

Received March 9, 2020, accepted March 19, 2020, date of publication March 26, 2020, date of current version April 14, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.2983429

What Happened to the CER Market? A Dynamic Linkage Effect Analysis

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This work was supported by the National Natural Science Foundation of China under Grant 71373065 and Grant 71971071.

ABSTRACT The certified emission reduction (CER) carbon trading market promoted by the clean development mechanism (CDM) has become an important platform for the development of the international carbon market. However, the CER carbon market has shown unsteady development with the present phenomena of price decrease, transaction inactivity, and recession. Against this backdrop, this study aims to explore the intuition behind CER price volatility from the new perspective of internal and external market dynamic linkages. By introducing three homogeneous carbon products of CER futures, namely, the daily dataset of CER spot, EUA (European Union Allowance) spot and EUA futures, and taking five heterogeneous market drivers comprising stock, exchange rates, coal, crude oil, and natural gas into account, we analyze the dynamic correlations and volatility spillovers between CER futures returns and these influencing factors using the DGC-MSV model. With sample data from January 2013 to May 2019, our empirical results show a persistent dynamic dependence between CER futures price and its factors. The homogeneous and heterogeneous markets have significant positive and negative spillover effects, respectively, on the CER futures market. The decline of CER futures price in the post-Kyoto era is due to two aspects: fluctuation of the exchange rate market, which is closely connected to the settlement of currency, and coal price volatility in energy markets. However, the CER futures market has no obvious spillover effect on other markets, except for its strong impact on the CER spot market and weak information spillover to the exchange rate market. Overall, this finding indicates the feeblest financial property of CER carbon futures market.

INDEX TERMS Clean development mechanism, CER carbon futures market, multivariate stochastic volatility, dynamic correlation, volatility spillover.

I. INTRODUCTION

In recent years, effective controls over greenhouse gas (GHG) emission, especially carbon emission, have received increasing attention from international scholars and political circles [1]. With more climate regulations set worldwide to encourage sustainable development, carbon emission has become a valuable asset for heavy-energy-using plants and industries [2], [3]. Notably, the carbon trading market of CER developed by the CDM is the only global carbon emissions trading market that connects developed and developing countries. Under the Kyoto Protocol, CDM allows developed parties to invest in emission reduction projects in

developing countries and claim CER for emission reductions. Such abatement might be cheaper than what could have been achieved from the partners of developing countries. Meanwhile, developing countries are willing to obtain funds and technologies through carbon trading. In this way, these countries help CDM projects achieve a “win-win” effect [4], thus promoting the development of the energy markets and the CER carbon market. Given that CER and EUA products are substitutes that can provide investors and regulators with opportunities to achieve their objectives, the CER market broadens the scope of the carbon trading institutionalized by EU ETS [5]. Moreover, CER price may be regarded as a proxy of the “world” carbon price because it represents carbon assets exchangeable at a global scale within the Kyoto Protocol [6].

The associate editor coordinating the review of this manuscript and approving it for publication was Alexander Micalef.

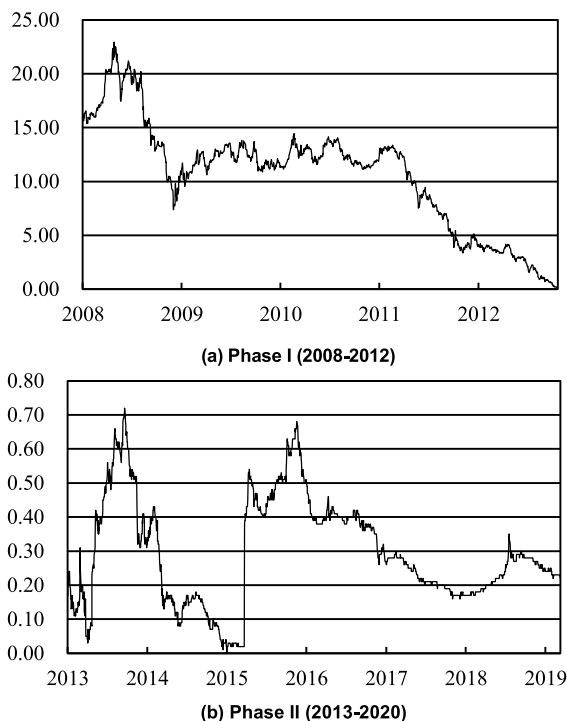


FIGURE 1. Time variations of CER futures price (Data from: Wind Databas).

However, since the inception of the CDM, CER price¹ has frequently fluctuated, a phenomenon that highlights the risk of the CER market. The reason behind this fluctuation is related to several determinants such as the financial crisis, the depressed energy consumption, the exit of some carbon actors² and buyers (e.g., Canada, Japan, New Zealand and Russia), the downturn of EUA price, and the uncertainty of the international carbon-reduction policy in the post-Kyoto era [7], [8]. As shown in Figure 1, after the 2008 financial crisis, CER price was relatively stable before 2011 but declined rapidly from 2011 to 2013. Since then, the price has remained in a state of depression. In general, the price for CER decreased from 22€/tCO₂ in mid-2008 to 0.3€/tCO₂ at the end of 2016. Such decline indicates that the price is unlikely to provide sufficient incentives for low-carbon technology investments and may increase the risk of carbon lock-in [9]–[10]. This context provides a compelling motivation for us to examine the drivers affecting the decline and downturn in CER price and thus determine existing problems in the process of CDM.

Remarkably, some energy carbon-reduction policies have been implemented to ensure the global cooperation of GHG reductions to a certain extent and provide a guarantee for

¹In this paper, CER price refers to the secondary CER price. The secondary CER trading, which is traded in the CDM secondary market after being sold into the ETS market by project developers, appears more standard than that of primary CER and ensures more transparent price and achieves higher market liquidity.

²For example, SGS withdrew from the validation and verification business in June 2014; in April 2015, Standard Bank closed its carbon desk, and Bunge announced it would close Climate Change Capital.

the substantial development of carbon markets. Among the policies are the confirmation of the second commitment period (2013-2020) of the Kyoto Protocol, the implementation of phase III of the EU ETS, and the establishment of the INDC mechanism of the Paris Agreement. According to data from the UNFCCC (United Nations Framework on Climate Change), from 2008 to 2018, China dominated the CDM market and accounted for approximately 57 % of all contracted CDM project supplies. The carbon-reduction costs and economic incomes of China, as the largest supplier of CER issuance, are bound to be affected by the fluctuations of CER price. Under this background, exploring the causes of international carbon price fluctuations in the CER market and analyzing the operational effectiveness of CDM, which developing countries can participate in, will help market regulators formulate practical and effective measures to ensure stable operation of the carbon market. The related knowledge is also particularly important for CDM project management and domestic carbon market construction in developing countries, such as China.

The volatility spillovers and correlations among financial markets, as the most important link of optimal portfolio selection and risk management, have always been the focus point of academic and policy makers. Many scholars have studied the risk contagion effects of stock, energy, and other major asset markets [11], [12]. The carbon market has become an important component of global commodity markets [13], [14]. With its rapid development and steady expansion in size, trading volume and complexity, the carbon market has shown increasingly close interaction with energy and financial markets [15]. Balcilar *et al.* [5] and Wen *et al.* [2] suggested that the development of risk management strategies for carbon risk is necessary because emission trading alone is insufficient to effectively achieve the targets. Therefore, the obvious financial attributes of the carbon market have spurred considerable interest from scholars, investors, and risk managers, and instigated researchers to conduct numerous studies on the pricing mechanisms, volatility, and risk measurement, among others, of the carbon market.

Scholars have discussed the uncertainty of carbon-reduction policy, CDM prospects, and other aspects, by using mathematical models to elaborate on the influence of EUA prices, and macroeconomic and energy price fluctuations [7], [16]–[18]. However, little attention has been directed toward the volatility spillovers between CER market and stock, exchange and energy markets. During the outbreak of the financial crisis and European debt crisis, the emerging carbon market volatility showed significant consistency with the international stock, energy, and other mature market fluctuations. This outcome indicates that the carbon market may be infected by the risk of international financial markets [8]. According to asset portfolio theory, with the enhancement of financial markets and the liberalization of carbon market, investors will reconfigure their resources in the carbon market and other markets once they lose or gain in any market.

This action will cause the cross-market transmission of assets volatility and result in spillover effects [19]. On top of this, the joint behavior of volatility is paramount for portfolios construction and for asset pricing and risk management, as it determines the benefits of diversification and the optimal hedge ratio against risk [20]. Hence, in the actual decision making in carbon trading, investors should not only consider the impact of similar carbon price (homogeneous market prices) fluctuations but also the effects of external financial market prices (e.g., energy, stock prices, and heterogeneous market prices) on the CER market. On the basis of these statements, this paper sheds light on the interaction between the CER market and its homogenous and heterogeneous markets, understanding of which is of crucial to investors, as it can help them build more effective investment portfolios and properly avoid the volatility spillovers of other markets. Such knowledge can also help regulators and policy makers monitor market dynamics by paying attention to the relevant markets.

The remainder of this article is organized as follows: Section II reviews the related literature from two aspects. Section III introduces the DGC-MSV-t model proposed to capture dynamic correlation and volatility spillovers. Section IV describes the data used and presents the empirical results and discussions. Section V concludes and puts forward some suggestions.

II. LITERATURE REVIEW

Many studies have considered the pricing mechanism in the carbon market, particularly the influencing factors of carbon price, such as macroeconomic situations, energy prices, major events, and weather conditions [14], [18], [21], [22]. Numerous scholars have also shed light on the volatility characteristics and risk measurement of carbon price for a single carbon market. They found that carbon price has highly non-stationary, nonlinear, and multi-scale features as well as a time-varying jump behavior [23]–[26]. Moreover, they have paid considerable attention to the interaction between the carbon market and other markets, such as stock, energy, and commodity markets. Related research is mainly focused on the following two aspects.

① Literature that deals particularly with the causality relationship between the price of similar carbon products and financial as well as energy prices.

With regard to carbon markets, different carbon trading mechanisms produce different types of carbon assets. Given the rational arbitrage behavior of participants, the interactions are brought about by similar carbon products and their derivatives [26], [27]. By employing the VAR model, impulse response analysis, and cointegration test, scholars found a long-term equilibrium relationship and interrelation among EUA futures, EUA spot, CER futures, and CER spot. EUA price has led to the price discovery of CER through the vector error correction mechanism [16], [17]. However, a nonlinear dynamic relationship between carbon futures and a spot has been suggested [28]. The research of Nazifi [29]

on EUA-CER spread feature indicated neither long-term time-varying correlation nor convergence.

The commodity nature of carbon emission permits gives the carbon market the same common property of general markets. Carbon-reduction products have financialization characteristics, such as “quasi-monetization” feature, the universality of global participation, and strategic competition and game between leading powers in the post-crisis era. These financialization features of carbon markets closely connect with financial and energy markets [15], [19], [30]. Different emission intensity energy varieties have different effects on carbon price. Using the SVAR model to investigate the short-term dynamic relationship between EUA and energy markets, Hammoudeh *et al.* [31] discovered that the response of EUA price is more significant to crude oil and natural gas. Nevertheless, the dependency research of Gronwald *et al.* [32] through the Copula model documented that EUA futures price has weak dependence on gas and oil but a certain degree of dependence on energy stock prices. With euro being the main settlement currency of carbon trading, the changes in exchange rates will affect the buying and selling decisions and transaction prices of both trading parties [6]. Research on the integration of multi-source risk indicated that China’s carbon permits lack market liquidity, and enterprises are facing the superposition of exchange rate risk and carbon price fluctuation risk [33].

② Research that devotes to the volatility transmission relationship between the price of similar carbon products and financial and energy prices.

Based on the Granger causality test and MGARCH-BEKK model, the relationship of information flow between EUA and CER markets is bidirectional, with a great volatility spillover from the EUA to CER futures market [34]. Zhang and Sun [35] and Yu *et al.* [36] used the multivariate DCC-GARCH model to detect the dynamic correlations between EUA and energy markets and proved the significant positive time-varying relationship between them.

Economic events and policy shifts can significantly change the dynamic linkage mechanism between the carbon market and other markets. From the perspective of extreme and regular risk transmissions, Song *et al.* [19] applied the ARMA (1, 1)-component GARCH model to build long and short volatility as risk measurement for EUA, financial, energy, and commodity futures prices. The Granger causality test demonstrated that the connection between the carbon and financial markets is stronger than that between other markets, and the risk transmission is different in different phases of EU ETS. Balçilar *et al.* [5] examined the risk spillovers between carbon and energy markets by adopting a Markov regime-switching GARCH model with dynamic conditional correlations. The results of their work pointed out that the volatility spillover from energy markets to the CER market is weaker than in the case of the EUA market.

As seen from the literature above: ① Existing studies concentrate on the volatility transmission between the EUA market and its heterogeneous markets, such as stock and

energy markets, but rarely cover the aspect of the CER market. The CER market reflects the expectations of developed countries for carbon trading prospects and the demand of developing countries for global carbon trading. Thus, CERs are more representative of world carbon products [37]. Under the special background of the post-Kyoto era, the downturn status of the CER market after the European debt crisis is not only related to carbon-reduction policy shifts and similar carbon products but can also be influenced by the impact of international financial markets' turbulence. The interactions among CER market, homogenous market, and heterogeneous markets must be investigated to provide a comprehensive and systematic reference for regulators and carbon trading investors.

② With Regard to the causality relationship analysis techniques, most previous studies were limited in scope to traditional static model with fixed parameters, such as Granger causality test, co-integration test, and VAR model. The interactions between markets vary over time because they are influenced by macroeconomic fluctuations and relevant policy changes. However, the parameters estimated by these models just represent the mean value of the sample, a value that cannot reflect the time-varying relation characteristics between two markets. Moreover, these static models can only reflect the linear correlation between variables in terms of level, and never the nonlinear spillover effects between variables in terms of volatility. Therefore, a model with dynamic correlation coefficients should be constructed and subjected to a volatility causality test.

③ GARCH models are basically used to investigate the interrelations between the carbon market and other markets. Although a GARCH model can depict the volatility of the financial time series, it relies on historical fluctuation information and cannot fully reflect the randomness of price volatility. It is likewise deficient in the depiction of "leptokurtosis and fat-tail," weak autocorrelation, and long tendency time series. The multivariate GARCH model (e.g., DCC-GARCH, BEKK) cannot provide the specific effect direction (positive or negative) of volatility spillover [35]. Compared with GARCH model, the SV (Stochastic Volatility) model has a significant advantage over volatility studies [38]. The second-order moment of the SV model is determined by an unobservable random process rather than a deterministic function, which is more suitable for depicting the fluctuation of financial data. The multivariate SV model is easy to estimate and can describe the magnitude and direction of volatility spillovers at the same time. Zhang and Wu [24] concluded that the asymmetric SV model can successfully capture the time-varying, strong persistence and weak asymmetric features of CER carbon price dynamics.

Analogous to previous studies, this article synchronously discusses the dynamic correlations and volatility spillovers (similar to the dynamic linkage effect) between the CER market and its homogenous and heterogeneous markets within the framework of the SV model. We use CER futures prices

as the research object. We construct a DGC-MSV model for this research topic by combining with the fixed coefficient of Granger causality MSV model (GC-MSV) and the dynamic correlation coefficient MSV model (DCC-MSV). With regard to the homogeneous markets, the CER spot, EUA futures, and EUA spot are taken into account. As for the heterogeneous markets, we select five international financial markets commonly used in most previous studies, namely, stock, foreign exchange, coal, oil, and gas markets. With an emphasis on the dynamic linkages between the CER, homogenous, and heterogeneous markets, this analysis strives to detect the market factors that may influence the operation of the CER market under the CDM and thus bring some problems in the implementation of CDM to light.

III. METHODOLOGY

Methodologically, we introduce the combination of the MSV model based on Bayesian theory, which can synchronously investigate the dynamic correlations and volatility spillovers between two markets. Exploring the extent to which volatility shocks in other markets are transmitted to the CER market or vice versa is also of great importance to investors, policymakers, and researchers. In view of this, we propose a significance level test of volatility spillover by structuring t -distribution statistics based on the relevant elements in the combined model.

A. BAYESIAN HEAVY-TAILED DGC-MSV MODEL

Economic and econometric reasons can explain the importance of the multivariate SV (MSV) model [39]. The MSV model has been developed in various forms depending on its applications and is gradually being applied to the research on volatility spillovers among financial markets. The binary GC-MSV model (MSV model with Granger causality test) is one of the widely used models. Granger test can judge the lead-lag relationship between two markets but cannot measure their volatility interactions. By contrast, the GC-MSV model can be used to explain the strength of two market volatility spillovers and their own volatility persistence, as well as measure the lead-lag relationship. However, the GC-MSV model cannot quantify the time-varying relationship between two markets. To solve this problem, Meyer [40] proposed a dynamic correlation coefficient MSV model (DCC-MSV).

Consequently, this study combines the advantages of the DCC-MSV and GC-MSV model to construct a DGC-MSV model. It then uses the new model to probe into the dynamic interactions between the CER market and other markets from the two aspects of time-varying behavior and volatility spillover effects. In consideration of the better non-Gaussian distribution for analyzing carbon price changes [41] and the stylized features (e.g., leptokurtosis, serial correlation, heteroscedasticity) of financial asset returns, we propose a

heavy-tailed DGC-MSV model.

$$\begin{cases} y_t = \Omega_t \varepsilon_t, \varepsilon_t | \Omega_t \sim i.i.d.N(0, \Sigma_{\varepsilon,t}, \nu) \\ h_{t+1} = \mu + \Phi(h_t - \mu) + \eta_t, \eta_t \sim N(0, \text{diag}(\sigma_{\eta_1}^2, \sigma_{\eta_2}^2)) \\ q_{t+1} = \psi_0 + \psi(q_t - \psi_0) + \sigma_\rho z_t, z_t \sim i.i.d.N(0, 1) \\ \rho_t = \frac{\exp(q_t) - 1}{\exp(q_t) + 1}, \quad t = 1, 2, \dots, T \end{cases} \quad (1)$$

Take for example the CER and EUA futures markets, $y_t = (y_{1t}, y_{2t})'$, represents the two market price returns after mean centralization. $h_t = (h_{1t}, h_{2t})'$, is the standard deviations of y_t . $\Omega_t = \text{diag}(\exp(h_t/2))$, indicates the potential volatility and possesses a t -distribution. $\Sigma_{\varepsilon,t} = \begin{pmatrix} 1 & \rho_t \\ \rho_t & 1 \end{pmatrix}$. ρ_t stands for the time-varying correlation coefficient. ψ represents the persistence of time-varying correlation coefficient. The closer the value is to 1, the longer the correlation between the two markets lasts. $\mu = (\mu_{1t}, \mu_{2t})'$, shows the average level of market volatility in the long run. $\Phi = \begin{pmatrix} \phi_{11} & \phi_{12} \\ \phi_{21} & \phi_{22} \end{pmatrix}$. ϕ_{11} and ϕ_{22} denote the volatility persistence of CER and EUA futures return respectively. While ϕ_{12} and ϕ_{21} respectively express the volatility spillover effects of EUA on CER market and CER to EUA market. By doing so, we can get the dynamic volatility correlation between CER and EUA futures market on the basis of ρ_t . Depending on the parameter of Φ , the magnitude and direction of volatility spillovers between them is also apparent.

The estimation of the DGC-MSV- t model involves a high-dimensional integral, which is difficult to obtain directly through independent sampling from the perspective of mathematical statistics [42]. The MCMC method based on Bayesian theory can resolve this problem. Unlike the classical statistical inference approaches based on the maximum-likelihood principle, the Bayesian inference relies on joint posterior distributions of unknown parameters [38]. In the case of the MCMC method, it treats the unknown parameters of volatility as random variables without numerical optimization and realizes the estimation according to the joint posterior distributions by constructing a Markov chain. This measure not only improves the estimation accuracy but is also superior when numerous parameters exist [43]. The prior distributions of unknown parameters should be set first to estimate the DGC-MSV- t model. This paper refers to the setting of Meyer [40] as follows.

$$\begin{aligned} \mu_1, \mu_2 &\sim N(0, 25) \\ \sigma_{\eta_1}^2, \sigma_{\eta_2}^2 &\sim IG(2.5, 0.025) \\ \phi_{11} &= 2\phi_{11}^* - 1, \phi_{11}^* \sim \text{Beta}(20, 1.5) \\ \phi_{22} &= 2\phi_{22}^* - 1, \phi_{22}^* \sim \text{Beta}(20, 1.5) \\ \phi_{12}, \phi_{21} &\sim N(0, 10) \\ v^* &= v/2, v^* \sim \chi^2(4) \\ \psi_0 &\sim N(0.7, 10) \\ \psi &= 2\psi^* - 1, \psi^* \sim \text{Beta}(20, 1.5) \\ \sigma_\rho^2 &\sim IG(2.5, 0.025) \end{aligned}$$

B. SIGNIFICANCE TESTS OF VOLATILITY SPILLOVERS

As mentioned above, we can test the volatility spillovers between the CER market and other markets by verifying and comparing the significance of the Granger causality coefficients (ϕ_{ij}) in the DGC-MSV model. First, we establish a significant original hypothesis $H_0: \phi_{ij} = 0 (i \neq j)$. Next, we construct a t -statistic with the following detailed steps:

① Obtain the estimation of ϕ_{ij} . It is assumed that after the L rounds of MCMC iterations based on Gibbs sampling method, the sampling sequence $\phi_{ij}^{(l)}$ with the length of L can be obtained. After a sufficient burn-in period m , the Gibbs sequence, which is independent of the initial value, can converge to a stationary distribution. As a result, the value of the Markov chain is realized after the previous m iterations are discarded and then the estimation value is obtained,

$$\hat{\phi}_{ij} = \frac{1}{L-m} \sum_{l=m+1}^L \phi_{ij}^{(l)}.$$

② Calculate the standard deviation of ϕ_{ij} through the formula $S_{\hat{\phi}_{ij}} = \sqrt{\text{var}(\hat{\phi}_{ij})}$.

③ Structure the t -statistic. Given that ϕ_{ij} follows normal distribution, $S_{\hat{\phi}_{ij}}$ is clearly subject to χ^2 distribution with L degrees of freedom. In this way, $t = \hat{\phi}_{ij}/S_{\hat{\phi}_{ij}}$ can be introduced as a t -distribution.

At a given level of significance, if $|t| < t(L)$, then we can accept the original hypothesis H_0 , which indicates that ϕ_{ij} is significantly equal to 0. Otherwise, we will reject H_0 , which means that the j market has a volatility spillover effect on the i market. Specifically, if both ϕ_{12} and ϕ_{21} are significantly different from 0, then two-way volatility spillovers will occur between the CER market and the EUA market. Meanwhile, when only one significant parameter indicates that the CER market is unidirectional in relation to EUA market, then one market volatility will precede the other.

IV. EMPIRICAL RESULTS AND DISCUSSION

A. DATA

Forward trading is far more liquid than spot trading and can better reflect market fundamentals. As previously argued, carbon forward price has better quality than do other prices [44] and is the best one to use in econometric analysis [21]. This study used the CER carbon futures price as the research object. Taking into account the changes in the international carbon-reduction policy and the economic situation before and after the second commitment period of the Kyoto Protocol, we chose data in the post-Kyoto era, specifically, a time series running from January 2, 2013 to May 8, 2019. Moreover, three typical homogeneous markets of the CER futures market were introduced, namely, CER spot, EUA futures, and EUA spot.

In addition to the three homogeneous markets, this analysis also considered five necessary heterogeneous markets that wield significant influence on the CER market. For the stock market indicator, this study used the S&P Global 1200 index, which covers 31 countries and provides efficient exposure to the global equity market, capturing approximately 70%

TABLE 1. Data sources.

| <i>Variable</i> | <i>Meaning</i> | <i>Unit</i> | <i>Source</i> |
|------------------|--------------------------------------|-----------------------|---------------|
| <i>CERf/EUAf</i> | carbon futures return | Euro per tonne | Wind database |
| <i>CERs/EUAs</i> | carbon spot return | Euro per tonne | Wind database |
| <i>SPG</i> | S&P Global 1200 return | Million dollars | S&P Dow Jones |
| <i>EUSA</i> | central parity in euro/dollar return | - | Wind database |
| <i>COAL</i> | Global coal Newcastle return | US Dollars per tonne | Wind database |
| <i>BRENT</i> | ICE Brent return | US Dollars per barrel | Wind database |
| <i>GAS</i> | UK natural gas return | Pounds per thermal | ICE |

TABLE 2. Descriptive statistics.

| | Mean | Max | Min | Std.dev. | Skew. | Kurt. | J-B | ADF |
|---------------|-------------|------------|------------|-----------------|--------------|--------------|------------|------------|
| <i>CERf</i> | 0.0164 | 294.4439 | -138.629 | 11.9546 | 8.9876 | 265.4858 | 4534036.00 | -12.6177 |
| <i>CERs</i> | -0.0103 | 302.0425 | -69.3147 | 12.1138 | 15.6287 | 401.0897 | 6484399.00 | -14.2339 |
| <i>EUAf</i> | 0.0794 | 24.0514 | -43.4735 | 3.5644 | -1.4438 | 21.5363 | 22848.13 | -11.2416 |
| <i>EUAs</i> | -0.0065 | 20.1866 | -40.9702 | 3.6076 | -1.3929 | 23.5578 | 17502.34 | -9.2500 |
| <i>SPI200</i> | 0.0360 | 2.5858 | -5.1345 | 0.6918 | -0.7832 | 7.2488 | 1343.14 | -18.9734 |
| <i>EUSA</i> | -0.0105 | 2.4664 | -3.6820 | 0.5188 | -0.2564 | 6.8003 | 963.21 | -10.9107 |
| <i>Coal</i> | -0.0004 | 10.3661 | -12.7155 | 1.2326 | -0.8353 | 20.9786 | 21354.39 | -19.4240 |
| <i>Brent</i> | -0.0334 | 10.4162 | -8.8574 | 2.0145 | 0.1318 | 5.9994 | 593.81 | -28.0510 |
| <i>Gas</i> | -0.0280 | 21.1323 | -12.0944 | 1.8669 | 1.2151 | 28.3955 | 42629.94 | -38.6731 |

of global market capitalization. The CDM is an international carbon trading mechanism between developed and developing countries. Therefore, we did better by not adopting national or regional stock indices, such as the British FTSE 100 index, and the Frankfurt DAX index [18]. For the exchange market indicator, we selected the central parity of the euro against the dollar by considering the CER settlement currency units and the hegemony of the U.S. dollar in the global economy [33]. With regard to fossil energy prices (e.g., coal, crude oil, and natural gas), this study referred to the international representative indicators commonly used by current scholars (e.g. [21], [29], [31]). Table 1 presents and describes the data.

To account for the large gap among some index values, this article employed the first natural log-differenced daily prices or indices. Take P_t as the price, the corresponding return is $R_t = 100 \times (\ln P_t - \ln P_{t-1})$. There are 1614 data in each group.

Table 2 reports that the skewness, kurtosis and standard deviation of the CER spot return are the largest, followed by the CER futures return, and lastly by the EUA price returns. This result indicates that price volatility in the emerging carbon market is more volatile than that in traditional financial markets. Moreover, the CER market has a greater

degree of right bias, whereas the EUA market has a left bias, indicating the different distributions of the two carbon market prices. In terms of the Jarque-Bera test and kurtosis, all series depart from normality, revealing a “fat-tailed” leptokurtic distribution. The unit root test also presents that all variables are stationary at the 1% level, that is, no potential structural break exists. Hence, the effectiveness of the model estimation is ensured.

B. EMPIRICAL RESULTS

1) MODEL CONVERGENCE TESTS

The WinBUGS software was used to deal with the series by first removing the mean. Afterwards, the Bayesian Gibbs sampling was conducted 20,000 times with two Markov chains. At this point, the Markov chains were non-stationary. To assure the convergence of the parameter estimation results and the randomness of the samples, pre-iteration was discarded. Finally, 80,000 iterations were processed to obtain more stable parameter evaluations of the model. To validate the performance of our proposed methodology, Figure 2 presents the convergence diagnostic diagrams of ϕ_{11} and ϕ_{12} in the DGC-MSV- t model based on the *CERf-EUAf* pair. For the sake of saving space, we only used these two parameters as an example.

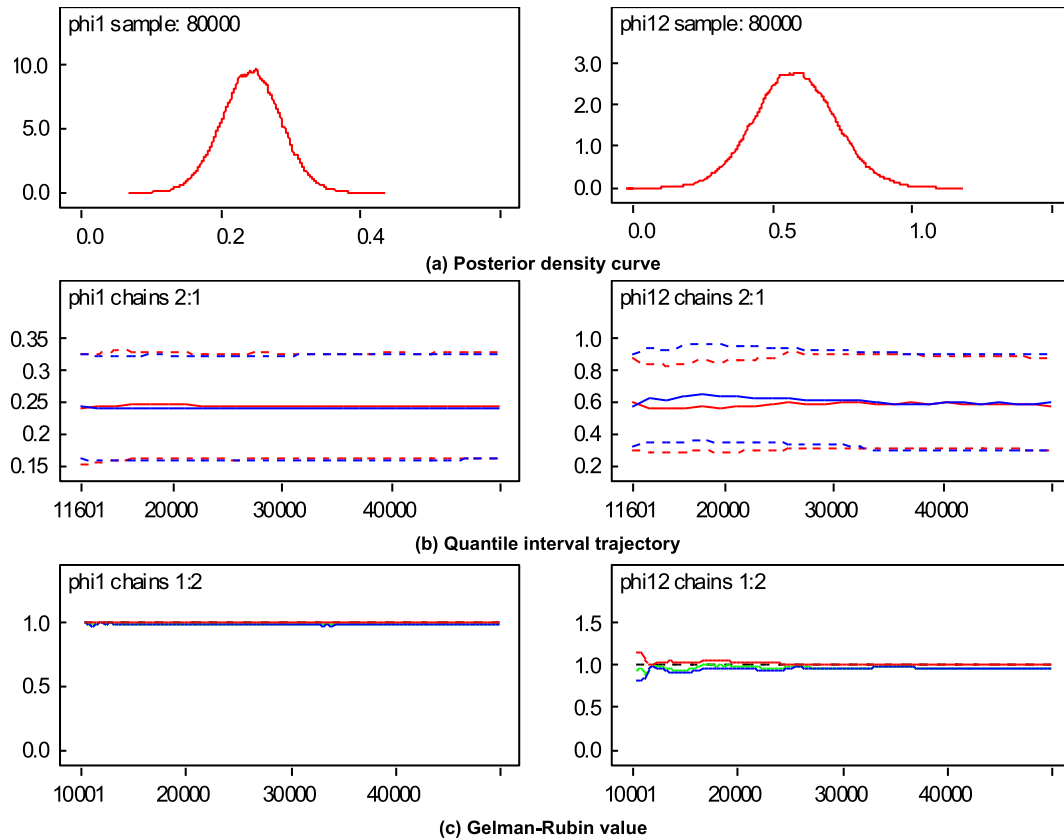


FIGURE 2. Convergence diagnosis of DGC-MSV-t mode.

TABLE 3. The volatility spillover effect between CER futures and EUA futures market.

| | Mean | Std.dev. | MC error | 2.5%Quantile | Median | 97.5%Quantile |
|-------------|---------|----------|----------|--------------|---------|---------------|
| μ_1 | -2.6430 | 0.2402 | 0.0059 | -3.0760 | -2.6540 | -2.1290 |
| μ_2 | 1.9710 | 0.3135 | 0.0136 | 1.4690 | 1.9310 | 2.7270 |
| ϕ_{11} | 0.2839 | 0.0297 | 0.0004 | 0.2252 | 0.2839 | 0.3423 |
| ϕ_{12} | 0.2976 | 0.1754 | 0.0071 | -0.0469 | 0.2969 | 0.6484 |
| ϕ_{22} | 0.9793 | 0.0082 | 0.0004 | 0.9613 | 0.9799 | 0.9936 |
| ϕ_{21} | 0.0009 | 0.0021 | 0.0001 | -0.0034 | 0.0006 | 0.0048 |
| ψ | 0.9064 | 0.0558 | 0.0038 | 0.7732 | 0.9182 | 0.9816 |
| ν | 9.6950 | 2.3070 | 0.1239 | 6.4480 | 9.2720 | 15.4300 |

Figure 2 illustrates that the posterior distribution density graphs of ϕ_{11} and ϕ_{12} (Figure 2a) are relatively smooth and basically symmetrical with obvious peaks. This finding means that the Bayesian estimation was close to the real value and the error was small. The trajectories of the two chains (Figure 2b) were generated from dispersed initial values but were stabilized in a horizontal line, signifying a consistent and robust result. The Gelman-Rubin test value (Figure 2c) was close to 1 and remained stable, indicating the status of the parameter convergence. Generally, the MCMC iterative process turns out to be smooth and steady, so that

the estimated parameters are convergent to the joint posterior distributions and the model estimation is valid. Consistent with the estimation results in Table 3, the MC error is far less than the standard deviation, illustrating that the distribution of each element has converged to its posterior distribution.

2) VOLATILITY SPILLOVER AND DYNAMIC CORRELATION FOR THE CERF-EUAF PAIR

By means of the DGC-MSV-t model, we explored the volatility spillover and dynamic correlation between the CER and

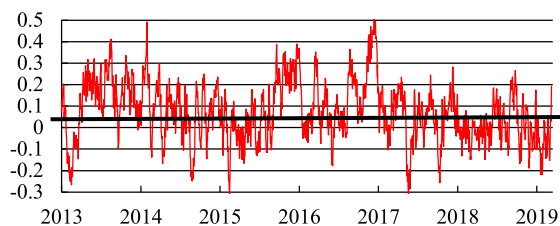


FIGURE 3. The dynamic correlation between CER and EUA futures market volatility.

EUA futures market (Table 3). Next, we estimated and inspected the dynamic linkage effects for other paired assets.

A comparison of the parameters that reflect the average fluctuation level, namely, μ_1 and μ_2 , revealed that the price volatility of the CER market is larger than that of the EUA futures market and has an opposite price trend. ϕ_{11} and ϕ_{22} demonstrated that the volatility persistence of the CER and EUA futures markets are 0.2839 and 0.9064, respectively. This result illustrates that the CER futures market is less affected by the ups and downs of the lag issue, thus leading to its weak long-term memory. Meanwhile, the EUA futures market exhibited significant volatility agglomeration. ϕ_{12} denotes the volatility spillover from EUA to CER market, with the value of 0.2976 and the corresponding t -statistics reaching 1.6967. ϕ_{21} measures the volatility spillover effect of the CER on the EUA market. Its coefficient is 0.0009, and the t -statistics is only 0.4378. At the 5% significance level, the t -value is 1.96 when the degree of freedom is infinite. Therefore, ϕ_{12} is significantly different from 0 under the 95% confidence level because its t -statistics (1.6967) is bigger than 1.96. However, the t -statistics value of ϕ_{21} is insignificant. Thus, the volatility spillover relationship between CER and EUA futures market is unidirectional, and the volatility of the EUA market is ahead of that of the CER carbon market, consistent with the majority of prior conclusions (e.g. [17], [34]). The posterior mean value of the time-varying correlation continuous parameter ψ is 0.9064. This outcome implies the long-memory property of the dynamic correlation between CER and EUA futures markets. At this point, the information digestion function between them is slow, and so the information liquidity is weaker. The parameter of ν is significantly greater than 2, showing the “fat-tailed” features of the two market returns and a consistency with the preliminary analysis in Table 2.

Another notable feature is their highly time-varying correlation, which provides support for the dynamic model specification against a constant correlation specification. As displayed in Figure 3,³ the dynamic correlation coefficient fluctuates in the vicinity of 0.1. In addition to a few abnormal negative values, the rest are positive over the entire period. When the parameter is positive, the changes in time-varying variances between the two markets becomes consistent, that is, risk synergy effect will exist between them,

³Because the MCMC iterative process uses two chains, so the simulation obtains two sets of values. We report their average value in Figure 3.

whereas the negative coefficient indicates a substitution relationship between the two carbon markets. In this way, the results obtained with our sample will challenge the priors’ viewpoint of a cointegrated relationship between the EUA and CER (e.g. [16], [17]). Although the correlation is dynamic, it has a mean reversion characteristic, with the mean value of ρ being 0.0746. At the same time, the fluctuation correlation has a strong sustainability and is consistent with the demonstrated ψ value of 0.9064 in Table 3. The DGC-MSV- t model can correctly capture the interactions between the CER and EUA futures market. In summary, the traditional fixed-coefficient model cannot accurately reveal the interaction between the two markets and cannot provide investors with nicety decision-making support to build a portfolio [35].

3) DYNAMIC LINKAGE EFFECTS TO CER FUTURES MARKET

The estimation results⁴ for CER and other markets depending on the DGC-MSV- t model report that, except for the CER spot, which has a weak volatility persistence (0.2491) similar to that of the CER futures market, these markets possess significant volatility clustering with a volatility persistence of over 0.9. The degree of freedom of ν in each model is significantly larger than 2. Owing to the “fat-tailed” characteristic of these market returns, the rationality of introducing Student- t distribution is confirmed. We detect the strength and direction of the spillover effects between CER and these markets by means of the significance test calculation (Table 4). The main findings are as follows.

① As mentioned above, ϕ_{12} indicates the spillover effects of other markets on the CER futures market. Table 4 reveals that the spillover effects of all market fluctuations reach the 1% significance level. Among them, similar carbon products (i.e., CER spot, EUA futures, and EUA spot) have significant positive spillover effects and play a leading role in the CER futures market. At nearly the same significance level, EUA futures and EUA spot display stronger volatility spillovers than the CER spot. Conversely, the heterogeneous markets (i.e., stock, foreign exchange, and energy markets) have significant negative spillover effects. The most powerful market is the exchange rate market, followed by the coal market, with the weakest role of going to the natural gas market. However, the volatility spillovers from these heterogeneous markets are stronger than those of homogeneous markets. As a result, the volatility of heterogeneous markets would lower the income of the CER futures market. The decline in price of CER futures in the post-Kyoto era is largely due to the fluctuations of the exchange rate and the coal markets.

By contrast, the volatility of homogeneous markets contributes to the movements of CER futures market. A possible explanation of this may be attributed to the climate change policy uncertainties in carbon trading markets. As the development of the EUA market matures, its volatility will

⁴To save space, detailed information about the model evaluation results of all paired assets is not provided, and it is available from the authors upon request.

TABLE 4. Test of significance between CER futures and other markets.

| Market portfolio | ϕ_{12} | | | ϕ_{21} | | |
|--------------------|-------------|----------|----------|-------------|----------|----------|
| | Mean | Std.dev. | <i>t</i> | Mean | Std.dev. | <i>t</i> |
| <i>CERf-CERs</i> | 0.1785*** | 0.0264 | 6.7716 | 0.3496*** | 0.04294 | 8.1416 |
| <i>CERf-EUAf</i> | 0.2976** | 0.1754 | 1.6967 | 0.0009 | 0.0021 | 0.4378 |
| <i>CERf-EUAs</i> | 0.2542** | 0.1498 | 1.6969 | 0.0007 | 0.0020 | 0.3191 |
| <i>CERf-SP1200</i> | -1.912*** | 0.2394 | -7.9866 | 0.0003 | 0.0024 | 0.1453 |
| <i>CERf-EUSA</i> | -7.959*** | 1.257 | -6.3317 | -0.0052** | 0.0025 | -2.1095 |
| <i>CERf-Coal</i> | -2.383*** | 0.3388 | -7.0336 | -0.0005 | 0.0029 | -0.1714 |
| <i>CERf-Brent</i> | -1.202*** | 0.2064 | -5.8236 | -0.0007 | 0.0012 | -0.6265 |
| <i>CERf-Gas</i> | -0.7407*** | 0.07433 | -9.9650 | 0.0005 | 0.0062 | 0.0882 |

Note: ***indicates significance at 1%, **at 5% and*at 10%.

accelerate the efficiency of information flow in the CER market. However, the reduction of demand and trading volume may lead to the diffident prospects of investors on the CER market and add to the CER market’s instability. On account of the intense negative volatility spillover, the CER price declined in the post-Kyoto era, corresponding with the practical situation.

② As for the other parameter, ϕ_{21} represents the spillover effects of the CER market on other markets. The findings identify that, in addition to the strong spillover effect on the CER spot market under the 1% significance level and a weak spillover to the exchange market at the 5% significance level, the connection between the CER futures market and the rest of these markets are insignificant. This finding may differ from the result of Zhang & Sun [35], who claimed that a unidirectional and overall positive volatility spillover exists from the coal market to the EUA market and from the EUA market to the natural gas market. As emphasized by Balcilar et al. [5], the CDM-driven nature of CER contracts and its long-term nature indicate a certain independence from the EUA and energy markets. In this sense, the empirical results of this study are easy to understand.

A comparison of the volatility spillovers between the CER futures and CER spot markets shows that the spillover effect of CER futures on CER spot is greater than the opposite. The price discovery function of the CER futures market is embodied. The bidirectional volatility spillover makes it clear to a certain extent that the CER carbon market tends to be more efficient and transparent along with its development, and the information flow within the market becomes unobstructed. In this regard, the CER spot market is gradually stepping forward to the center of the volatility spillovers. However, the development of the CER market is inferior to that of the EUA market at present because it is influenced by international carbon reduction policy uncertainties.

The imperfect market mechanism brings about insufficient information fusion with traditional financial and

energy markets. Nevertheless, well-developed financial and energy markets and the emerging EUA market have a swift response to the impact of the CER market. They can rapidly absorb internal and external market information (e.g., psychological expectations of investors, relevant policy changes, etc.) and reflect on the previous day’s price. Given that the sensitivity to information and feedback speed of these markets are obviously higher than those of the CER market, the intuition behind this result points to the fact that unidirectional volatility spillovers emerge from other markets to the CER market. An analysis of the feeble linkages of CER market on foreign exchange market reveals that the CER carbon futures product is not only a price volatility recipient but is also gradually influencing the international capital market price fluctuations.

As shown in Figure 3, we can obtain the dynamic correlation coefficients between CER futures and its heterogeneous markets and show their descriptive statistics. The dependence parameters of ρ demonstrated in Table 5 are all dynamic, confirming the presence of time-varying correlations. From the aspect of the mean value, the CER futures market has the strongest correlation with its homogeneous markets, followed by the exchange rate market. On average, the relatively low value of the correlations indicates the diversification potential of portfolios comprising CER futures and other markets. Moreover, the largest change of interaction is within the CER market, and the pair of CERf-Coal is inferior to this market. The minimum variation is the correlation coefficient for CERf-Brent oil. The persistence of time-varying correlation parameters is large and close to 1 (between 0.8111 and 0.9875). The dynamic interactions between CER futures and its driver markets have a long memory. The market information digestion is slow, and the information liquidity is relatively weak. This situation further validates the obtained results, that is, the information conducted between CER futures and other markets is so far mainly unidirectional and difficult to eliminate in a short time.

TABLE 5. The dynamic correlations between CER futures and other markets.

| | Mean | Max | Min | Range | Std.dev. | $\bar{\psi}$ |
|--------------------|---------|--------|---------|--------|----------|--------------|
| <i>CERf-CERs</i> | -0.2077 | 0.8267 | -0.9608 | 1.7876 | 0.4921 | 0.9875 |
| <i>CERf-EUAf</i> | 0.0746 | 0.5108 | -0.3181 | 0.8289 | 0.1380 | 0.9064 |
| <i>CERf-EUAs</i> | 0.1081 | 0.3962 | -0.2314 | 0.6277 | 0.0970 | 0.8874 |
| <i>CERf-SP1200</i> | -0.0124 | 0.2669 | -0.3047 | 0.5717 | 0.1044 | 0.8945 |
| <i>CERf-EUSA</i> | -0.0619 | 0.1701 | -0.3154 | 0.4855 | 0.0812 | 0.8323 |
| <i>CERf-Coal</i> | 0.0266 | 0.7743 | -0.6608 | 1.4350 | 0.2798 | 0.8917 |
| <i>CERf-Brent</i> | -0.0094 | 0.2089 | -0.1919 | 0.4008 | 0.0622 | 0.8111 |
| <i>CERf-Gas</i> | 0.0176 | 0.4349 | -0.5047 | 0.9396 | 0.1616 | 0.9513 |

V. CONCLUSION AND IMPLICATIONS

Recently, the CER carbon product became an important underlying instrument of carbon financial asset allocation and increasingly interconnected with stock and energy prices. However, the lack of research on the dynamic linkages between CER and various market prices in existing literature may cause the omission of the dynamic portfolio, volatility forecasting, and risk management in the CER carbon market, which is of paramount importance for policymakers and investors. What’s more, there has been an unstable development of the CER market since the inception of CDM. In particular, it has experienced a price downturn in the post-Kyoto era. Potential reasons for such phenomenon include the international carbon-reduction policy changes and the climate debate among all nations, among others. In light of this, we attempt to explore the influencing factors of the CER market by focusing on the interactive relationship between CER and several typical influential markets to figure out existing problems in the CDM operation.

In this paper, we shed light upon the CER futures market, and select three representative homogeneous markets (i.e., CER spot, EUA spot and EUA futures) and five typical heterogeneous markets (i.e., stock, foreign exchange, coal, crude oil and natural gas markets) that can have an impact on CER price volatility. We investigate the issue of the dynamic linkages between the CER market and others. In contrast with most of the previous empirical literature on spillover effects, we construct a DGC-MSV-*t* model to synchronously explore the dynamic correlations and volatility spillovers between CER futures market and each of these influencing markets. The empirical results report that the emerging EUA carbon market and traditional financial markets have different spillover effects on the CER futures market.

① The volatility spillover direction indicates that the homogeneous markets play a positive guiding role on the CER futures market, whereas the heterogeneous markets have a negative impact. In the post-Kyoto era, the decline of the CER futures price is caused by the fluctuation of the foreign

exchange market, which has a direct impact on the transaction price of carbon products and coal price volatility, on behalf of the energy market swings. In view of this, the downturn of the CER price is partly caused by the international financial situation rather than the deterioration of fundamentals. Therefore, we still need to maintain an optimistic attitude on the development prospects of the CER carbon market.

② In light of the spillover effects strength, an asymmetric two-way volatility spillover occurs between CER futures and CER spot. As the intension of the CER futures spillover is stronger, the price discovery function gets performed in the CER futures market. However, the development of the emerging CER market is still immature. With weak information liquidity, in addition to a feeble information overflow on the exchange market closely connected with the settlement price, the CER futures market demonstrates an insignificant volatility spillover effect on other markets. So far, the volatility transmission is mainly from the EUA market and heterogeneous markets to the CER futures market, but not vice versa. However, along with the improvement and enhancement in the trend of financialization of the CER market, we cannot exclude the possibility that the CER market and these influential markets come to play a game of reciprocal influences.

③ As for the volatility dependence, a time-varying correlation exists between the volatility of the CER futures market and others but with slow information fusion and strong persistence. The volatility impacts from these influencing markets to the CER market do not easily fade within a short period of time. This result suggests that CER credits are still driven by the CDM specific factors, and the climate change policy uncertainties are important factors impeding the development of the carbon market, resulting in the feeblest financial property of the CER market.

The aforementioned results provide insightful implications for regulators and investors, especially in the managerial aspects of the CER market. First, the market regulators should loosen restrictions and buoy the CER market because the price depression will cause market participants

to lose confidence. Restrictions on the purchase of CER in phase III of the EU ETS have created a major shock to the CER market. The uncertainty factors of the carbon-reduction policy are also a main cause. Thus, short-term and long-term development policies should be planned for the CER market, such as relaxing the restrictions, stimulating the demand for CER, facilitating the procedure for approval and issuance of CDM projects, and shortening the gap with other carbon products. Second, policymakers should strive to promote the marketization and financialization of the CER market to improve the influence of the CER market on other markets. When the connection between markets has a sound development, it will be conducive to the sustainable development of the global economy. Third, to avoid the “market failure” situation and improve the effectiveness of policy implementation, market regulators should take the relevant market price changes into account, as the ability to resist external market impacts will be enhanced. Lastly, policymakers and traders should be aware that the volatility spillovers of financial and energy markets work differently for EUA and CER carbon markets. Under the circumstance that the CER market is becoming mature, investors should focus on the fluctuation of the exchange rate in CER transactions to hedge the risks transmitting from other markets. By doing so, they can adjust the investment strategy in a timely manner and obtain a precise and rational arbitrage. At the same time, investors in the CER spot market should keep a watchful eye on the volatility from CER futures market to proactively take risk control and aversion.

By relying on the framework of the SV model, the model built in this article not only overcomes the defects of fixed-coefficient models (such as Granger causality test with constant coefficient, VAR model), which cannot describe the dynamic relationship between CER and other markets, but, also captures the volatility feature of carbon price and financial time series. The true linkage between CER and its driver markets can well be reflected as well. Most importantly, the DGC-MSV model can provide the magnitude and direction of volatility spillovers simultaneously, which cannot be obtained from most volatility models. Remarkably, our model cannot depict the variables’ structure change yet, and solving this problem to improve accuracy will require further research. The Markov regime switching algorithm may be introduced into the MSV model to examine the dynamic interactions of the CER market and various markets under different volatility regimes.

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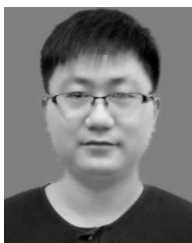
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