]. Yet again, how the verification events impart their impacts on the comoves between trading behaviors and carbon prices is still missing in the microeconomic EU ETS literature. Moreover, non-compliance trading can also have significant impacts on carbon prices, an issue that has been almost ignored. A better understanding of the carbon pricing mechanism is crucial for policymakers [31], as carbon price can provide a strong signal to stimulate long-term investments and to adopt low-carbon technologies [32], as well as regulatory implications for managing carbon markets across the globe.

In this study, we seek to fill the knowledge gap by analyzing the impacts of verification events on the comoves between trading behaviors and carbon prices in EU ETS, using an event study approach.

Based on the firm-level trading data from CITL and EUTL, we sort the microtrading behaviors of the participants in EU ETS into two categories, i.e., “trading with compliance purpose” and “trading with non-compliance purpose.” Compliance trading holds a significant volume in EU ETS, as over one billion metric tons of carbon allowances have been purchased for compliance purpose in this carbon market, according to Newell et al. (2014). The classification is determined based on the dynamic relationship between the position (i.e., long or short) and trading direction (i.e., buy or sell) of each firm. We construct modified generalized autoregressive conditional heteroskedastic (GARCH) models to investigate the comoves between the micro-behaviors and carbon prices. We employ dummy variables to represent different periods, including the complete periods, the announcement periods, and the pre- and post-announcement periods. A dummy variable is commonly used in event studies to characterize the occurrence of certain events [33,34], and has already been applied for examining the related impacts of the verification events in EU ETS [15,16,19,22,26]. According to Jia et al. [15], the ex-ante and ex-post impacts of the verified emissions announcements on the carbon future prices are differentiated. This work explores how the verification announcements affect the carbon prices through micro-level trading behaviors in different periods, on the basis of introduced dummy variables and firm-level big data. Specific attention has been paid to identifying potential differences in the ex-ante and ex-post influences of the verification events through the carbon trading on the carbon price return volatility.

Based on the analysis of the verification announcements’ impacts on the comoves of trading behaviors and carbon prices in Phase I and Phase II, the major contribution of this work is threefold. First, we exploit firm-level trading data to identify how verification events channel their impacts through firm-level trading behaviors to the prices of carbon allowances. Second, we identify the differences in the ex-ante and ex-post impacts of these announcements on the comoves between the trading behaviors and carbon prices, on the basis of dividing the event windows into pre-announcement periods and the post-announcement periods. Third, we try to observe the changes in firm-level trading behaviors, aiming at answering the following question: “Is EU ETS still a simple compliance instrument or has it become a mature market?” The answer to this particular question will reshape the regulatory paradigm for all cap-and-trade carbon markets—not only EU ETS, but also similar carbon trading schemes that have been or are being built all over the world.

The remainder of the paper is structured as follows. Section 2 describes the aggregated data used in this study. Section 3 parameterizes the empirical models. The observational and empirical results are presented in Section 4. Section 5 discusses the results. The last section gives conclusive remarks, as well as policy implications for regulating capped carbon markets.

2. Data

Since the modeling is based on firm-level trading data, we introduce the data prior to the methodological section. CITL and EUTL are open databases that collect allowance transaction information on the account level, available from the official website (ec.europa.eu/environment/ets/), where the accounts of firms and a complete log of allocations, surrenders, and transactions of EUAs are available. Adopting the pre-processing procedure from the work of Liu et al. [25], all transactions from 1 February 2005 to 30 April 2012 are extracted, including 124,817 records in Phase I and 499,426 records in Phase II. It is worth noting that the micro-behaviors of financial intermediaries are excluded in this study because they have no compliance obligation and act as a counterpart to the emitters [29].

Based on the assumption that the surrenders of an emitter can be accurately predicted, we adopt the definition of “positions” [29]: if the allowances held by an emitter are greater than the amount it shall surrender, its position is long (surplus), otherwise its position is short (deficit). As EU ETS is essentially a cap-and-trade scheme, to fulfill the obligation of compliance, firms at long positions are supposed to sell the surplus allowances, while firms at short positions would buy more allowances to match their expected surrenders. In this work we denote the transactions that aim at closing the gaps between on-hold allowances and surrendered allowances as “trading with compliance

purpose.” We therefore refer to those transactions that widen the gaps as “trading with non-compliance purpose.” We further classify all the trading behaviors into four categories: compliance buying (CB) and compliance selling (CS), and non-compliance buying (NB) and non-compliance selling (NS); their volumes are plotted in Figure 1.

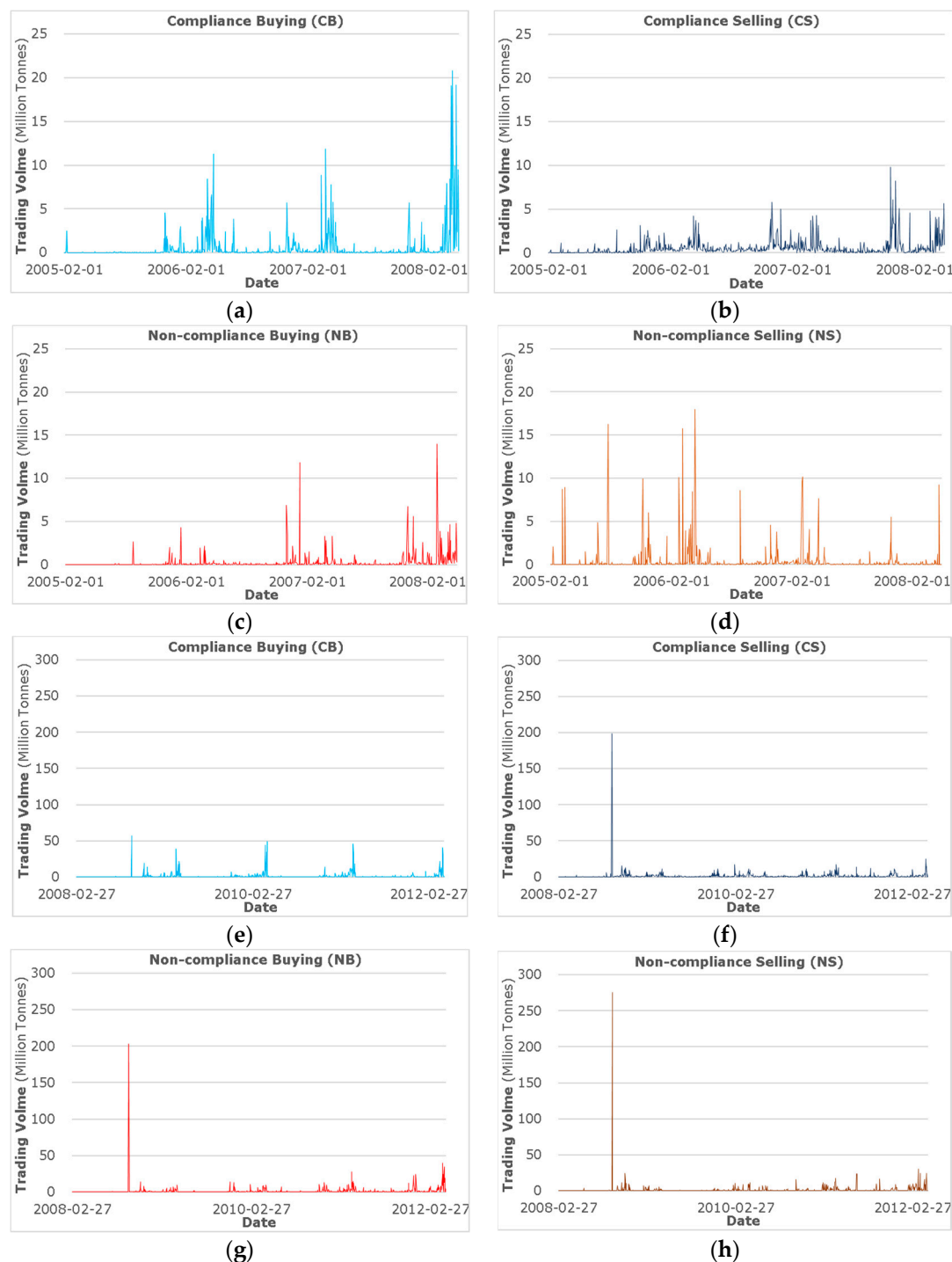


Figure 1. Volumes of trading with compliance or non-compliance purposes: (a–d) belong to Phase I, and (e–h) belong to Phase II.

Three initial observations can be made from Figure 1. The first can be made when the trading volumes of Phase I and Phase II are directly compared: the volumes of the transaction activities

occurring in the second phase (see Figure 1e–h) are significantly higher than those of the first phase (see Figure 1a–d). This probably resulted from an increased number of participants in EU ETS; the market has enjoyed dramatic development since 2008 [14]. In Phase I, the relatively low number of market transactions is highly concentrated among a few leading participants [35,36]. Most of the trading occurred within certain periods before important announcements such as emission verifications and national allocations [29], as the trading volumes show a distinctive periodical pattern in Figure 1a–d. Consequently, the market of Phase I can easily be destabilized by extremely large transactions, which result in large negative returns and sudden volatility movements [14,35,36], and thereby compromise the market mechanism. In Phase II, despite there being several spikes, the periodical characteristic of the trading volumes had been weakened. This change in the trading pattern agrees with the extant literature; the volatility estimates of the EUA prices approach that of the Standard & Poor's 500 Index (SP500) [14] and the market fundamentals play a more important role [37], indicating that EU ETS shows a higher degree of market maturity.

The second observation comes from comparing the volumes of compliance trading (see Figure 1a,b,e,f) and non-compliance trading (see Figure 1c,d,g,h). In Phase I, the volumes of “trading with compliance purpose” are significantly greater than those of their non-compliance counterparts, as the total volume of the former category is equal to 1.76 times that of the latter category. However, the total trading volumes of compliance purpose are almost equivalent to the summed non-compliance trading volumes in Phase II. This implies that there could be a paradigm shift in EU ETS: the carbon market is indeed gradually becoming a market, rather than a simple environmental regulatory instrument.

The third observation can be made when the volumes of buying (see Figure 1a,c,e,g) and selling (see Figure 1b,d,f,h) are compared. The selling volumes in Phase I are greater than those of buying, for both compliance trading or non-compliance trading. This finding suggests that the EUAs were overallocated in Phase I, which is compatible with the literature on the allocation issue [38,39]. Since each country is capable of allocating free allowances to its own firms prior to Phase I, the allocation mechanism is intrinsically flawed, and the overallocation of allowances is inevitable [40]. In Phase II, the total selling volume is still greater than the total buying volume, indicating that the overallocation of carbon allowances continues to exist in this phase. The observation agrees with the findings of Brouwers et al. [23], as overallocations are found in both phases. However, the pattern of Phase II is quite different from that of Phase I: the combined volume of CB is lower than that of CS, while the combined volume of NB is higher than that of NS.

The spot prices of EUAs are adopted in this work for two reasons: (1) the dataset is much easier to obtain than the future prices, and (2) the differences between spot prices and their adjacent future prices are indeed quite minor [29]. The returns of EUAs are also calculated in accordance with the following equation (Equation (1)):

$$RCP_t = \log(CP_t) - \log(CP_{t-1}), \quad (1)$$

where RCP_t denotes the daily logarithm return of the carbon prices at time t , and CP_t refers to the logarithmic price of EUAs at time t .

3. Methods

The methodology section consists of two parts: (1) the first part describes the iterated cumulative sums of squares (ICSS) algorithm that defines the event windows of the verified emissions announcements, and (2) the second part illustrates the GARCH (1, 1) model that investigates the comoves between trading behaviors and carbon prices in different periods.

3.1. Determination of Event Windows

Determination of event windows is a crucial task in event studies [41]. For EU ETS, the announcement events usually take place at the beginning of April from 2007 to 2012 except for 2006, i.e., 25 April 2006, 2 April 2007, 2 April 2008, 1 April 2009, 1 April 2010, 1 April 2011, and 2 April 2012.

The ICSS algorithm is originally proposed by Inclan and Tiao [42]: it assumes that the variance of a time series is stationary over an initial period until a sudden change occurs; the variance then reverts to stationary until the next shock. The details of this algorithm are presented in the work of Inclan and Tiao (1994). Owing to its simplicity and robustness, the algorithm is widely applied for detecting changes in the markets triggered by particular events [43,44]. We employ the ICSS algorithm here to determine the beginnings and endings of these events based on the sudden changes in the volumes of compliance trading.

Based on the ICSS results of Phase I, we define 45 workdays (excluding weekends) before and after the announcements as the event windows, that is, 90 workdays for each verified emissions announcement. We further define the 45 workdays before the event as “the pre-announcement period” and the 45 workdays after the event as “the post-announcement period.” To yield a reliable comparison, we apply the same event windows to the verified emissions announcements in Phase II, including both the pre-announcement period and the pre-announcement period. It is worth noting that the announcement period in 2008 is considered in the calculation due to the extreme trading volumes observed during 28 January 2008 to 7 June 2008, which probably resulted from the rapid decline in carbon prices and strong compliance obligation [25]. Transaction data from this period are removed since unusual transactions weaken the comoves of micro-behaviors and carbon prices.

3.2. Modeling of Comoves

In essence, this study is an event study; the changes in the comoves between trading behaviors and carbon prices are supposed to be relevant to the verified emissions announcements. On the basis of the previous event study literature on the energy market [45], we here construct GARCH (1, 1) models to investigate the volatility of carbon price returns affected by micro-behaviors inside and outside the event windows of the verification events. Univariate GARCH models are selected, due to these models generating more accurate outcomes when compared to their multivariate counterparts [46]. Moreover, because we focus on the volatility behaviors in carbon price returns, the exponential generalized autoregressive conditional heteroscedastic (EGARCH) is not considered, as the model aims at exploring potential asymmetry effects [47]. In the extant literature, GARCH models have been extensively applied examining the volatility of carbon price returns in EU ETS [48–50].

The studied trading behaviors occurred in the four types of periods in Phase I and Phase II—that is, the full periods, the announcement periods, the pre-announcement periods, and the post-announcement periods. The impacts of “trading with compliance purpose” on the carbon prices are evaluated using the mean equations of the GARCH models. Based on the aggregated data, a review of the autocorrelation function (ACF) and partial autocorrelation function (PACF) of the logarithm returns of the carbon prices shows: (1) in Phase I, ACF tails off gradually, PACF cuts off after 1 lag; (2) in Phase II, both ACF and PACF tail off gradually. The finding indicates that the carbon price returns of Phase I show some degree of temporal correlation, while those of Phase II can almost be considered white noise. Therefore, we propose different mean equations to model the logarithm returns of the carbon prices in Phase I and Phase II: (1) in Phase I, we add the volumes of “trading with compliance purpose” of the first-order lag for further explaining the temporal correlation observed in the residual of autoregressive (AR) (1); (2) in Phase II, we find that autoregressive and moving average (ARMA) (1, 1) is quite sufficient, as the residual is white noise. The mean equations of Phase I and Phase II are parameterized according to Equations (2) and (3), respectively:

$$RCP_t = \theta_1 + \theta_2 RCP_{t-1} + \theta_3 VCB_{t-1} + \theta_4 VCS_{t-1} + \varepsilon \quad (2)$$

$$RCP_t = \theta_1 + \theta_2 RCP_{t-1} + \theta_3 \xi_{t-1} + \varepsilon, \quad (3)$$

where VCB_{t-1} and VCS_{t-1} are the volumes of CB and CS of the emitters, respectively; ξ_{t-1} presents the first-order moving average (MA (1)) of the logarithm return of the carbon prices; θ_i are the coefficients; and ε is the residual error.

The impacts of “trading with non-compliance purpose” on the returns of the carbon prices in Phase I and Phase II are evaluated using the following variance equation (Equation (4)):

$$\sigma_t^2 = \beta_1 + \beta_2 Z_{t-1} + \beta_3 \sigma_{t-1}^2 + \gamma_1 VNB_{t-1} + \gamma_2 VNS_{t-1} + \varepsilon, \quad (4)$$

where Z denotes the ARCH, σ denotes the GARCH; VNB_{t-1} and VNS_{t-1} are the volumes of NB and NS, respectively; and β_i and γ_i are the coefficients.

The dummy variable D_a is added to the GARCH (1, 1) model to distinguish the effects of micro-behaviors that occurred in the announcement period or other period (Equation (5)):

$$D_a = \begin{cases} 1, & \text{Announcement Period} \\ 0, & \text{Complete Period without Announcement Period} \end{cases} \quad (5)$$

For both Phase I and Phase II, the variance equation with dummy variable D_a addition is shown as follows (Equation (6)):

$$\sigma_t^2 = \beta_1 + \beta_2 Z_{t-1} + \beta_3 \sigma_{t-1}^2 + (\gamma_1 + \lambda_1 D_a) VNB_{t-1} + (\gamma_2 + \lambda_2 D_a) VNS_{t-1} + \varepsilon, \quad (6)$$

where λ_i are the coefficients.

To further investigate the potentially heterogeneous ex-ante and ex-post impacts of the verified emissions announcements on the carbon price return volatility, dummy variables are employed— D_b for the pre-announcement period, and D_c for the post-announcement period—and their value assignments are shown as follows (Equations (7) and (8)):

$$D_b = \begin{cases} 1, & \text{Pre – Announcement Period} \\ 0, & \text{Complete Period without Pre – Announcement Period} \end{cases} \quad (7)$$

$$D_c = \begin{cases} 1, & \text{Post – Announcement Period} \\ 0, & \text{Complete Period without Post – Announcement Period} \end{cases} \quad (8)$$

We here add D_b and D_c into the following variance equations for Phase I and Phase II, respectively (Equations (9) and (10)):

$$\sigma_t^2 = \beta_1 + \beta_2 Z_{t-1} + \beta_3 \sigma_{t-1}^2 + \gamma_1 VNB_{t-1} + (\gamma_2 + \lambda_1 D_b + \lambda_2 D_c) VNS_{t-1} + \varepsilon \quad (9)$$

$$\sigma_t^2 = \beta_1 + \beta_2 Z_{t-1} + \beta_3 \sigma_{t-1}^2 + \gamma_1 VNS_{t-1} + (\gamma_2 + \lambda_1 D_b + \lambda_2 D_c) VNB_{t-1} + \varepsilon \quad (10)$$

Before applying the modified GARCH (1, 1), we employ an augmented Dickey–Fuller (ADF) test to examine the smoothness of the transaction dataset. The testing results lead to the rejection of the null hypothesis with significance levels of 1%, 5%, and 10%, indicating that the dataset is smooth in all the periods.

4. Results

4.1. Observational Results

Table 1 summarizes the statistical characteristics of the volumes of the trading behaviors (CB, CS, NB, and NS) in all the periods, the announcement periods, the pre-announcement periods, and the

post-announcement periods. It worth noting that the minimum value for all the trading behaviors in all the periods is zero.

Table 1. Summary statistics (in millions of tons).

| | | Mean | Std. dev | Skewness | Kurtosis | Maximum |
|----------|--------------------------|------|----------|----------|----------|---------|
| Phase I | Complete Period | CB | 0.515 | 1.867 | 6.713 | 58.889 |
| | | CS | 0.552 | 0.922 | 4.291 | 28.492 |
| | | NB | 0.412 | 1.730 | 7.210 | 61.974 |
| | | NS | 0.243 | 0.895 | 8.982 | 110.484 |
| | Announcement period | CB | 0.924 | 1.990 | 3.198 | 14.246 |
| | | CS | 0.710 | 0.811 | 2.776 | 11.013 |
| | | NB | 0.826 | 2.421 | 4.736 | 27.658 |
| | | NS | 0.218 | 0.505 | 4.306 | 23.141 |
| | Pre-announcement period | CB | 1.148 | 2.396 | 2.832 | 11.008 |
| | | CS | 0.815 | 0.834 | 2.448 | 8.969 |
| | | NB | 1.302 | 3.182 | 3.505 | 15.611 |
| | | NS | 0.279 | 0.587 | 3.397 | 14.759 |
| | Post-announcement Period | CB | 0.708 | 1.425 | 2.797 | 11.152 |
| | | CS | 0.627 | 0.826 | 3.049 | 12.349 |
| | | NB | 0.313 | 0.910 | 6.523 | 51.567 |
| | | NS | 0.155 | 0.387 | 6.420 | 50.994 |
| Phase II | Complete Period | CB | 0.585 | 1.893 | 6.090 | 46.328 |
| | | CS | 0.568 | 2.236 | 25.823 | 762.295 |
| | | NB | 0.614 | 3.119 | 17.510 | 351.245 |
| | | NS | 0.599 | 3.429 | 24.226 | 649.108 |
| | Announcement period | CB | 1.046 | 2.278 | 3.881 | 20.482 |
| | | CS | 0.711 | 1.177 | 4.613 | 32.619 |
| | | NB | 0.847 | 1.708 | 4.089 | 23.243 |
| | | NS | 0.806 | 1.432 | 3.229 | 15.934 |
| | Pre-announcement period | CB | 1.201 | 2.441 | 3.790 | 19.164 |
| | | CS | 0.872 | 1.179 | 3.518 | 18.238 |
| | | NB | 1.140 | 2.029 | 3.435 | 16.650 |
| | | NS | 1.088 | 1.600 | 2.771 | 12.804 |
| | Post-announcement Period | CB | 0.598 | 1.673 | 4.785 | 30.448 |
| | | CS | 0.432 | 0.754 | 3.943 | 22.566 |
| | | NB | 0.321 | 0.611 | 3.043 | 12.854 |
| | | NS | 0.298 | 0.553 | 3.096 | 13.972 |

There are four initial observations that remain consistent for both the studied phases. First, it can be seen that transactions of carbon allowances are concentrated in the announcement period; for both Phase I and Phase II, the average trading volumes of “trading with compliance purpose” and “trading with non-compliance purpose” are generally greater than their counterparts in the complete period. Second, in both the pre- and post- announcement periods, the volumes of allowance buying are higher than those of allowance selling. Third, the carbon allowance trading is more clustered in the announcement period compared to the complete period, indicated by the lower skewness and Kurtosis values. Fourth, most of the allowance transactions occurred prior to the verified emissions announcements, i.e., in the pre-announcement period, and these micro-behaviors exhibit a higher degree of clustering than took place in the post-announcement period. These observations demonstrate that a majority of the emitting companies in EU ETS trade, or to be more specific, buy carbon allowances to fulfill their compliance obligations, which agrees with the literature on EU ETS [28–30].

Apart from the aforementioned similarities, the trading behaviors in Phase I are generally different from those in Phase II, as several distinctive patterns can only be found in Phase I. First, in Phase I, the volumes of “trading with compliance purpose” are generally greater than those of “trading with

non-compliance purpose,” except for NB in the pre-announcement period, and NS always has the lowest trading volumes. Moreover, higher maximum values are also concentrated in Phase I. Second, indicated by the skewness and Kurtosis values in Table 1, the “trading with compliance purpose” in Phase I is more highly clustered than their counterparts for non-compliance purposes. Third, the values of standard deviation imply that the transactions of allowance selling are more evenly distributed than the buying behaviors. The above findings confirm that the carbon market is gradually becoming mature: (1) in Phase I, this cap-and-trade market is a pure compliance instrument and the firms seem to be passive in allowance trading, that is, transactions are made mainly for the purpose of matching their predicted surrenders [25,28]; (2) the macro-behaviors become more balanced in Phase II, implying that carbon allowances have been recognized as some kind of financial asset, as Balcilar et al. [51] pointed out.

4.2. Empirical Results

The quantitative results of the modified GARCH (1, 1) models for the complete announcement periods are shown in Table 2. Since the daily spot prices of EUAs are adopted in this work, there are 846 observations and 1066 observations in Phase I and Phase II, respectively, and the announcement period, the pre-announcement period, and the post-announcement period have 90, 45, and 45 observations, respectively.

Table 2. Results of parameters in the modified GARCH (1, 1) model for the complete period and the announcement period in Phases I and II.

| | Variable | Coefficient | Z-Statistic | Pr. |
|---------------------|---|------------------------|-------------|-----------|
| Phase I | <i>Mean Equation (Equation (2))</i> | | | |
| | θ_1^{LC} | 7.04×10^{-4} | 0.141 | 0.888 |
| | θ_2^{LC} | −0.205 | −3.115 | 0.002 *** |
| | θ_3^{LC} | 2.54×10^{-3} | 2.879 | 0.004 *** |
| | θ_4^{LC} | -4.73×10^{-3} | −1.744 | 0.081 * |
| | <i>Variance Equation (Equation (4))</i> | | | |
| | β_1^{LC} | 2.10×10^{-3} | 4.779 | 0.000 *** |
| | β_2^{LC} | 0.145 | 3.641 | 0.000 *** |
| | β_3^{LC} | 0.550 | 6.608 | 0.000 *** |
| | γ_1^{LC} | -1.38×10^{-4} | −743.052 | 0.000 *** |
| | γ_2^{LC} | -4.70×10^{-4} | −14.844 | 0.000 *** |
| | <i>Mean Equation (Equation (2))</i> | | | |
| | θ_1^{LA} | 1.30×10^{-3} | 0.268 | 0.789 |
| | θ_2^{LA} | −0.196 | −3.080 | 0.002 *** |
| | θ_3^{LA} | 2.53×10^{-3} | 3.010 | 0.002 *** |
| | θ_4^{LA} | -4.92×10^{-3} | −1.880 | 0.060 * |
| Announcement Period | <i>Variance Equation (Equation (6))</i> | | | |
| | β_1^{LA} | 2.07×10^{-3} | 4.487 | 0.000 *** |
| | β_2^{LA} | 0.143 | 3.757 | 0.001 *** |
| | β_3^{LA} | 0.540 | 6.195 | 0.000 *** |
| | γ_1^{LA} | -8.47×10^{-5} | −0.413 | 0.680 |
| | γ_2^{LA} | -4.34×10^{-4} | −1.701 | 0.089 * |
| | λ_1^{LA} | -5.95×10^{-5} | −0.296 | 0.768 |
| | λ_2^{LA} | -6.24×10^{-4} | −1.698 | 0.090 * |

Table 2. Cont.

| | | Variable | Coefficient | Z-Statistic | Pr. |
|----------|---------------------|----------------------------------|------------------------|-------------|-----------|
| Phase II | Complete Period | Mean Equation (Equation (3)) | | | |
| | | $AR(1)^{II,C}$ | 2.76×10^{-2} | 0.036 | 0.971 |
| | | $MA(1)^{II,C}$ | -1.59×10^{-2} | -0.021 | 0.984 |
| | | Variance Equation (Equation (4)) | | | |
| | | $\beta_1^{II,C}$ | 9.92×10^{-6} | 3.045 | 0.002 *** |
| | | $\beta_2^{II,C}$ | 0.128 | 8.267 | 0.000 *** |
| | | $\beta_3^{II,C}$ | 0.862 | 51.658 | 0.000 *** |
| | | $\gamma_1^{II,C}$ | -8.11×10^{-4} | -1.624 | 0.105 |
| | | $\gamma_2^{II,C}$ | 1.61×10^{-3} | 1.997 | 0.046 ** |
| | Announcement Period | Mean Equation (Equation (3)) | | | |
| | | $AR(1)^{II,A}$ | 0.968 | 25.979 | 0.000 *** |
| | | $MA(1)^{II,A}$ | -0.971 | -26.478 | 0.000 *** |
| | | Variance Equation (Equation (6)) | | | |
| | | $\beta_1^{II,A}$ | 9.83×10^{-6} | 2.943 | 0.003 *** |
| | | $\beta_2^{II,A}$ | 0.119 | 7.904 | 0.000 *** |
| | | $\beta_3^{II,A}$ | 0.868 | 53.023 | 0.000 *** |
| | | $\gamma_1^{II,A}$ | -1.84×10^{-4} | -0.189 | 0.850 |
| | | $\gamma_2^{II,A}$ | 2.14×10^{-3} | 1.109 | 0.268 |
| | | $\lambda_1^{II,A}$ | -2.97×10^{-3} | -2.344 | 0.019 ** |
| | | $\lambda_2^{II,A}$ | 1.53×10^{-3} | 0.693 | 0.488 |

Note: * Significance at 10% level; ** Significance at 5% level; *** Significance at 1% level.

We summarize the empirical results of the pre- and post- announcement periods in Table 3. From Table 3, the empirical findings of the mean equation for Phase I (Equation (2)) are consistent with the previous observations on the complete period and the announcement period that are shown in Table 2, which proves the model valid. The testing results of the mean equation for Phase II (Equation (3)) are comparable to those of the complete period of Phase II (see Table 2), implying the validity of the model.

Table 3. Results of parameters in the modified GARCH (1, 1) model for the pre-announcement period and the post-announcement period in both Phase I and Phase II.

| | | Variable | Coefficient | Z-Statistic | Pr. |
|---------|------------------------------------|----------------------------------|------------------------|-------------|-----------|
| Phase I | Pre- and Post-Announcement Periods | Mean Equation (Equation (2)) | | | |
| | | $\theta_1^{I,PP}$ | 9.69×10^{-4} | -0.207 | 0.836 |
| | | $\theta_2^{I,PP}$ | -0.196 | -3.095 | 0.002 *** |
| | | $\theta_3^{I,PP}$ | 2.50×10^{-3} | 2.954 | 0.003 *** |
| | | $\theta_4^{I,PP}$ | -4.99×10^{-3} | -1.905 | 0.057 * |
| | | Variance Equation (Equation (9)) | | | |
| | | $\beta_1^{I,PP}$ | 2.07×10^{-3} | 4.513 | 0.000 *** |
| | | $\beta_2^{I,PP}$ | 0.143 | 3.741 | 0.000 *** |
| | | $\beta_3^{I,PP}$ | 0.542 | 6.245 | 0.000 *** |
| | | $\gamma_1^{I,PP}$ | -1.33×10^{-4} | -6.812 | 0.000 *** |
| | | $\gamma_2^{I,PP}$ | -4.22×10^{-4} | -5.581 | 0.000 *** |
| | | $\lambda_1^{I,PP}$ | -6.11×10^{-4} | -2.532 | 0.011 ** |
| | | $\lambda_2^{I,PP}$ | -1.01×10^{-3} | -2.277 | 0.023 ** |

Table 3. Cont.

| | | Variable | Coefficient | Z-Statistic | Pr. |
|----------|--|-----------------------------------|------------------------|-------------|-----------|
| | | Mean Equation (Equation (3)) | | | |
| | | $AR(1)^{II,PP}$ | -1.96×10^{-2} | -0.027 | 0.978 |
| | | $MA(1)^{II,PP}$ | 3.13×10^{-2} | 0.043 | 0.966 |
| | | Variance Equation (Equation (10)) | | | |
| Phase II | Pre- and Post-Announcement Periods | $\beta_1^{II,PP}$ | 6.68×10^{-6} | 2.138 | 0.033 ** |
| | | $\beta_2^{II,PP}$ | 0.103 | 7.409 | 0.000 *** |
| | | $\beta_3^{II,PP}$ | 0.885 | 58.115 | 0.000 *** |
| | | $\gamma_1^{II,PP}$ | 3.87×10^{-3} | 3.501 | 0.001 *** |
| | | $\gamma_2^{II,PP}$ | -8.45×10^{-4} | -1.247 | 0.212 |
| | | $\lambda_1^{II,PP}$ | -2.73×10^{-3} | -3.544 | 0.000 *** |
| | | $\lambda_2^{II,PP}$ | -7.77×10^{-5} | -0.043 | 0.966 |

Note: * Significance at 10% level; ** Significance at 5% level; *** Significance at 1% level.

5. Discussion

5.1. Full Impacts on Comoves

According to the empirical results of the mean equation for Phase I (Equation (2)), the carbon price returns of the complete period are significantly negatively self-correlated, indicating that the fundamentals of supply and demand of carbon allowances have not been disrupted. The trends of carbon prices are also significantly affected by the volumes of “trading with compliance purpose” in small values, and the impacts of CB are more significant ones. The similar pattern is observed in the carbon price returns of the announcement period in Phase I; the carbon price returns are significantly negatively self-correlated, and also are under the influences of CB and CS, in which CB has more significant impacts. For Phase I, the carbon price returns in both the complete period and the announcement periods are correlated to CB and CS, and their values are not white noise.

The results of the mean equation for Phase II (Equation (3)) show that the fundamentals of the carbon prices are disrupted, as the influences of both AR (1) and MA (1) are insignificant for the complete period. The returns of carbon prices are white noise, indicating that Phase II exhibits a higher efficiency than Phase I. However, for the announcement period, the impacts of AR (1) and MA (1) on the carbon price returns are highly significant, which provides evidence to support the conclusion of Jia et al. [15]: the verified emissions announcements would facilitate the discovery of the carbon prices.

In general, the testing results of the variance equation for the complete period (Equation (4)) show that the variance model is validly constructed. In Phase I, “trading with non-compliance purpose” exerts its significant negative impacts on the volatility of the carbon price returns, yet in small values. The influential magnitude of NS is almost three times that of NB, indicating that the impacts of different trading behaviors are asymmetric. Only the selling activities (NS) in “trading with non-compliance purpose” significantly affect the carbon price return volatility for both phases, and the impacts are quite different in the two phases; NS in Phase I slightly lowers the volatility, while NS in Phase II tends to increase the volatility more substantially. Due to the flawed allowance allocation mechanism, there is overallocation of carbon allowances in Phase I [40], and therefore “trading with non-compliance purpose” acts as a market buffer; the trading activities of NB and NS reduce the volatility of carbon price returns. In Phase II, with the restrictions on allowance allocation [20], the carbon market becomes more mature [52]; the carbon price returns are much closer to white noise. However, the GARCH effect is still significant; NS introduces more volatility into the carbon price returns. This could be attributed to the pessimistic trading psychology that is deeply affected by the structural breaks of carbon prices in Phase I [19].

For the announcement period in Phase I, the testing results of Equation (6) demonstrate that the variance is modeled validly, because both the ARCH and GARCH variables are highly significant.

Comparing the buying and selling in “trading with non-compliance purpose,” only the bearish trading behaviors (i.e., NS) exert their significant negative impacts on the volatility of the carbon price returns in Phase I. These influences are ascertained; the negative impacts of NS on the carbon price return volatility are significant for both the complete period and the announcement period. It is worth noting that the negative impacts of NS on the volatility are more substantial in the announcement period, averaging 0.32-fold higher than for the complete period (comparing $\lambda_2^{I,A}$ against $\gamma_2^{I,C}$). This pattern can also be considered an outcome of the overallocation of carbon allowances in Phase I [40]. As shown in Figure 1, “trading with compliance purpose” is highly concentrated during the announcement period in Phase I. Owing to the overallocation problem, the fundamentals of the EU-ETS are intrinsically flawed, and the imbalance between the supply and demand of carbon allowances becomes highly noticeable during the period of the verified emissions announcements. Since the buying behaviors for compliance (i.e., CB) are much more intensive in the announcement period of Phase I, NB is suppressed while NS is triggered, consequently introducing more volatility into the carbon price returns.

In Phase II, the significance of the values of ARCH and GARCH variables proves the validity of this variance model, that is, Equation (6). According to the testing results of Equation 6, “trading with non-compliance purpose” of the complete period of Phase II ($\gamma_1^{II,A}$ and $\gamma_2^{II,A}$) seems to have no significant impacts on the volatility of carbon price returns. Only the buying activities of “trading with non-compliance purpose” (i.e., NB) in the announcement period of Phase II significantly decrease the carbon price return volatility. These empirical findings are compatible with the observations on Figure 1: when the supply and demand of carbon allowances become more balanced, buying behaviors of “trading with non-compliance purpose” are stimulated, and thereby absorb the dumping of carbon allowances. Consequently, NB significantly reduces the volatility of carbon price returns. According to Farmer [53], EU ETS is more mature in Phase II, indicated by the more balanced impacts of the buying and selling behaviors on the carbon price volatility, for both the complete period and the announcement period.

5.2. Ex-Ante and Ex-Post Impacts

Table 3 confirms that “trading with non-compliance purpose” in Phase I could affect the volatility of the carbon price returns; the negative impacts of both NB and NS are significant in minor values (see the testing results of Equation (9)). All the micro-behaviors of NS in the pre-announcement period and the post-announcement period of Phase I impart significant impacts on the carbon price return volatility. The magnitude of the ex-post impacts is 1.65 times higher than that of the ex-ante impacts, indicating that these selling behaviors facilitate the discovery of carbon allowance overallocation; the total volume of carbon allowances is found to be higher than the expected volume of surrenders, and firms therefore dump their allowances while these assets still have some value. From a microeconomic perspective, these trading behaviors could explain the structural breaks in the carbon prices [19,20]. These numerical findings contradict the conclusion reached by Jia et al. [15]; from the perspective of micro-behaviors, the verified emissions announcements decrease the volatility of the carbon prices through the selling of “trading with non-compliance purpose,” and the impacts both ex-ante and ex-post have a similar effect.

In Phase II, only the impacts of NS of the announcement period and NB of the pre-announcement period on the volatility of the carbon prices are significant. From the perspective of ex-ante and ex-post analysis, the impacts of the former micro-behaviors are positive. However, this finding is somehow contradictory to the results presented in Table 2, which can probably be attributed to the instability of the variance model (Equation (10)). The buying behaviors of “trading with non-compliance purpose,” i.e., NB, during the pre-announcement period decrease the carbon price return volatility to a limited extent, while the buying activities of “trading with non-compliance purpose,” i.e., NB, during the post-announcement period have no significant impact on the volatility during the announcement period. The ex-ante impacts of these trading behaviors on the volatility of carbon price returns are more significant than their ex-post impacts and their counterparts in Phase I. This can also be regarded

as a sign of market maturity; there could be more efficient information-sharing within the market, and the carbon allowances can be regarded as financial assets.

6. Conclusions

This paper analyzes the impacts of verified emissions announcements on the comoves between trading behaviors and carbon prices in EU ETS based on firm-level transaction data. We observe that verification events trigger massive transactions, and the volumes of trading behaviors occurring in the announcement periods in Phase I are greater than in Phase II. “Trading with compliance purpose” significantly affect the returns of carbon prices in Phase I, while these behaviors have no significant effect in Phase II. The trading pattern indicates that EU ETS is simply a compliance instrument in Phase I, and has become more like a market in Phase II.

We observe that the impacts of different types of micro-behaviors in “trading with non-compliance purpose” on the volatility of carbon price returns are differentiated. In Phase I, “trading with non-compliance purpose” reduces the carbon price return volatility, while non-compliance buying behaviors introduce more volatility. During the announcement periods, non-compliance selling in Phase I and non-compliance buying in Phase II reduce the volatility significantly; these trading behaviors act as buffers, and their heterogeneous effects could be attributed to the allowance overallocation problem in Phase I.

Furthermore, the ex-ante and ex-post influences of the verified emissions announcements on the comoves between “trading with non-compliance purpose” and the carbon price return volatility are investigated. We find that the ex-post impacts of NS in Phase I are more substantial than its ex-ante impacts, suggesting the overwhelming influence of the overallocation. In Phase II, all the impacts of “trading with non-compliance purpose” in the pre- and post-announcement periods significantly reduce the volatility of the carbon price returns, except for the non-compliance buying in the post-announcement period of Phase II. In Phase II, the ex-ante impacts of “trading with non-compliance purpose” on the carbon price return volatility are more significant than their ex-post impacts, indicating that a solution to the overallocation problem and a higher level of market maturity have been achieved.

Based on the empirical findings, we confirm that institutional information disclosure such as verified emissions announcements plays an important role in managing EU ETS; during the announcement periods, the trading volumes spike and the carbon prices fluctuate. As Chevallier et al. [18] pointed out, other than these official announcements, most of the information available in the early stage of EU ETS is purely speculative. Despite the participating emitting firms seeming to adapt to the regulatory paradigm in Phase II, transactions were still concentrated during the announcement periods. A more frequent and regular information disclosure mechanism is highly desirable, particularly considering that EUAs are a special commodity only valued for a compliance year and no intertemporal trading is currently allowed [54]. Increased information availability reduces uncertainties and risks in carbon allowance trading.

The impacts of overallocation are more substantial than those of the verified emissions announcements; massive selling behaviors near the end of Phase I could explain the structural breaks in the carbon prices. In response to the overallocation issue, allocation caps were tightened in Phase II, and we confirm the effectiveness of this regulatory action. However, the impacts of “trading with non-compliance purpose” on the volatility of the carbon price returns are still limited, though they are quite significant. To further reduce the allocations might be a potentially effective measure for promoting the maturity of EU ETS. Auction is recommended by scholars [55,56]; however, our findings show that, as the carbon market gradually matures, whether the firms can accurately predict their surrenders has less influence over the carbon price returns; the significance of “trading with compliance purpose” and “trading with non-compliance purpose” is weakened in Phase II. Reducing allocated allowances can push the firms towards adopting more sustainable technologies and business models, without sacrificing the firms’ competitiveness [57]. A detailed sectorial analysis of the micro-behaviors

could be helpful in formulating a suitable allocation strategy, as different industrial sectors have distinctively different carbon emissions patterns [58–60].

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Nomenclature

Abbreviations

| | |
|--------|--|
| ACF | Autocorrelation function |
| ADF | Augmented Dickey–Fuller |
| AR | Autoregressive |
| ARMA | Autoregressive and moving average |
| CB | Compliance buying |
| CITL | Community Independent Transaction Log |
| CS | Compliance selling |
| EU ETS | European Union emissions trading scheme |
| EUA | European Union Allowance |
| EUTL | European Union Transaction Log |
| GARCH | Generalized autoregressive conditional heteroskedastic |
| GHG | Greenhouse gas |
| ICSS | Iterated cumulative sums of squares |
| MA | Moving average |
| NB | Non-compliance buying |
| NS | Non-compliance selling |
| PACF | Partial autocorrelation function |

Symbols

| | |
|-----------|--|
| CP | Carbon price |
| D_i | Dummy variable |
| RCP | Logarithm return of the carbon price |
| VCB | Volume of compliance buying |
| VCS | Volume of compliance selling |
| VNB | Volume of non-compliance buying |
| VNS | Volume of non-compliance selling |
| Z | ARCH, autoregressive conditional heteroskedastic |
| σ | GARCH |
| θ | Coefficient |
| β | Coefficient |
| γ | Coefficient |
| λ | Coefficient |

Superscripts

| | |
|------|--|
| A | The announcement period |
| C | The complete period |
| I | Phase I |
| II | Phase II |
| PP | The pre- and post-announcement periods |

Subscripts

| | |
|-----------|------------|
| a, b, c | Count |
| i | Count |
| t | Time point |

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