Artykuły
Articles

PRZESTRZEŃ Społeczna Social SPACE

Volume 24 Issue 01
2024

Analysis of Determinants Influencing the Demand for Cold Supply Chain in China's Fresh Farm Produce Sector

Yuanyuan Chen*

Faculty of Economics and Business, Universiti Malaysia Sarawak, 94300, Kota Samarahan, Sarawak, Malaysia.

Fujian Business University, 350012, Fu Zhou, Fu Jian, China.

Mohammad Affendy Arip

Faculty of Economics and Business, Universiti Malaysia Sarawak, 94300, Kota Samarahan, Sarawak, Malaysia.

Muhammad Ali*

School of Accounting & Finance, Taylors University, Malaysia, Iqra University Karachi, Pakistan.

Abstract

The significance of the cold supply chain arises from the perishable characteristics inherent in fresh agricultural goods. This investigation employs a static panel data model to scrutinize the variables impacting the demand for cold supply chain services concerning fresh agricultural produce within China. The research outcomes reveal that the factors influencing the demand for cold supply chain services for fresh agricultural produce in China comprise primary industrial value added, cargo turnover, civilian freight vehicle ownership, household internet broadband access, and the ramifications of the COVID-19 pandemic. The study proposes specific developmental suggestions for enhancing the cold chain logistics infrastructure concerning fresh agricultural products in China, targeting these influential variables, with the aim of elevating the overall standards of cold chain logistics for fresh agricultural produce and amplifying consumer well-being.

Keywords: Cold Supply Chain, Fresh Farm Produce, China.

Introduction

The inception of the cold supply chain can be traced back to the early 1800s. The rapid strides in refrigeration technology during the early 1930s in industrialized nations facilitated the establishment of cold supply chain systems for food (Dong et al., 2023). Frozen food emerged as a valuable commodity in the 1950s, catalysing the successful development and refinement of various cold storage chains in Europe and the United States (Ndraha et al., 2020). The evolution of the cold supply chain has attained a mature stage in industrialized nations such as Japan, the United States, Germany, the United Kingdom, and Canada (Tang et al., 2023).

In China, the inception of the cold supply chain sector can be traced back to the 1960s, marked notably by the export of beef (Xu, 2021). By the year 2001, the rudimentary frameworks of the cold supply chain were laid down, albeit at an early developmental stage (Ye et al., 2022). The trajectory of China's economic expansion, coupled with heightened urbanization trends and shifts in consumer preferences, served as catalysts for the accelerated growth of the cold supply chain (Han et al., 2021). Concurrently, changing lifestyles and an increased emphasis on health consciousness fuelled a rising demand for fruits, vegetables, and fresh produce necessitating stringent temperature management during transit, thereby amplifying the need for the cold supply chain sector (Awad et al., 2021).

However, as per the scrutiny of the 2022–2027 iteration of the business blueprint for the cold supply chain initiative conducted by the Collaborative Regional Research Programme Research Institute, the construction of cold storage facilities within China's cold supply chain infrastructure trails the rapidly burgeoning consumer demand (Gao et al., 2021). Despite witnessing consistent expansion in refrigerated storage capacity from 2015 to 2019, the cumulative capacity by 2019 significantly fell short of meeting demand, consequently resulting in supply chain disruptions and escalated spoilage rates (Aung & Chang, 2022). Thus, it is imperative to investigate the pivotal factors influencing the evolution of the cold supply chain in China to augment the supply capacity of the cold chain infrastructure (Centobelli et al., 2021). This investigation not only serves as a critical point of reference for formulating pertinent policies but also lays the groundwork for investments in refrigerated transportation facilities and equipment.

Literature Review Review on Production of Fresh Farm Produce

The "Report on the Development of the Cold Chain Supply Chain in China" (2010) underscored the imperative nature of conducting a thorough assessment of the overall demand within the cold chain supply chain. The report advocated for considering the aggregate production of refrigerated goods (encompassing meat, seafood, frozen pasta, fruits, vegetables, dairy, and other perishable commodities) as the comprehensive measure of transportation volume within the cold supply chain. Li et al. (2021) utilized predictive modelling techniques to anticipate the total demand for the cold chain supply chain within specific economic regions. Their model was predicated on the holistic output of meat, eggs, seafood, fruits and vegetables, dairy, and other agricultural products necessitating refrigerated transport. Meanwhile, Zhang (2020) conducted a prognostication study on cold supply chain demand in Hebei Province, basing the analysis on the total production of perishable commodities such as vegetables, fruits, meat, poultry, eggs, dairy, seafood, and other items requiring cold chain logistics.

Zeng et al. (2022) studied the demand projection of citrus fruits, particularly grapefruits, mandarins, oranges, and tangerines, within Liuzhou City's cold supply chain. They analysed production data from 2014 to 2020 and employed grey models to forecast citrus fruit output for the coming decade. The researchers also conducted residual tests and rigorously scrutinized the predictive results. Furthermore, Zeng et al. (2022) utilized historical production data of fresh agricultural products in Hunan Province from 2010 to 2021 as the basis for their model, projecting outcomes from 2022 to 2026. Chen et al. (2024) carried out a prognostic study on the demand for cold supply chains in Fujian Province, utilizing the total production figures of perishable commodities, including vegetables, fruits, meat, poultry, eggs, dairy products, and seafood, as the basis for the analysis.

Within this investigation, the dependent variable encompasses the production output of six distinct categories of fresh agricultural commodities, namely vegetables, fruits, meat, poultry, eggs, dairy products, and aquatic items.

Review on Selected Indicators of Independent Variables

The selected independent variables for this study include the value added of the primary industry, freight turnover, civilian goods vehicle ownership, internet broadband access subscribers, and the impact of the COVID-19 pandemic.

Value Added of the Primary Industry

Historically, China has predominantly focused on agriculture, particularly the production of fresh agricultural goods (Ju et al., 2005). As the production of fresh farm produce increases, the unit price decreases, thereby enhancing consumers' purchasing power. The rising awareness of public health has significantly boosted residents' online demand for fresh farm produce, escalating the necessity for a cold supply chain (Li, 2022). (Li et al., 2022); Qiu et al. (2021) assert that agriculture serves as the primary industry, with the primary industry's added value predominantly influencing the circulation of agricultural products. Wu and Han (2015) identified the economic impact of the increased value of the primary industry on the demand for a cold supply chain in Jiangsu Province. Wang et al. (2018) investigated the use of the added value of the primary industry as an economic indicator to forecast the demand for the cold supply chain of agricultural products in the Beijing, Tianjin, and Hebei regions of China. LV and Chen (2020) explored the supplementary benefits provided by the primary sector while analysing the factors influencing the demand for the cold supply chain of aquatic products.

Freight Turnover

Freight turnover is a metric that quantifies the total volume of goods transported over a specified distance, reflecting the demand for transportation services across various economic sectors (Li et al., 2022). According to Zhang et al. (2022), freight turnover is a crucial parameter for statistical analysis in the logistics sector, providing insights into the demand for cargo transportation across all sectors of the national economy within a given timeframe. In predicting the demand for the cold supply chain for fresh farm produce, Su and Huang (2023) selected freight turnover as an indicator of transportation capacity. Zhang et al. (2022) observed that freight turnover significantly influences transportation capacity, thereby affecting the growing demand for the cold supply chain.

Ownership of Civilian Goods Vehicles

Since 2008, China has witnessed rapid advancements in its economy and technology, leading to a significant increase in commodity demand and a notable expansion in the number of road-operated vehicles due to improved infrastructure (Wang & Yan, 2018). Wang et al. (2018) identified the scale of logistics demand as a pivotal factor influencing the need for the cold supply chain of agricultural products, with the ownership of civilian goods vehicles serving as a metric to assess the impact of logistics demand. Qi and Tai (2021) conducted a study predicting the demand for the cold supply chain for fresh farm produce in China, using civilian cargo vehicle ownership as an index to evaluate the level of logistics improvement. Similarly, Liang et al. (2018) forecasted the demand for the cold supply chain for fresh farm produce in Tianjin, determining that civilian goods vehicle ownership is a reliable indicator of logistical expansion. Wang et al. (2018) emphasized the reliance of cold chain agricultural products primarily on road transport. They employed the quantity of goods transported and the ownership of civilian goods vehicles in Beijing, Tianjin, and Hebei as key indicators to assess the extent of logistics advancement.

Internet Broadband Access Subscribers

The number of internet users is a key indicator of internet development and coverage in a specific region. Progress in internet connectivity enhances various aspects of the cold supply chain for fresh farm produce, including information processing, sharing, temperature monitoring, and food traceability (Wang, 2022). Guo et al. (2022) emphasized the significance of internet broadband access subscribers in evaluating the advancement of the cold supply chain for fresh agricultural items in Henan Province. Huang and Wang (2020) investigated the factors influencing the demand for the cold supply chain in the fresh agricultural goods sector, focusing on the number of internet broadband access subscribers. Similarly, Zhang and Zhang (2018) suggested that the number of internet broadband access subscribers could indicate potential growth in the cold supply chain, particularly due to the rapid expansion of e-commerce. The significant growth of rural e-commerce in recent years has posed challenges for the cold supply chain and impacted the demand for these services.

COVID-19

Yao et al. (2021) observed that COVID-19 significantly altered the trajectory of short-term economic growth, impacting all sectors, including fresh farm produce logistics. The industry faced manpower and manufacturing capacity shortages at every stage of the supply chain, from procurement and shipping to packaging and sales. This led to supermarket shortages and higher prices in urban areas, while rural areas experienced a surplus of fresh produce, causing an imbalance in the agricultural market. Consequently, COVID-19 was expected to significantly affect the demand for logistics in the agricultural sector. Fu et al. (2022) described COVID-19 as an unpredictable factor that disrupted supply chains globally, significantly influencing the substantial economy and circulation of goods, thereby affecting the need for the cold supply chain.

Summary of Variables Selection

This study selects the following factors based on a comprehensive review of research conducted by multiple scholars. The variables are chosen considering data availability, completeness, and logical relevance. Please refer to Table 1 for the list of selected variables.

Table 1: Variable's Descriptions.

Variables	Literatures
QFAP: Production of fresh farm produce	Li et al. (2021), Zeng et al. (2022); Zhang et al. (2022); Zeng et al. (2022)
XVP: Value added of primary industry	Li (2022); LV et al. (2020); Qiu et al. (2021); Wang et al. (2018); Wu et al. (2015)
XFT: Freight Turnover	(Li et al., 2022), Zhang et al. (2020); Zhang et al. (2022); Zhang et al. (2020), Su et al. (2023)
XOCGV: Ownership of Civilian Goods Vehicles	Liang et al. (2018); Qi et al. (2021); Wang et al.(2018); Wang et al. (2018)
XIBS: Internet Broadband Access Subscribers	Guo et al. (2022); Huang et al. (2020); Wang (2022); Zhang et al. (2018)
XCOVID-19: COVID-19	Fu et al. (2022); Yao et al. (2021)

Materials and Methods

Research Methodology

A comprehensive review of the literature provides valuable insights into the factors influencing the demand for the cold supply chain of fresh farm produce. This study employs panel data analysis models to examine the correlation between independent variables and the dependent variable in China. By leveraging panel data analysis, researchers can capture both time-series and cross-sectional variations, offering a robust framework for understanding the intricate dynamics of the cold supply chain market for fresh farm produce in China.

Data Description Sampling

This study defines China as comprising only the 31 provinces, direct-controlled municipalities, and autonomous regions within mainland China. It excludes Hong Kong, Macau, and Taiwan due to the lack of accurate data for these regions. Therefore, when referring to China in this study, it specifically pertains to the mainland region, encompassing the 31 provinces, municipalities, and autonomous regions.

Data Collection Methods

This study primarily relies on secondary data. Initially, pertinent variables are identified through a thorough examination of literature sources. Subsequently, historical data pertaining to the demand for the cold supply chain within the fresh farm produce sector across diverse regions of China is amassed. The data collection period spans from 2015 to 2022, with information sourced from the China Statistical Yearbook.

Static Panel Data Models

Zulfikar and STp (2018) classifies panel data models into three categories: Random Effects (RE) model, Fixed Effects (FE) model, and Pooled Ordinary Least Squares (Pooled OLS) model.

Model Selection

Zulfikar et al. (2018) mentioned the availability of several tests to determine the most suitable model, which can be directly conducted using STATA17 software.

F-Test

The F-test is a statistical method employed to ascertain the most suitable model for panel data analysis between the Pooled Ordinary Least Squares (Pooled OLS) and Fixed Effects (FE) models (Baltagi & Yuliadi, 2015). This test is founded on:

H0: Select the Pooled OLS model if the probability (p) is more than 0.1.

H1: Select the FE model if the probability (p) is less than 0.1.

$$F = \frac{(RRSS-URSS)/[(N-1)(K+1)]}{URSS/[(N(T-K-1)]} \quad (1)$$

Here, RRSS and URSS denote the residual sums of squares of the restricted and unrestricted models, respectively, while [(N-1) (K+1)] and [(N(T-K-1)] represent the degrees of freedom.

Hausman Test

The Hausman test is a statistical method employed to determine the most suitable model, whether it be the FE or RE model to be utilized (Youssef et al., 2023).

H0: Select the RE model if the p-value is greater than 0.1.

H1: Select the FE model if the p-value is less than 0.1.

$$H = (\widehat{\boldsymbol{\beta}}_{\mathbf{FE}} - \widehat{\boldsymbol{\beta}}_{\mathbf{RE}})' \Sigma^{-1} (\widehat{\boldsymbol{\beta}}_{FE} - \widehat{\boldsymbol{\beta}}_{RE}) \quad (2)$$

$\widehat{\boldsymbol{\beta}}_{\mathbf{FE}}$: vector estimation of FE parameter; $\widehat{\boldsymbol{\beta}}_{\mathbf{RE}}$: vector estimation of RE parameter; Σ^{-1}: the inverse variance-covariance matrix $\widehat{\boldsymbol{\beta}}_{\mathbf{FE}} - \widehat{\boldsymbol{\beta}}_{\mathbf{RE}}$. The Hausman test statistic follows an asymptotic chi-squared distribution with K degrees of freedom under the null hypothesis that u_i is uncorrelated with x_n. The test indicates that the RE model is superior to the FE model when the null hypothesis is accepted.

Breush-Pagan Lagrange Multiplier (Breush-Pagan LM) Test

The Breusch-Pagan LM test is utilized to evaluate whether the RE model exhibits better performance in comparison to the OLS model (King'wara, 2020).

H0: Select the Pooled OLS model (p > 0.1).

H1: Select the RE model (p < 0.1).

$$Breush - Pagan\ LM = \frac{NT}{2(T-1)}\left[\frac{\Sigma_{i=1}^{N}\left[\Sigma_{t=1}^{T}v_{it}\right]^2}{\Sigma_{i=1}^{N}\Sigma_{t=1}^{T}v_{it}^2} - 1\right]^2 \quad (3)$$

The v_it represents the residual from the Pooled OLS regression. The Breusch-Pagan LM test statistic follows a chi-squared distribution with one degree of freedom under the null hypothesis. Acceptance of the null hypothesis indicates that the random effects do not exist.

Estimation Static Panel Data Model

In this study, the variable data underwent logarithmic transformation to mitigate the scale effect. Panel data spanning from 2015 to 2022 were employed to construct a panel regression model, aiming to investigate the relationship between the demand for cold supply chain of fresh farm produce and the dependent variable in China.

$$lnQ_{NFAPit} = \alpha + \beta_1 lnX_{VPit} + \beta_2 lnX_{FTit} + \beta_3 lnX_{OCGVit} + \beta_4 lnX_{IBSit} + \beta_5 lnX_{COVID-19it} + \varepsilon_{it} \quad (4)$$

Where $i = 1, 2, \ldots, N;\ t = 1, 2, \ldots, T$, N represents the number of provinces, T signifies the number of years of research. lnQ_{NFAPit} represents the logarithm of national demand for cold supply chain of fresh farm produce, lnX_{nit} represents the logarithm of the independent variable. The coefficient is represented by β_n, and the intercept is denoted by α. Additionally, ε_it signifies other unobservable factors that vary individually over time, and both α and β_n (n=1, ..., 5) remain constant across different values of i and t.

Results

Descriptive Statistics

Table 2 provides the observed values, means, standard deviations, minimum values, and maximum values of the variables included in the static panel data model. These variables consist of the output of fresh farm produce, value added of primary industries, freight turnover, ownership of civilian goods vehicles, internet broadband subscribers, and the presence of COVID-19.

Except for the COVID-19 variable, all variables exhibit positive mean, maximum, and minimum values, as well as standard deviations. The COVID-19 variable has binary values of 0 and 1. A value of 0 signifies the absence of COVID-19 during that year, while a value of 1 indicates the presence of COVID-19 during the corresponding time period.

Table 2 presents the statistical attributes of variables relevant to the demand for the cold supply chain in China's fresh farm produce. Descriptive statistics are computed from a dataset covering an 8-year period (2015-2022) and encompassing 31 provinces, resulting in a total of 248 data points.

Table 2: Descriptive Statistics for Variables in China.

Variables	Obs	Mean	Std. dev.	Min	Max
Q_{FAP}: Production for fresh farm produce (unit: 10,000 tons)	248	3911.85	3226.71	60.09	14609.56
X_{VP}: Value added of primary industry (unit: 10,000 yuan)	248	22,800,000.00	15,700,000.00	936,000.00	63,000,000.00
X_{FT}: Freight turnover (unit: 10,000 tons kilometres)	248	62,300,000.00	66,900,000.00	1,196,400.00	341,000,000.00
X_{OCGV}: Ownership of civilian goods vehicles (unit: 10,000 vehicles)	248	86.88	61.09	12.10	327.00
X_{IBS}: Internet broadband subscribers (unit: 100,00 households)	248	1359.22	1038.70	29.60	4628.70
$X_{COVID-19}$: COVID-19	248	0.38	0.49	0	1

Examination of Table 2 indicates that the standard deviation of the COVID-19 variable exceeds its mean, indicating greater variability in its values. Conversely, the standard deviations of variables such as fresh agricultural food production, value added of the primary industry, freight turnover, ownership of civilian goods vehicles, and internet broadband subscribers are all smaller than their respective mean values, implying relatively lower fluctuations in these variables.

Correlation Matrix

Table 3 displays the correlation analysis results for factors linked to the cold supply chain of fresh farm produce in China.

Significant correlations are observed between the dependent variable and the increased value of the primary industry, ownership of civilian goods vehicles, and the number of Internet broadband subscribers. These independent variables show a growth pattern aligned with the dependent variable. Moreover, a direct relationship is noted between the volume of goods transported and the efficiency of the cold supply chain for perishable agricultural products. However, the association between COVID-19 and the logistics of cold chains for fresh agricultural items is relatively modest.

Table 3: Correlation Matrix for Variables in China.

Variables	*QFAP*	*XVP*	*XFT*	*XOCGV*	*XIBS*	*XCOVID-19*
QFAP	1.00	-	-	-	-	-
XVP	0.92	1.00	-	-	-	-
XFT	0.59	0.48	1.00	-	-	-
XOCGV	0.87	0.87	0.66	1.00	-	-
XIBS	0.84	0.83	0.72	0.92	1.00	-
XCOVID-19	0.08	0.18	0.07	0.21	0.27	1.00

Results of Static Panel Data Model in China

This section explores the correlation among factors impacting China's demand for the cold supply chain of fresh farm produce. The identified factors include COVID-19, the number of Internet broadband customers, ownership of civilian goods vehicles, freight turnover, and the value added of major industries. Additionally, it discusses the specific results obtained from tests conducted to assess multicollinearity, heteroskedasticity, and serial correlation.

Table 4 displays the empirical findings obtained from applying the static panel data analysis model to explore the correlation between the demand for the cold supply chain in China's fresh farm produce sector and its influencing factors. The F-test resulted in a value of 120.23, which is statistically significant at the 1% level. This suggests the rejection of the null hypothesis and indicates that the data can be pooled together.

Following this, the Breusch-Pagan LM test was conducted to ascertain the preference between the OLS model and the RE model. Table 4 displays a Breusch-Pagan LM test statistic of 751.48, which is statistically significant below the 1% level. This rejects the null hypothesis in favour of the Pooled OLS model, indicating that the

RE model is more suitable than the Pooled OLS model.

Table 4: Results of a Static Panel Data Model of the Relationship Be- tween Cold Supply Chain Demand for Fresh Farm Produce and Various Influencing Factors in China.

Variables	Pooled OLS	RE	FE	RE (Robust Standard Errors)
Constant	-6.88*** (-12.25)	-4.84*** (-6.36)	-2.94** (-2.22)	-6.88*** (-25.04)
LXVP	0.68*** (21.95)	0.61*** (11.53)	0.53*** (7.00)	0.68*** (62.96)
LXFT	0.09*** (2.66)	-0.01 (-0.56)	-0.02 (-0.84)	0.09*** (4.40)
LXOCGV	0.23*** (3.15)	0.22** (2.56)	0.09 (0.7)	0.23*** (8.26)
LXIBS	0.17** (2.44)	0.31*** (5.25)	0.32*** (4.77)	0.17*** (3.68)
XCOVID-19	-0.40*** (-4.48)	-0.46*** (-9.30)	-0.37*** (-4.62)	-0.40*** (-16.54)
F test (*P*-value)		120.23*** (0.00)		
Breusch-Pagan LM Test (*P*-value)	751.48*** (0.00)		-	-
Hausman Test (*p*-value)	-	4.21 (0.96)		-
Multicollinearity	-	-	3.55	-
Serial Correlation (*P*-value)	-	-	89.58*** (0.00)	-
Observations	248	248	248	248

Note: Significance levels are denoted by asterisks: ***, **, and * represent 1%, 5%, and 10% levels of significance, respectively. T-statistics are enclosed in brackets.

Regarding the selection between the FE and RE models, the Hausman test yielded a statistic of 4.21, which is statistically insignificant at all levels of significance. Consequently, the null hypothesis that the RE model is superior to the FE model cannot be dismissed. Therefore, the relationship between the cold supply chain of fresh farm produce in China and its influencing factors is most accurately described by the RE model.

Furthermore, additional tests including multicollinearity, heteroskedasticity, and serial correlation tests were performed to validate the robustness of the model. The VIF was employed to assess multicollinearity, revealing a VIF value of 3.55, indicating the absence of multicollinearity issues. However, the serial correlation test rejected the null hypothesis at a significance level of 1%, suggesting the presence of serial correlation issues. Nevertheless, these concerns can be mitigated by re- estimating the RE model using panel corrected standard errors.

Table 4 presents the findings of the RE panel-corrected standard error model, indicating that all determinants displayed expected signs. Specifically, the value added of the primary industry significantly influenced China's demand for fresh agricultural items in the cold supply chain at the 1% level. For every 1 unit increase in the natural logarithm of the value added of the primary industry, China's demand for fresh agricultural goods in the cold supply chain increased by 0.68 units. Moreover, freight turnover demonstrated a significant association at the 1% significance level with the demand for the cold supply chain of fresh farm produce in China. For every 1 unit rise in the natural logarithm of the freight turnover, there was a 0.09 unit increase in demand for the cold supply chain. Ownership of civilian goods vehicles also significantly influenced the demand for the cold supply chain of fresh farm produce in China at the 1% level, showing a positive correlation. For every 1 unit increase in the natural logarithm of the number of households owning civilian goods vehicles, demand for the cold supply chain increased by 0.23 units. Additionally, the count of internet broadband subscribers exhibited a statistically significant effect at the 1% level, positively correlating with the demand for the cold supply chain in China's fresh farm produce. For each 1-unit rise in the natural logarithm of internet broadband subscribers, there was an increase of 0.17 units in the demand for the cold supply chain. Additionally, COVID-19 exhibited a statistically significant relationship at the 1% level, positively associated with the demand for the cold supply chain of fresh farm produce in China. During a year impacted by COVID-19, there was a negative correlation, resulting in a decrease of 0.40 units in demand for the cold supply chain.

Discussion

The demand for the cold supply chain of fresh farm produce in China is notably influenced by the primary industry. As reported by the China Bureau of Statistics in

2003, the primary sector encompasses agriculture, forestry, animal husbandry, and fisheries. Therefore, a strong correlation exists between newly harvested agricultural products and the primary sector. The growth in value-added within the primary industry stimulates the production of fresh agricultural goods, thereby increasing the demand for the cold supply chain within this sector.

The demand for specialized transportation services for fresh farm produce is directly influenced by the volume of transported goods. The increase in freight turnover has resulted in heightened market demand for fresh commodities, consequently driving the need for the cold supply chain. The cold supply chain plays a pivotal role in preserving the quality and safety of fresh farm produce throughout the supply chain, meeting stringent transportation and storage requirements. An increase in freight turnover indicates heightened market activity, amplifying the demand for the cold supply chain for perishable goods and highlighting their significant interdependence.

Road transport remains the primary mode for shipping fresh agricultural items in China's cold-chain logistics. There is a significant positive correlation between the quantity of civilian goods vehicles and the demand for cold-chain logistics services for fresh farm produce. As China's economy expands and urbanization accelerates, the quantity of civilian goods vehicles continues to rise, reflecting increasing societal demand for commodity transportation and logistics. Ensuring the efficient operation of the supply chain for fresh agricultural items is crucial for maintaining their freshness and quality, essential for daily life. The cold supply chain system implements stringent temperature control and freshness preservation protocols to comply with strict environmental requirements, including temperature and humidity, during the transportation of fresh farm produce. The increasing number of civilian goods trucks corresponds to a growing demand for the cold supply chain.

The demand for the cold supply chain in China for fresh farm produce is also influenced by the number of Internet broadband access subscribers. As civilization and technology advance, the Internet has become an integral aspect of people's lives, facilitating their daily activities. With the rapid proliferation of the Internet, e-commerce in China has thrived, allowing consumers to easily overcome geographical barriers and purchase a variety of fresh farm produce online to meet their diverse needs.

COVID-19 has had an adverse impact on the demand for the cold supply chain of fresh farm produce in China. During the COVID-19 pandemic, the demand for the cold supply chain of fresh farm produce in China experienced a decline due to the country's implementation of stringent closure and control measures aimed at effectively containing the spread of the virus. Concurrently, consumers faced challenges in accessing fresh agricultural items.

Conclusion

The importance of the cold supply chain in the realm of fresh farm produce is indisputable. It involves precise regulation of temperature and humidity to extend the shelf life of fresh produce, slow metabolic processes, and maintain the product's freshness and flavour. Quality assurance is paramount for agricultural products, particularly in preventing any deterioration. The cold supply chain system ensures quality by maintaining optimal temperatures during transportation and storage, inhibiting microbial growth, and reducing the risk of bacterial contamination, thereby addressing food safety concerns effectively. Additionally, the cold supply chain plays a crucial role in minimizing product loss during transit, preventing waste due to expiration or spoilage, improving resource efficiency, and promoting positive environmental outcomes. Implementation of the cold supply chain facilitates global trade of perishable items, stimulates demand for agricultural products from various regions, and fosters market growth within the agricultural industry. It is essential for preserving the freshness and quality of fresh farm produce, supporting the sustainable development of the agricultural sector, and ensuring the smooth operation of the global supply chain. As the agriculture sector navigates global integration and evolving market demands, managing temperature-controlled supply chains remains critical, highlighting the importance of knowledge and innovation in this field. This endeavour contributes to food safety, resource optimization, and economic advancement. The cold supply chain plays a pivotal role in preserving the quality of fresh products in both developed and developing nations. This study aims to promote the expansion of the cold supply chain industry for fresh farm produce in China and develop appropriate development policies by examining the key factors influencing the growth of this industry in China.

This study investigates the key factors influencing the demand for the cold supply chain of fresh agricultural products in China and proposes corresponding recommendations based on the research findings. The analysis employs the static panel data model, including the pooled OLS, FE, and RE models. Model selection relies on the outcomes of the Breusch-Pagan LM test and the Hausman test. Diagnostic tests, such as evaluations for multicollinearity and serial correlation, validate the adequacy of the model. Empirical evidence highlights the suitability of the RE model for examining the relationship between the demand for the cold supply chain and influencing factors in China's fresh farm produce sector.

The research findings indicate that the value added of the primary industry, goods turnover, ownership of civilian goods vehicles, Internet broadband access users, and the presence of COVID-19 significantly influence demand nationwide.

Recommendations

To fulfil consumers' demand for high-quality agricultural products, it is imperative for both the government and enterprises to bolster support and guidance for agricultural product processing, packaging, and value augmentation. By incorporating advanced processing technologies and enhancing product packaging, the added value and quality of agricultural products can be elevated, thereby enhancing market competitiveness and driving demand for the cold supply chain.

Addressing the escalating demand for the cold supply chain of fresh farm produce necessitates reinforcing the planning and management of logistics transportation networks. The government should offer policy support to incentivize enterprises to invest in transportation network infrastructure while enhancing the capacity and efficiency of transportation vehicles. This will ensure the safety and quality of fresh farm produce during transportation, effectively meeting market demand.

To meet the rising demand for the cold supply chain of fresh farm produce, both government and enterprises must boost investment in cold supply chain facilities and technological advancements. This entails expanding cold storage warehouses, refrigerated trucks, and implementing advanced temperature control technologies and logistics systems to enhance coverage and transportation efficiency and cater to the increasing market demand.

Integrating internet technology into the cold supply chain can elevate informatization levels and logistics efficiency, fostering the development and modernization of the cold supply chain. Government and enterprises should prioritize research and development and promote the adoption of internet technology, facilitating seamless integration between the cold supply chain and the internet. This enables consumers to access more convenient and efficient agricultural product purchasing and delivery services.

To counter the adverse effects of COVID-19 on cold supply chain demand, the government and enterprises must enhance epidemic prevention and emergency management. This involves establishing a robust cold supply chain emergency response mechanism, bolstering health management for logistics personnel, and improving cleaning and disinfection protocols for logistics facilities. These measures ensure the stable operation and product safety of the cold supply chain, mitigating the epidemic's negative impact.

Author Contributions

Chen Yuanyuan: Writing; Mohammad Affendy Arip: Giving guidance.

Institutional Review Board Statement

Not applicable.

Data Availability Statement

Data will be made available on request.

Acknowledgments

I would like to express my heartfelt thanks to Universiti Malaysia Sarawak.

Conflicts of Interest

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

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