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Supply chain management based on volatility clustering: The effect of CBDC volatility

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ABSTRACT

A Central Bank Digital Currency (CBDC) launched by the Bank of England could enable businesses to directly make electronic payments. It can be argued that digital payment is helpful in supply chain management applications. However, the adoption of CBDC in the supply chain could bring new turbulence since the CBDC value may fluctuate. Therefore, this paper intends to optimize the production plan of manufacturing supply chain based on a volatility clustering model by reducing CBDC value uncertainty. We apply both GARCH model and machine learning model to depict the CBDC volatility clustering. Empirically, we employed Baltic Dry Index, Bitcoin and exchange rate as main variables with sample period from 2015 to 2021 to evaluate the performance of the two models. On this basis, we reveal that our machine learning model overwhelmingly outperforms the GARCH model. Consequently, our result implies that manufacturing companies' performance can be strengthened through CBDC uncertainty reduction.

1. Introduction

Cryptocurrencies, represented by Bitcoin, have exhibited a significant impact on the current financial system (Easley et al., 2019; Zhang and Li, 2020; Huynh et al., 2021; Jin et al., 2021; Prat and Walter, 2021), especially after the outbreak of COVID-19 (Guo et al., 2021; Diniz-Maganini et al., 2021) and Fintech development (Le et al., 2021; Chaudhry et al., 2022). As a result, to confront and replace such an emerging private digital currency system, the Bank of England announced the launch of a Central Bank Digital Currency (CBDC), which served as a new form of digital currency issued by the Bank of England and can be used by households and businesses (BenDhaou and Rohman, 2018; Vessio, 2021).

Since CBDC is still under development, copious of scholars advocate the adoption of blockchain techniques into CBDC systems, which can yield a number of benefits, such as increased payment safety and information transparency (Sun et al., 2017; Sethaput and Innet, 2021). Moreover, several countries have already signified the adoption of blockchain in their CBDC payment systems (Xu and Zou, 2021). On the other hand, bitcoin is an exceedingly representative digital coin based on the blockchain technique (Hughes et al., 2019; Jiang et al., 2022). Consequently, we use bitcoin to depict blockchain-based digital currency, which aligns with the future development trend of digital currency like CBDC.

Actually, the adoption of blockchain techniques into supply chains has been documented in recent Supply Chain Management

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(SCM) studies see (Cole et al., 2019; Saberi et al., 2019; Kshetri, 2021; Gökalp et al., 2022), proposing an advanced technology application blending with supply chain management in the leading research of supply chain management. As a result, companies, especially manufacturing companies, value SCM highly, and the influence of digital currency on the supply chain becomes increasingly crucial.

Therefore, the research questions of the paper are twofold. What is the impact of CBDC volatility on SCM for manufacturing companies, and more importantly, how can those firms reduce the uncertainty brought by CBDC through SCM? On this basis, this paper addresses how manufacturing companies can manage their supply chain under volatile circumstances, focusing on volatile CBDC value and transportation cost. In particular, we contribute to the literature by formulating an effective production plan to reduce costs and increase revenue associated with currency value and transportation cost uncertainties as the CBDC applies in SCM. Empirically, our results illustrate that CBDC volatility plays a crucial role in the SCM of manufacturing companies. Moreover, we also unfold the fact that our SCM framework can aid manufacturing companies in saving transportation costs as well as increasing operating revenue by frustrating the impact of digital currency uncertainty.

In fact, digital currency has been widely used during the payment process in supply chains. Massive companies have embraced digital currency for their business transactions (Viriyasitavat et al., 2021). The adoption of digital currency payments would be beneficial for both payers and receivers, leading to a more liquidated and automated transaction along the supply chain (Choi, 2021). It is thereby valuable to investigate the effect of CBDC volatility on supply chain management. Since the CBDC was still at the starting stage, we need to use a proxy to simulate CBDC volatility. Because the CBDC holds both digital currency and sovereign currency characteristics, we use Bitcoin (BTC) as the proxy of digital currency and Great British Pound (GBP) as the proxy of sovereign currency. As a result, this paper intends to reveal the impact of the CBDC volatility effect on supply chain management from the combination of both BTC and GBP by using the machine learning approach to meld both effects.

In practice, Supply Chain Management (SCM) plays an important role in manufacturing companies in terms of resource allocation and cost minimization (Olhager and Selldin, 2004). More recently, Xu et al. (2019) proposed a manufacturing industry supply chain management system integrated with the digital currency of Ethereum. Pranesh et al. (2020) also suggest an Ethereum-based counterfeited product detection system to enhance supply chain management.

However, the value of CBDC would be volatile from both digital currency and sovereign currency properties. A sound supply chain and logistics management are challenged by risk factors and environmental uncertainties (Aqlan and Lam, 2016). As a result, the ability to respond to those uncertainties can assist companies in strengthening their core competence and alleviating their long-term business suffering, leading to better cost and revenue management (Hendricks and Singhal, 2005). Therefore, the supply chain decision-making framework, which takes uncertainty into account to reduce cost, has become largely demanding in recent years (Guerra-Zubiaga and Young, 2008).

In particular, uncertainties play pivotal roles in SCM. Van der Vorst and Beulens (2002) argue that lessening uncertainties should be a key consideration of companies for improving their performance. They used a case study to show that service levels have been substantially enhanced by controlling uncertainties in food chain management. More recently, Thun et al. (2011) unveiled that the increasingly fluctuating business environment places a heavy burden on manufacturing companies with risk issues in their supply chains. Wong et al. (2011) advocate that environmental uncertainty plays a crucial role in influencing the effectiveness of a managing system. More importantly, currency value uncertainty, referred to as exchange rate risk, is a vital consideration for supply chain management see (Huchzermeier and Cohen, 1996; Kim and Park, 2014; De Soyres et al., 2021).

As a result, the main contribution of this paper is to develop a framework for manufacturing companies to formulate their production plans via the reduction of market uncertainties with the adoption of CBDC. Our framework is based on the volatility clustering model, and we schedule all market-related activities into low-volatility periods of CBDC and BDI. Under such a framework, we can thereby reduce the overall currency value uncertainty faced by manufacturing companies as well as the transportation cost uncertainties through rescheduling. We adopt a decision tree method to determine the next production stage in the supply chain based on the volatility clustering result to optimize the production plan. Our results unravel that the supply chain management can be enhanced by scheduling firm activities to low volatility periods as high market uncertainties can be neutralized. We thereby demonstrate that the accuracy of volatility forecasting plays a vital role in supply chain scheduling and therefore our machine learning approach outperforms traditional GARCH model in strengthening supply chain scheduling plans.

Empirically, we use three key business variables to extract transportation cost and currency value uncertainties, which are the Baltic Dry Index (BDI), Bitcoin (BTC) and exchange rate (GBP). For the exchange rate, we take the British Pound against Dollar as the CBDC issued by the Bank of England is concerned. These three key business variables represent the transportation cost and currency value, respectively. We adopt the GARCH (generalized autoregressive conditional heteroscedasticity) model for the conditional volatility estimation and volatility clustering. It has been well documented that GARCH estimation of volatility is consistent with volatility clustering patterns exhibited in financial time series see (Bai et al., 2003; Ardia et al., 2019; Kenc et al., 2021; Venter and Maré, 2022).

Based on the data of three key business variables, we deliver empirical results to reveal that our framework can aid manufacturing companies in saving operating costs as well as increasing operating revenue by decreasing market uncertainty. We first discover that the GARCH model has a negative improvement for the cost savings and revenue increase of the production plan. The GARCH model delivers as much as −9.49 % of the overall improvement rate. Then, we changed to the machine learning model, and the model performance was improved. For transportation cost, our framework can help manufacturing companies to save 6.68 % cost. For the sale price of export regarding the currency value, our framework can raise the revenue as much as 2.86 % for BTC and 9.77 % for GBP. The overall cost savings and revenue generation of our machine learning model through production scheduling is approximately 20 %. Therefore, it is arguable that our machine learning framework would be helpful to manufacturing companies for cost savings and revenue increases, especially in volatile periods.

The remainder of the paper is organized as follows. Section 2 covers the data description of key variables, including BDI, BTC and GBP exchange rates, as well as the GARCH-type model setup. Section 3 presents the empirical result of model performance for the GARCH model. We reveal that the GARCH model has inferior performance. Therefore, in section 4, we introduce the Density Based Spatial Clustering of Applications with Noise (DBSCAN) model and show the empirical model performance of DBSCAN. Section 5 concludes the paper.

2. Data and methodology

2.1. Data of key business variables

In this paper, we focus on the volatilities of three key business variables, namely, the Baltic Dry Index (BDI), Bitcoin (BTC) and exchange rate (Great Brain Pound (GBP) against dollars). The BDI indicates the transportation cost, BTC indicates the CBDC from the blockchain-based currency side and GBP indicates the CBDC from the sovereign currency side.

The sample data we collect are for the Baltic Dry Index (BDI), Bitcoin (BTC) and exchange rate (Great Brain Pound (GBP) against dollars) from the WIND database on a daily basis. The sample covers the period from 1 January 2015–31 December 2021 (1775 daily total observations for each series). To eliminate the size effect of all prices when we conduct the GARCH model, we take the natural log of oil price, BDI, BTC and GBP, where the logged price moving trend is plotted in Fig. 1. The corresponding statistical summary for all three variables is presented in Table 1.

2.2. Volatility estimation through the GARCH model

It is noticeable that there might be a heteroscedasticity effect rooted in business variable volatilities. The conditional heteroscedasticity or autocorrelation embedded in a time series is called an autoregressive conditional heteroscedasticity (ARCH) effect. The ARCH-LM (Lagrange-Multiplier) test is used to assess the significance of ARCH effects for a particular time series. As a result, we report the ARCH-LM test results in Table 2 for the three key business variables with the null hypothesis that the time series has no ARCH effects. It is observable that all three key business variables have rejected the null hypothesis on the 10% significance level, indicating that the heteroscedasticity effect existed within those time series.

On this basis, we use generalized autoregressive conditional heteroscedasticity (GARCH) to model all volatilities in this paper. The advantage of employing the GARCH model has been well documented in the literature. The GARCH model prevails to provide the estimation of stochastic volatility instead of traditional constant volatility, and the model can converge parameters to their long-term

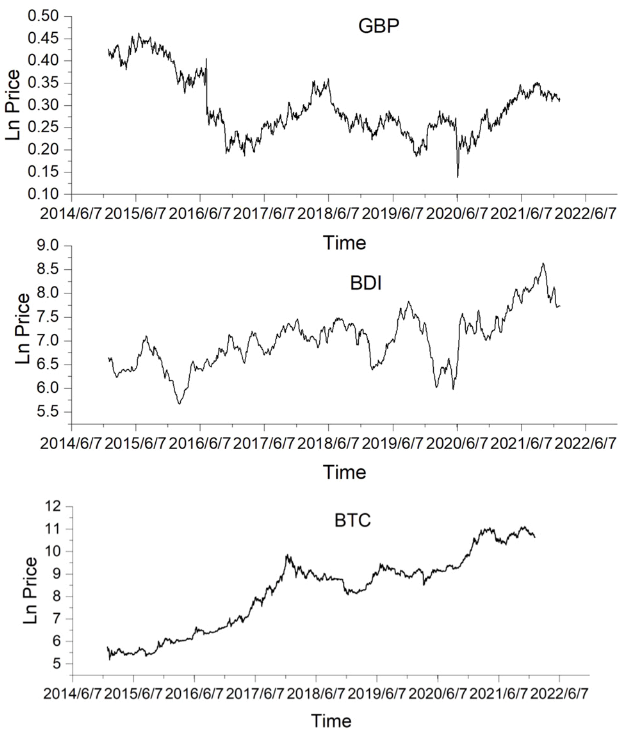

Figure 1. Price trend movement of three key business variables.

Table 1
Statistical summary of three key business variables.

Key Business Variables	Obs	Mean	Std. Dev.	Min	Max
BDI	1775	7.01	0.57	5.67	8.63
BTC	1775	8.22	1.71	5.180	11.12
Exchangle Rate	1775	0.29	0.0670	0.13	0.46

Table 2
ARCH-LM test results of three key business variables.

Key Business Variables	Chi^2	P-value	lag (s)
BDI	490.24	0.00	1
BTC	13.26	0.00	1
Exchange Rate	6.68	0.01	1

values as the model intakes enough time series observations (Alexander, 2002). Moreover, the GARCH model considers the heteroscedasticity effect, which can imply the volatility clustering trend of the time series (Choudhry and Wu, 2009). In order to show the volatility clustering features indicated by the heteroscedasticity effect, all volatilities in our paper are conditional volatilities based on the GARCH model, and since the time lag in the ARCH-LM test is 1, we use the GARCH (1, 1) model for our study. Nevertheless, a number of scholars have pointed out the limitations of using the GARCH model. For instance, the GARCH may fail to capture nonlinear effects of the time series, and it is difficult to include direct long memory effects (Gavrishchaka and Banerjee, 2006). Given the limitations of the GARCH model, we adopt another method in this study, the machine learning approach. Compared with the GARCH model, one main drawback of using machine learning methods is that this method may lead to a black box model, which normally is not inherently interpretable. Moreover, sound hyperparameter configurations are always desired for machine learning algorithms, and this procedure can be time-consuming compared with the GARCH model procedure.

GARCH family models are widely applied in volatility modeling and forecasting in finance and economics, including Baltic Dry Index (BDI) volatility (Ding et al., 2019); BTC volatility (Katsiampa, 2017; Troster et al., 2019; Aharon et al., 2022; Bergsli et al., 2022) and GBP exchange rate volatility (Kenourgios et al., 2015; Sun and Yu, 2020; You and Liu, 2020).

The standard GARCH (1, 1) model has the following form:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \sigma_{t-1}^2 + \alpha_2 \varepsilon_{t-1}^2. \tag{1}$$

where σ_t is the volatility of the target time series and ε_t is the residual term from the return prediction equation, which is:

$$r_t = \phi + \varepsilon_t, \tag{2}$$

where ϕ is the conditional mean, and $\varepsilon_t \sim N(0, \sigma_t^2)$.

Based on the GARCH model, we estimate conditional volatilities for all three key business variables, and the corresponding statistical summary is exhibited in Table 3. From Fig. 2, it is clear that all volatilities are clustered into two areas, the upper half area and the lower half area, with certain thresholds, which is according to the long-run equilibrium of the volatility series. For example, the threshold of BTC volatility clustering is approximately 3.2. As a result, a volatility level above 3.2 can be categorized as high volatility, whereas a volatility level below 3.2 can be categorized as low volatility.

3. Production planning for manufacturing supply chain based on GARCH model

3.1. Preliminary settings

According to Maravelias and Sung (2009), the supply chain for a manufacturing company mainly comprises three activities, namely, raw material procurement, manufacturing finished product from the raw material, and distributing finished products to customers. Since three stages are involved in the manufacturing process, we need to allocate time into different stages. Based on Gnoni et al. (2003), we take a manufacturing production capacity of approximately 9600 min per month as our example, equivalently, 20 days per month with 8 h per day. If we presume there are 30 days in one month, then we can assume 5 days for material procurement from suppliers and 5 days for distribution to customers. Practically, purchasing raw materials is a prerequisite for production, and

Table 3
Statistical summary for conditional volatilities of three key business variables.

Key Business Variables	Obs	Mean	Std. Dev.	Min	Max
BDI	1755	0.34	0.008	0.003	2.47
BTC	1755	3.36	2.75	0.001	13.92
Exchange Rate	1755	0.45	0.005	0.0002	0.036

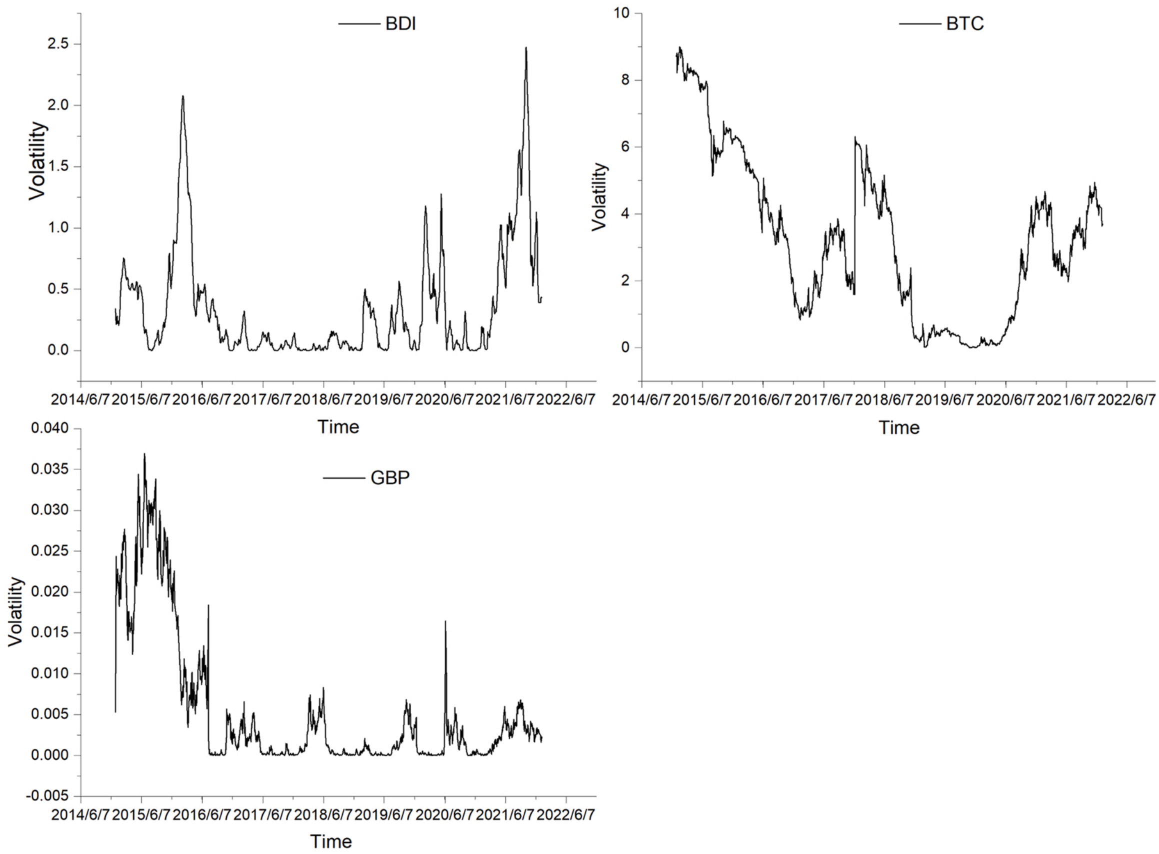

Figure 2. Plotting of conditional volatilities for all three key business variables.

similarly, manufacturing products is a prerequisite for distribution. Therefore, the supply chain shall be strictly on the procurement-production-distribution sequence, so we cannot interrupt this sequence for annual production scheduling.

On this basis, formulating the annual production plan of the supply chain is as follows:

1. We divide all days in one year into 73 blocks, with 72 blocks of 5 days plus one Remaining Block (RB). The RB can be 5 days in normal years and 6 days in leap years, which can be considered holidays without scheduling, and we leave them at the end of the year. Therefore, we only have 360 days for the annual production plan.

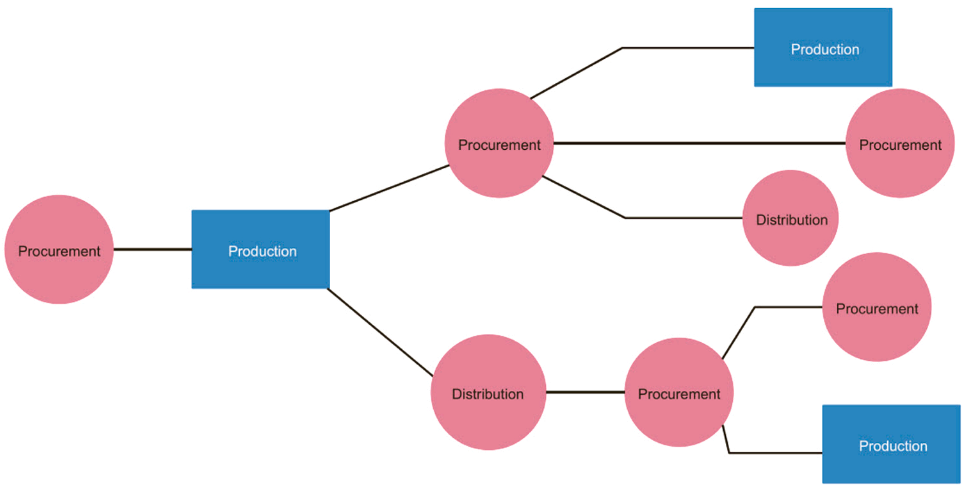

Figure 3. Decision tree example.

2. Since we have 5 days for material procurement from suppliers, 20 days for manufacturing and 5 days for distribution to customers for each month, the numbers of corresponding blocks are 12 blocks for material procurement from suppliers, 48 blocks for manufacturing and 12 blocks for distribution to customers for the annual production plan. Therefore, the number of blocks for the procurement-production-distribution sequence shall be 1 block – 4 blocks – 1 block matched.
3. Because of the procurement-production-distribution sequence, the first five blocks in January must be one block for procurement and four blocks for production, whereas the last block in December must be for distribution. As a result, those six blocks in the supply chain cannot be rescheduled.
4. Our optimized production plan of the supply chain is based on the volatility clustering result, which is presented in Fig. 2. The principle of optimization is that we schedule all purchase and distribution activities in the low market volatility periods to keep our cost low or keep our revenue high. The BDI is associated with the transportation cost. The transportation cost is related to the procurement and distribution stages. On the other hand, the exchange rate (BTC and GBP) relates to the sale price of overseas distribution for UK companies. Both are related to production and distribution stages.
5. To formulate such an optimized production plan, we adopt the decision tree method. We present an example of our decision tree method in Fig. 3. As demonstrated in Fig. 3, the first stage in January should be procurement, and the second stage in January should be production (here, the pink block stands for 5 days (i.e., 1 block), the blue production block represents a total of 20 days (i.e., 4 blocks in the figure), so there are no branches between those two blocks. Then, we have two branches after the production stage, which are the procurement stage and the distribution stage in pink. If the transportation cost stays in the low volatility area, which can be observed in Fig. 2. Then, we continue to the procurement stage; otherwise, we follow the production branch.
6. For the upward procurement stage in pink, we can have three branches followed. We can continue to purchase materials if material transportation cost volatility remains in the low volatility area, or we can distribute production from the previous blue production stage if the exchange rate volatility stays in the low volatility area. If both key business variable volatilities are all in the high volatility area, we can continue the production stage alternatively.
7. By the downward distribution stage in pink, we complete one production sequence, so we have to start with the procurement stage, where only one branch is followed after the downward distribution stage. After the procurement stage, we can continue to purchase materials if material purchase price volatility remains in the low volatility area. Otherwise, we continue to the production stage, and because we do not finish the production stage, we have no distribution stage followed.

3.2. Empirical results for the GARCH model

This Fig. 3 is only a demonstration and one part of our scheduling procedure, and we continue on the figure to finish all 72 blocks for one year. We repeat the procedure for the 12-year market price sample. Then, we calculate averaged prices for those 72 scheduled blocks regarding the procurement and distribution stages for the whole sample. On this basis, we can obtain an annual average price for each year and each time series presented in Tables 4 to 6.

We compare our optimized result with the benchmark procedure with no scheduling. As stated at the beginning of this section, the benchmark procedure is based on the standard procurement-production-distribution sequence, where 6 blocks are for one sequence and we have 12 standard sequences per year. Then, we calculate averaged prices related to the procurement and distribution blocks, and we have an annual average price for each year and each time series presented in Tables 4 to Tables 6 for the whole sample.

By using the supply chain volatility clustering scheduling technique based on the GARCH model, we have developed annual production plans for manufacturing companies. The results of annual production plans are exhibited in Tables 4 to Tables 6, where Tables 4 and Tables 5 are on the revenue side and Table 6 is on the cost side.

On the other hand, from the revenue side, in Tables 4 and 5, our model demonstrates an overall improvement rate of – 0.84 % and – 8.18 % (decrease the currency value). In fact, the exchange rate is assumed to be related to the revenue side. Consequently, when we sell products at a higher exchange rate, we can earn more in terms of BTC and GBP. The overall performance of our GARCH model is quite weak, so we will analyze the reasons and try to improve our result in the next section.

For the transportation cost shown in Table 6, our GARCH model exhibits noteworthy improvements in 2017 and 2019. Fig. 2 shows that 2015 and 2017 were in high volatility areas. Under such circumstances, our GARCH model is able to schedule market-related activities from high-volatility periods into low-volatility periods, gaining superior performance. Nevertheless, the overall performance is negative (increase the transportation cost), indicating that our GARCH model may have shortcomings in production planning.

Table 4
Model comparison regarding Bitcoin for GARCH Model.

Bitcoin	Year	Benchmark	GARCH model	Improvement[a]
	2015	5.83	5.78	– 0.87 %
	2016	6.33	5.98	– 5.85 %
	2017	7.88	7.82	– 0.77 %
	2018	8.88	9.01	1.44 %
	2019	8.83	8.77	– 0.68 %
	2020	9.25	9.22	– 0.33 %
	2021	10.75	10.88	1.19 %
	Average	8.25	8.2	– 0.84 %

[a] : for the bitcoin price, we are dealing with the sale price for export, so when the bitcoin price is higher, we can earn more.

Table 5
Model comparison for exchange rate for GARCH model.

Exchange Rate (GBP)	Year	Benchmark	GARCH model	Improvement[a]
	2015	0.42	0.38	− 10.53 %
	2016	0.31	0.32	3.13 %
	2017	0.24	0.25	4.00 %
	2018	0.29	0.22	− 31.82 %
	2019	0.25	0.21	− 19.05 %
	2020	0.26	0.27	3.70 %
	2021	0.32	0.3	− 6.67 %
	Average	0.29	0.28	− 8.18 %

[a] : for the exchange rate of GBP/USD, we are dealing with the sale price for export, so when the exchange rate is higher, we can earn more.

Table 6
Model comparison for transportation cost for the GARCH model.

Transportation Cost (BDI)	Year	Benchmark	GARCH model	Improvement
	2015	6.88	6.63	− 3.77 %
	2016	6.46	6.44	− 0.31 %
	2017	7.04	6.57	− 7.15 %
	2018	7.18	8.02	10.47 %
	2019	7.12	7.11	− 0.14 %
	2020	6.86	6.93	1.01 %
	2021	7.93	8.22	3.53 %
	Average	7.06	7.13	0.52 %

4. Production planning for manufacturing supply chain based on machine learning model

To our surprise, our GARCH model has this inferior performance, and we believe there are several reasons for this result. First, as mentioned in Section 3.1, we have three time series to manage simultaneously. Therefore, the correlations among the key business variables play a vital role in supply chain management. It is arguable that the traditional GARCH model considers volatility separately. As a result, if we can consider volatilities in two time series (CBDC with BDI) simultaneously, the result could be improved. More importantly, if we can consider volatilities in both time series simultaneously, the correlation between the two time series shall also be taken into account. Second, when we estimate volatility, there could be noise involved in the time series without useful information (Bandi and Russell, 2006). Consequently, if we can filter the noise from the volatility time series, the model might provide us with more valuable information, and thus, we can formulate more effective production plans compared with the traditional GARCH model. To address the two key issues, we introduce the machine learning technique to help us formulate effective production plans, and the formulation process follows Section 3.1.

4.1. Density based spatial clustering of applications with noise

In this section, we adopt an unsupervised learning machine learning algorithm, namely, Density Based Spatial Clustering of Applications with Noise (DBSCAN), to cluster the data for model building. DBSCAN is a representative density-based algorithm that has considerable advantages over partitional and hierarchical clustering algorithms because they are not limited to finding spherical-shaped clusters but can find clusters of arbitrary shapes. In addition, density-based algorithms can effectively identify noise points, which is desired for this work because there could be a significant noise ingredient within the volatility process (Merville and Pieptea, 1989). This noise ingredient may interfere with the information reflection role of the whole volatility process. Therefore, noise filtration of the volatility process could be helpful for our information extraction from the volatility process.

DBSCAN clusters the data points by density. It is primarily based on the concepts of density-reachability and density-connectivity. There are two important input parameters, epsilon(*eps*) and the minimum number of points (*minPts*). Epsilon is used to define its eps-neighborhood by using the distance around a point object. In this work, we calculate the Euclidean distance between two point objects. For a given point object q, if there are at least *minPts* point objects that lie within its eps-neighborhood, then q is defined as a core point object, and all point objects within its eps-neighborhood are considered density reachable from q. In addition, a point object p is density reachable if it is within the eps-neighborhood of an object that is directly density reachable or density reachable from q. Furthermore, two point objects p and q are density-connected if there is another point object o that both p and q are density-reachable from o.

The notions of density-reachability and density-connectivity are primarily used to find the clusters. In DBSCAN, a cluster is defined as the set of point objects that are density-connected to a particular core point object. Any point objects that are not part of a cluster will be classified as noise. This is different from other unsupervised clustering algorithms (for example, K-means), which assign every object to a cluster.

The DBSCAN procedure is simple and works as follows: first, all point objects are assumed to be unassigned. Next, it randomly selects a point object p; if it finds that p is a core point object, it may find all the density-connected point objects based on the given *eps* and *minPts*. All these point objects may form a new cluster. If it finds that p is not a core point object, then p is considered to be noise at the moment and may move to the next unassigned point object. Once every point object is processed, the algorithm stops.

By using DBSCAN, we attempt to emphasize the effect of CBDC. It has a clear advantage over volatility estimation using a single key business variable, as it can capture the correlation between each two key business variables. The correlation between two time series would be highly useful because it allows us to consider volatility clustering of both time series simultaneously. The overall results are shown in Figs. 4 to 7. Fig. 4 presents the volatility clustering result of BTC volatility against BDI volatility, where the red nodes represent high volatility periods, blue nodes represent low volatility periods and green nodes represent noise within the volatility process. To clearly show the periods of volatility clustering, we add a time domain to make Figure 3-D, which is Fig. 5. From Fig. 5, we can easily identify different volatility clustering periods in the time axis. Then, we can schedule all our procurement activities into those low volatility periods. Similarly, Fig. 6 presents the volatility clustering result of GBP volatility against BDI volatility, where the red nodes represent high volatility periods, blue nodes represent low volatility periods and green nodes represent noise within the volatility process. To clearly show the periods of volatility clustering, we also add a time domain to make Figure 3-D, which is Fig. 7. From Fig. 7, we can easily identify different volatility clustering periods in the time axis. Further, we also plot the GBP volatility against BTC in Fig. 8, and the GBP volatility against BTC with time dimension in Fig. 9. Those two figures illuminate the combination effect of GBP with BTC to represent the effect of CBDC. Then, we can schedule all our distribution activities into those low volatility periods. Therefore, we are able to shift all manufacturing company activities into low volatility areas for both CBDC and BDI in supply chain management. These results can be helpful for firms to take advantage of production rescheduling based on CBDC volatility, which also yields the effect of CBDC volatility represented by two different currencies.

4.2. Empirical results for the volatility clustering model with machine learning

By using the supply chain volatility clustering scheduling technique with DBSCAN, we have developed new annual production plans for manufacturing companies. The detailed machine learning volatility clustering can be found in Figs. 4 to 7, as mentioned in the last section. The results of annual production plans from the machine learning model are exhibited in Tables 7 to 9, where Tables 7 and Tables 8 are on the revenue side and Table 9 is on the cost side.

In particular, we meld both BTC volatility and GBP volatility in the rescheduling model, where BTC represents the digital currency side of CBDC and GBP represents the sovereign currency side of CBDC. We undertake production plan optimization by considering both currency volatilities. From the BTC side, most years from our machine learning model have a positive improvement rate for all subsample years, resulting in a higher revenue for manufacturing companies. The detailed result is shown in Table 8. Similarly, from the GBP side, our model has positive improvement in all years, also resulting in a higher revenue for manufacturing companies. The detailed result is shown in Table 8 From our machine learning model, we both have positive overall performance in two currencies, which is more desirable than the GARCH model.

From saving transportation costs, the model comparison results are presented in Table 9. Table 9 indicates that our machine learning model presents an overall improvement rate of 6.68% and that all years have positive improvement rates. BDI represents the

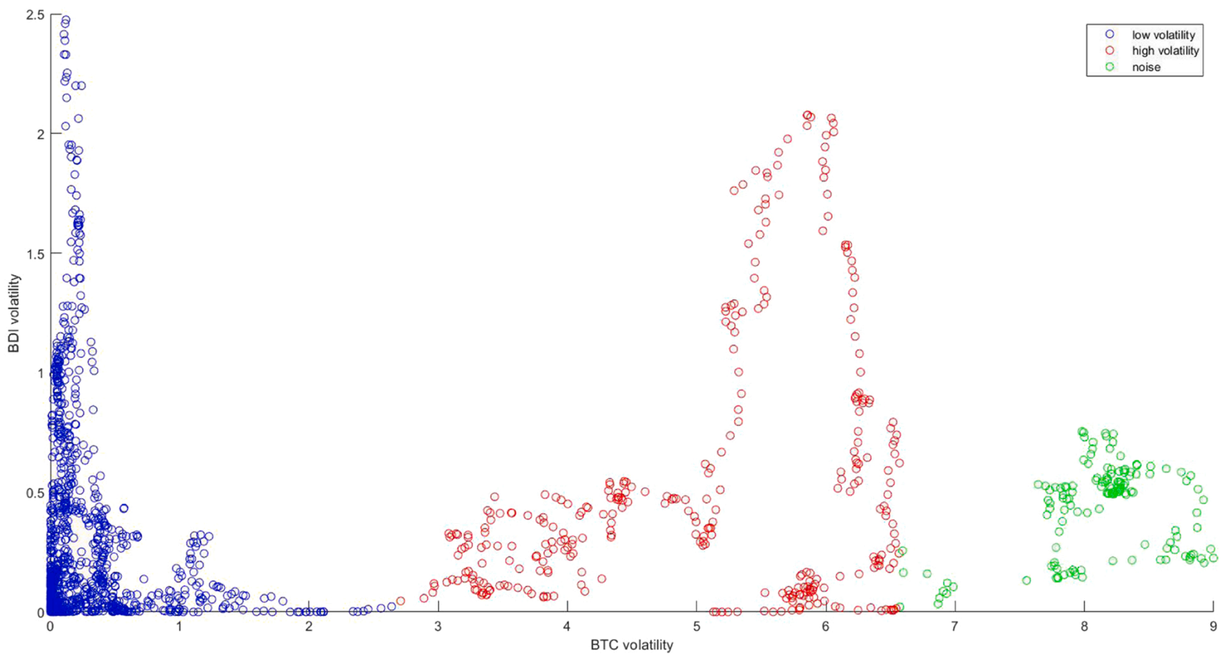

Figure 4. Plotting of BTC volatility against BDI volatility.

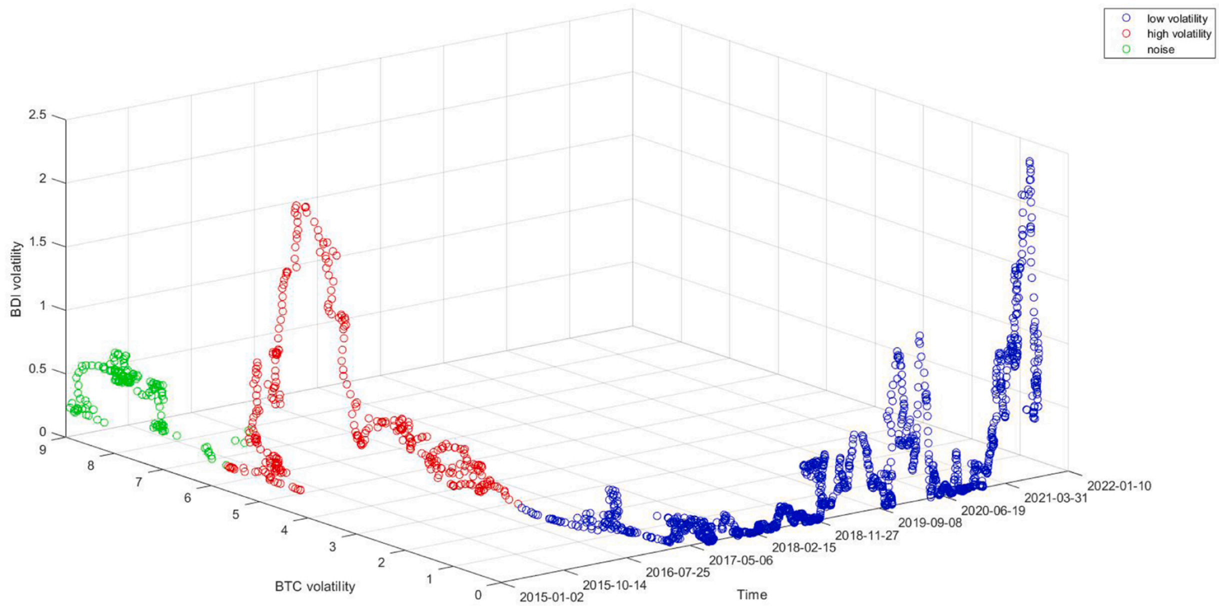

Figure 5. Plotting of BTC volatility against BDI volatility with time domain.

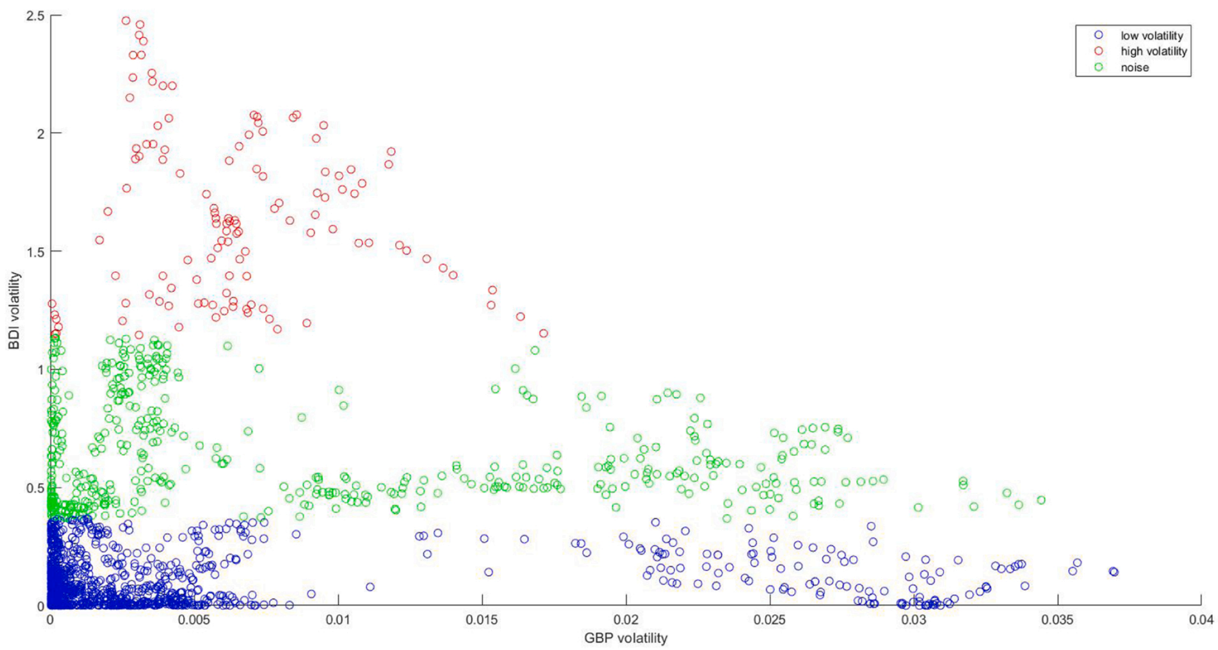

Figure 6. Plotting of GBP volatility against BDI volatility.

overall transportation cost level, and reducing the transportation price level can help manufacturing companies save costs. Therefore, our machine learning model would be helpful in reducing the cost, as shown in Table 9.

Tables 10 and 11 summarize the overall performance of the GARCH model and our model compared with the benchmark model. The overall improvement rates for the other three time series, namely, BDI, BTC and GBP, are 0.52 %, − 0.84 %, and − 8.18 %, respectively for the GARCH model presented in Table 10. As a result, it is arguable that our GRACH model has a quite weak performance in the production planning performance. On the other hand, our machine learning model results in Table 11 show that the overall improvement rates for the other three time series, namely, BDI, BTC and GBP, are − 6.68 %, 2.86 %, and 9.77 %, respectively. As a result, it is arguable that our machine learning model can help manufacturing firms save approximately 7 % of the overall cost and raise approximately 12 % revenue, which is more favored than the previous GARCH model.

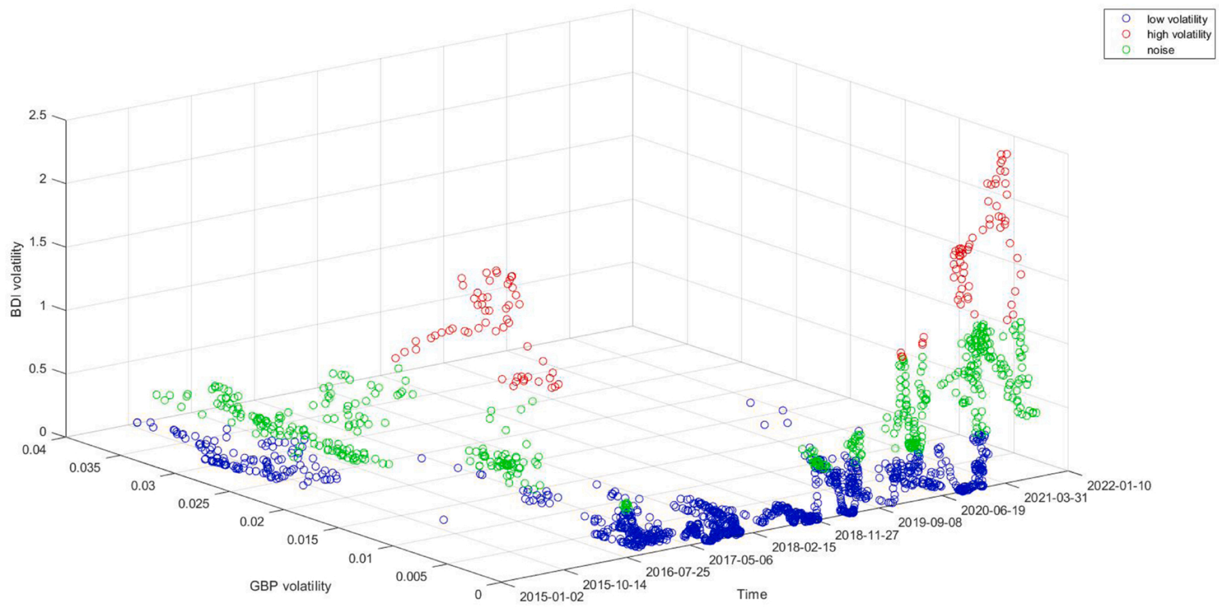

Figure 7. Plotting of GBP volatility against BDI volatility with time domain.

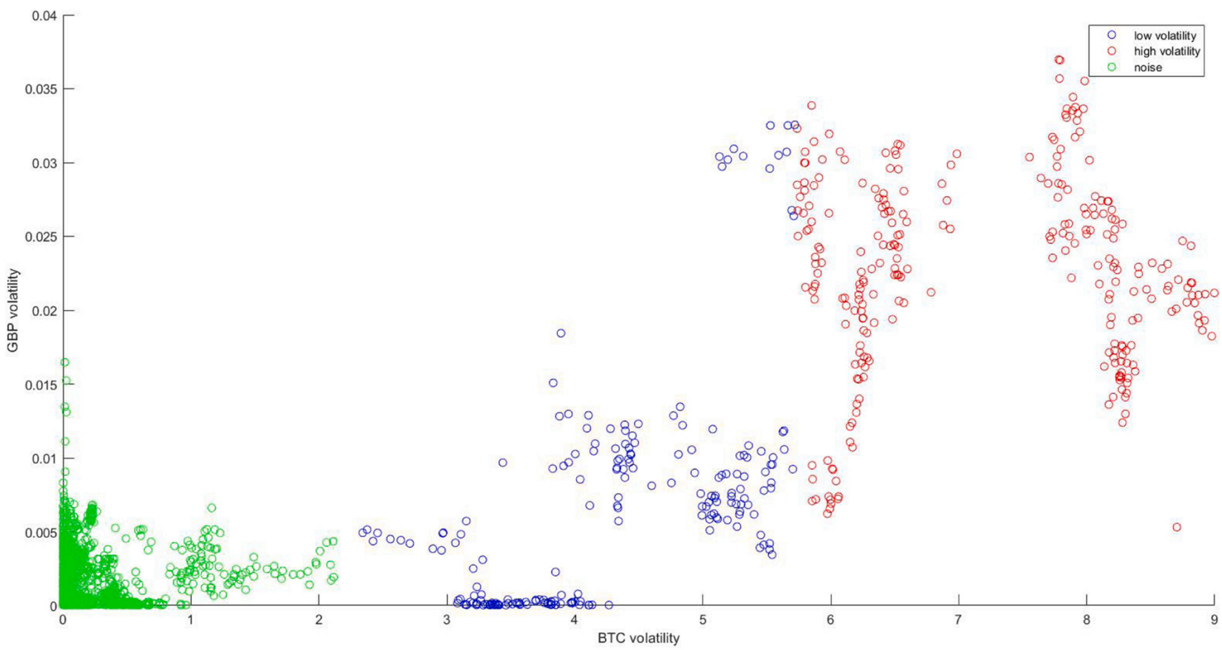

Figure 8. Plotting of GBP volatility against BTC volatility.

5. Conclusion

In summary, the main issue for this paper to accommodate is to deliver a sensible production plan based on the volatility clustering model regarding manufacturing companies with the application of CBDC in the supply chain. We unravel the fact that CBDC volatility can generate considerable effect on the supply chain management for manufacturing companies. Consequently, manufacturing companies formulate the production plan based on volatility clustering model can be helpful in the reduction of uncertainties from both CBDC and BDI. Our framework is based on the volatility clustering model, and we schedule company-related activities into low-volatility periods. Under such a framework, we can thereby reduce the overall uncertainty levels faced by manufacturing companies, as both CBDC and BDI uncertainties can be lessened through rescheduling.

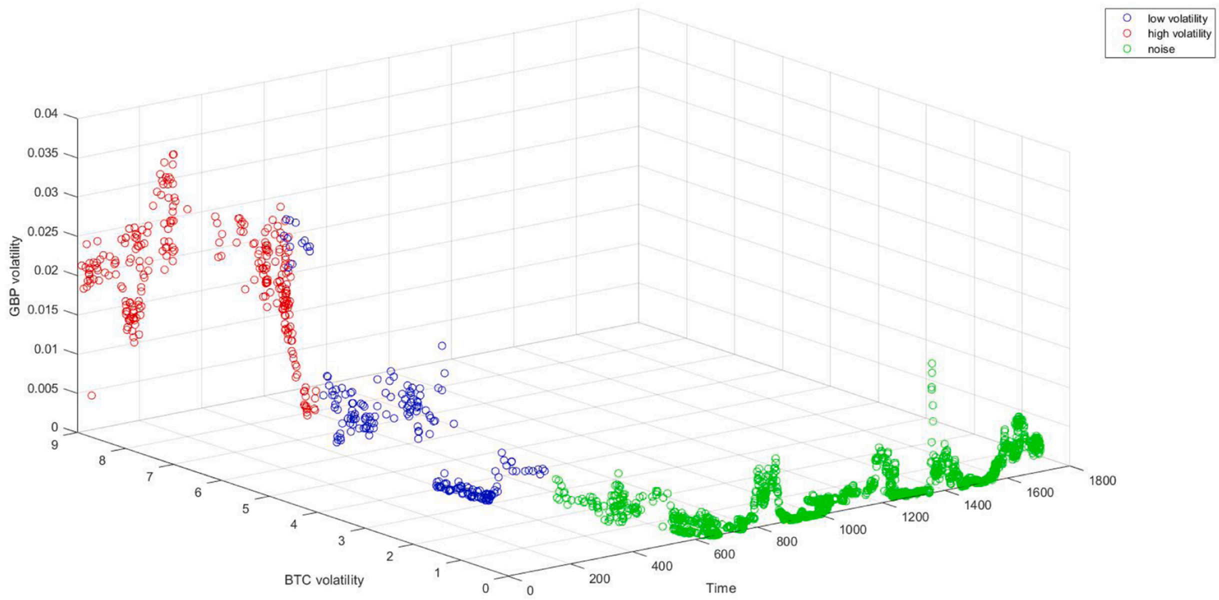

Figure 9. Plotting of GBP volatility against BTC volatility with time domain.

Table 7
Model comparison regarding Bitcoin for machine learning model.

Bitcoin	Year	Benchmark	Our model	Improvement[a]
	2015	5.83	6.1	4.43 %
	2016	6.33	6.55	3.36 %
	2017	7.88	8.02	1.75 %
	2018	8.88	9.02	1.55 %
	2019	8.83	9.15	3.50 %
	2020	9.25	9.36	1.18 %
	2021	10.75	11.23	4.27 %
	Average	8.25	8.49	2.86 %

[a] : for the bitcoin price, we are dealing with the sale price for export, so when the bitcoin price is higher, we can earn more.

Table 8
Model comparison for exchange rate for machine learning model.

Exchange rate (GBP)	Year	Benchmark	Our Model	Improvement[a]
	2015	0.42	0.44	4.55 %
	2016	0.31	0.35	11.43 %
	2017	0.24	0.32	25.00 %
	2018	0.29	0.3	3.33 %
	2019	0.25	0.28	10.71 %
	2020	0.26	0.29	10.34 %
	2021	0.32	0.33	3.03 %
	Average	0.29	0.33	9.77 %

[a] : for the exchange rate of GBP/USD, we are dealing with the sale price for export, so when the exchange rate is higher, we can earn more.

To capture the feature of CBDC volatility, we meld both BTC volatility and GBP volatility in the rescheduling model, where BTC represents the digital currency side of CBDC and GBP represents the sovereign currency side of CBDC. We first used the GARCH model as the volatility clustering model for production planning, where the model performance is inferior. We argue that if we can consider volatilities in both time series simultaneously and filter the noise from the time series, the model performance could be enhanced. Hence, we adopt the DBSCAN technique, which is a type of machine learning approach to achieve these two goals, and the performance actually has been improved. Thus, we can conclude that manufacturing companies' production plans can be strengthened through uncertainty reduction. We combine BTC volatility with GBP volatility to reveal the CBDC volatility effect on SCM, and we schedule the production plan within those low volatility periods for both BTC and GBP accordingly. On this basis, our model verifies that the enhanced production plan can help companies to have better cost and revenue management, as it reduces costs and increases

Table 9
Model comparison for transportation cost for machine learning Model.

Transportation cost (BDI)	Year	Benchmark	Our Model	Improvement
	2015	6.88	6.77	− 1.51 %
	2016	6.46	6.31	− 2.38 %
	2017	7.04	6.22	− 13.18 %
	2018	7.18	6.98	− 2.87 %
	2019	7.12	6.36	− 11.95 %
	2020	6.86	6.27	− 9.41 %
	2021	7.93	7.52	− 5.45 %
	Average	7.06	6.63	− 6.68 %

Table 10
Summary of key variable overall improvement rates by taking the exponential function for the GARCH model.

Key Business Variables	Overall improvement
BDI	0.52 %
BTC	− 0.84 %
Exchange Rate	− 8.18 %
Overall	− 9.49 %

Table 11
Summary of key variable overall improvement rates by taking the exponential function for the machine learning model.

Key business variables	Overall improvement
BDI	− 6.68 %
BTC	2.86 %
Exchange Rate	9.77 %
Overall	19.31 %

revenue.

Furthermore, our study also yields significant policy implications. As we demonstrate in the empirical part, companies that arrange their activities into a low-volatility period of CBDC could generate a vast amount of benefits. Therefore, the stable operation of CBDC becomes crucial. This financial stability issue of CBDC has also been mentioned in Williamson (2021). Therefore, the selection of a CBDC operation platform and the efficiency of transactions tackling become pivotal before the issuance of CBDC. As a result, the decentralized distributed databases will be preferred as they can handle tremendous transactions simultaneously based on the blockchain technique. This thereby ensures the stability of CBDC and thus reduces the uncertainty. More importantly, the adoption of blockchain techniques can inspire the future development of intelligentized supply chains, such as the integration of smart contracts with supply chains (Chang et al., 2019). As Dolgui et al. (2020) illuminate, smart contract integration in a supply chain can be helpful in the automatic execution of physical operations in the supply chain and can also be valuable in improving cybersecurity. We thereby shed light on the integration of digital currency in the supply chain, which further envisages a luminous blueprint for future CBDC development.

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Authorship contributions

Please indicate the specific contributions made by each author (list the authors' initials followed by their surnames, e.g., Y.L. Cheung). The name of each author must appear at least once in each of the three categories below.

Declarations of Competing Interest

None.

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