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Analysis of Commodity Retail Price Indicators in Chinese Provinces Based on Matrix Factor Model

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Abstract: This paper explores the application of matrix factor models to analyze high-dimensional time series data on commodity retail price indicators across Chinese provinces. The research addresses the gap in existing literature that often focuses on simpler models and smaller datasets, which do not adequately capture the complex interdependencies and structural dynamics inherent in provincial economic data. By employing matrix factor models, this study leverages the inherent matrix structure of the data for significant dimensional reduction, enhancing the clarity and reliability of the analysis. The findings provide a detailed insight into regional economic behaviors and market conditions, offering a nuanced understanding that is crucial for precise macroeconomic policy-making and financial risk management. The study demonstrates the potential of matrix factor models to effectively manage high-dimensional datasets, thereby contributing valuable tools for economists and policymakers to better predict and respond to economic fluctuations across different regions. This research is essential for designing targeted interventions that promote balanced regional development and economic resilience, particularly in the diverse economic landscape of China.

1. Introduction

The analysis of commodity retail price in Chinese provinces is crucial for understanding the economic dynamics and consumer behavior across diverse regions in China. This research is essential due to the significant regional disparities in economic development, consumption patterns, and market potentials within the country. Studying these indicators helps policymakers and businesses tailor their strategies to local conditions, promoting balanced regional development and efficient resource allocation. Moreover, the rapid economic growth and urbanization in China have led to evolving retail landscapes, necessitating continuous monitoring and analysis to capture emerging trends and shifts in consumer demand.

The necessity of this research is underscored by the complex interplay between local economies and national economic policies. Accurate and region-specific retail data analysis can inform better policy decisions, enhance economic forecasting, and drive targeted marketing strategies. Previous studies, such as those by Xu et al on regional consumption differences[1], and Liu et al on the impact of urbanization on retail sales, highlight the importance of detailed regional analysis[2]. Additionally, Zhang et al have demonstrated the influence of regional policies on retail growth[3], while Wang et al emphasized the role of local economic conditions in shaping retail environments[4]. These studies collectively underscore the importance of region-specific retail analysis in fostering sustainable economic development.

In current research, the analysis of high-dimensional time series data on commodity retail prices remains significantly underexplored. Most existing studies focus on analyzing single time series or apply traditional statistical methods to smaller datasets, which often fail to effectively capture the complex interactions and inherent structures among multiple variables. Additionally, as the dimensionality of data increases, traditional models face challenges in handling large-scale provincial commodity retail data, often resulting in "curse of dimensionality" issues that decrease the stability and reliability of the analyses. Therefore, employing matrix factor models to analyze commodity retail price indicators across different provinces is particularly critical. Wang et al present the inaugural factor models specifically designed for matrix-valued time series, significantly advancing the field. Their methodology leverages the inherent matrix structure of the data to achieve substantial dimensional reduction and clarity in interpreting complex data interactions, thereby providing a more nuanced and efficient analytical framework[5]. Subsequently, Chen et al. utilized matrix factor models to analyze dynamic international trade networks, effectively managing high-dimensional data to uncover significant structural dynamics. Their approach revealed crucial insights into trading hubs, centrality trends, and the impacts of trade policies across various countries, highlighting the models' utility in predicting and understanding global trade patterns[6]. Tang et al applied matrix factor models to forecast high-dimensional financial functional time series, specifically analyzing constituent stocks of the Dow Jones Index. Their approach significantly enhanced forecasting accuracy by managing the dimensionality and preserving the structural intricacies of financial data, thus providing more reliable financial forecasts[7]. In summary, the practical applications of matrix factor analysis methods have demonstrated unexpected benefits. By effectively managing high-dimensional data and preserving complex structural relationships, these models significantly enhance the accuracy and reliability of analyses across various fields, from international trade to financial markets. This underscores the potential of matrix factor models to provide insightful solutions to complex data challenges.

In this paper, we plan to apply the projection estimation method described in the article to analyze commodity retail price indicators across Chinese provinces. This method effectively handles large-dimensional matrix data, improving the accuracy and speed of convergence in extracting and interpreting latent structures within the data[8]. This approach will allow for a detailed and robust analysis of the retail dynamics specific to various provinces, providing insights that are critical for strategic planning and policy-making.

2. Methodology

2.1. Model Interpretation

Let $\boldsymbol{Y}_t = \left(y_{i,j,t}\right), t = 1, \ldots, T$ be a $p \times q$ matrix time series. there are pq recorded values at each time t from, for example, p Commodity retail price variables for q provinces, and $y_{i,j,t}$ is then the value of the i-th variable on the j-th province at time t.

$$\boldsymbol{Y}_t = \begin{pmatrix} Y_{t,11} & \cdots & Y_{t,1q} \\ \vdots & \ddots & \vdots \\ Y_{t,p} & \cdots & Y_{t,pq} \end{pmatrix}, t = 1, \dots, T$$

For matrix valued time series, we propose the following factor model based on following decomposition:

$$\boldsymbol{Y}_t = \boldsymbol{R}\boldsymbol{F}_t\boldsymbol{C}^\top + \boldsymbol{E}_t,\ t = 1,2,\cdots,T \tag{1}$$

where, $\boldsymbol{F}_t$ is a $k_1 \times k_2$ unobserved matrix-valued time series of common fundamental factors, $\boldsymbol{R}$ is a $p \times k_1$ front loading matrix, $\boldsymbol{C}$ is a $q \times k_2$ back loading matrix, and $\boldsymbol{E}_t$ is a $p \times q$ error matrix.

To gain a better understanding of the meanings of the preloading matrix $\boldsymbol{R}$ and the postloading matrix $\boldsymbol{C}$, we first need to separate $\boldsymbol{R}$ and $\boldsymbol{C}$, we assume that k_1 is equal to p, and $\boldsymbol{R}$ is the identity matrix $\boldsymbol{I}_p$. As a result, the equation $\boldsymbol{Y}_t = \boldsymbol{F}_t\boldsymbol{C}^\top + \boldsymbol{E}_t$ holds true. In this scenario, each column of $\boldsymbol{Y}_t$ can be expressed as a linear combination of the columns in $\boldsymbol{F}_t$. We assume that the first column of $\boldsymbol{Y}_t$ represents the retail price indices of various commodities in Beijing, as shown below.

$$\overset{\text{Beijing}}{\begin{pmatrix} \text{Food} \\ \text{Furniture} \\ \text{Cosmetics} \\ \text{Textile} \end{pmatrix}_t} = \boldsymbol{C}_{11} \overset{f_{t,1}\ \cdots}{\begin{pmatrix} \text{F-Food} \\ \text{F-Furniture} \\ \text{F-Cosmetics} \\ \text{F-Textile} \end{pmatrix}_t} + \cdots + \boldsymbol{C}_{1k_2} \overset{f_{t,k_2}}{\begin{pmatrix} \text{F-Food} \\ \text{F-Furniture} \\ \text{F-Cosmetics} \\ \text{F-Textile} \end{pmatrix}_t} + \mathbf{e}_{t,Beijing}.$$

It is evident that the Beijing Food retail price indices solely relies on the first row of $\boldsymbol{F}_t$. Similarly, the Food retail price indices of other provinces also solely depends on the first row of $\boldsymbol{F}_t$. Consequently, we can interpret the first row of $\boldsymbol{F}_t$ as the Food retail price indices factors. Similarly, the second row of $\boldsymbol{F}_t$ can be interpreted as the Furniture retail price indices factors. In this setting (when $\boldsymbol{R} = \boldsymbol{I}$), there is no interaction among the indicators. The loading matrix $\boldsymbol{C}$ depicts the extent to which each province (column of $\boldsymbol{Y}_t$) depends on the columns of $\boldsymbol{F}_t$, thus reflecting column interactions or interactions between the provinces. Therefore, we shall refer to $\boldsymbol{C}$ as the column loading matrix.

$$\begin{aligned} &\quad\ \text{BJ}\qquad \text{SH}, \dots\dots, \text{GZ} && \qquad\quad \text{BJ} \qquad \text{SH}, \dots\dots, \text{GZ} \\ &(\text{ Food , Food , ..., Food }_t && = \boldsymbol{R}_{11}(\text{ F} - \text{BJ}, \text{F} - \text{SH}, \dots, \text{F} - \text{GZ})_t \boldsymbol{f}_{t,1} \cdot \\ & && +\boldsymbol{R}_{12}(\text{ F} - \text{BJ}, \text{F} - \text{SH}, \dots, \text{F} - \text{GZ})_t \boldsymbol{f}_{t,2} \\ & && + \cdots \vdots \\ & && +\boldsymbol{R}_{1k_1}(\text{ F} - \text{BJ}, \text{F} - \text{SH}, \dots, \text{F} - \text{GZ})_t \boldsymbol{f}_{t,k_1}. \\ & && +\mathbf{e}_{t,\text{ Food .}} \end{aligned}$$

It is observed that all retail price indices movements within each provinces are determined by a set of k_1 common factors (rows). For instance, each retail price indices of the Beijing solely relies on the first column of $\boldsymbol{F}_t$. Therefore, we can interpret the first column of $\boldsymbol{F}_t$ as the Beijing factor, while the second column represents the Shanghai factor. The loading matrix $\boldsymbol{R}$ demonstrates the extent to which each retail price indices is influenced by the rows of $\boldsymbol{F}_t$, reflecting the interactions between retail price indices within each provinces. Consequently, we refer to $\boldsymbol{R}$ as the row loading matrix.

2.2. Model Estimation

Due to the lack of identification conditions for $\boldsymbol{R}$ and $\boldsymbol{C}$, assume that $\boldsymbol{R}$ and $\boldsymbol{C}$ satisfy the orthogonal property. Without loss of generality, we assume that $\frac{1}{p}\boldsymbol{R}^\top\boldsymbol{R} = \boldsymbol{I}_{k_1}$ and $\frac{1}{q}\boldsymbol{C}^\top\boldsymbol{C} = \boldsymbol{I}_{k_2}$ for identifiability. In order to estimate $\boldsymbol{R}$ and $\boldsymbol{C}$, we view each column as an individual vector observation and use the conventional PCA method for vector time series. Define the scaled mode-wise sample covariance matrix

$$\begin{aligned}\widehat{\boldsymbol{M}}_R &= \frac{1}{Tpq}\sum_{t=1}^{T}\sum_{j=1}^{q}\boldsymbol{Y}_{t,j}\boldsymbol{Y}_{t,j}^\top = \frac{1}{Tpq}\sum_{t=1}^{T}\boldsymbol{Y}_t\boldsymbol{Y}_t^\top \\ \widehat{\boldsymbol{M}}_C &= \frac{1}{Tpq}\sum_{t=1}^{T}\sum_{i=1}^{p}\boldsymbol{Y}_{t,i}\boldsymbol{Y}_{t,i}^\top = \frac{1}{Tpq}\sum_{t=1}^{T}\boldsymbol{Y}_t^\top\boldsymbol{Y}_t\end{aligned} \tag{2}$$

By Davis-Kahan's theorem, the k_1 leading eigenvectors $\hat{u}_1, \dots, \hat{u}_{k_1}$ of $\widehat{\boldsymbol{M}}_R$ share the same column space and the k_2 leading eigenvectors $\hat{v}_1, \dots, \hat{v}_{k_2}$ of $\widehat{\boldsymbol{M}}_C$ share the same column space. Therefore, estimate the projection loading matrix $\boldsymbol{R}$ and $\boldsymbol{C}$ by

$$\begin{aligned}\widehat{\boldsymbol{R}} &= \sqrt{p}\,\widehat{U} = \sqrt{p}\left(\hat{u}_1, \dots, \hat{u}_{k_1}\right) \\ \widehat{\boldsymbol{C}} &= \sqrt{q}\,\widehat{V} = \sqrt{q}\left(\hat{v}_1, \dots, \hat{v}_{k_2}\right)\end{aligned} \tag{3}$$

For the factor number k_1 and k_2, we apply the general ratio-based estimators to estimate，define $k_{\max}$ as a preassigned upper bound, and $\hat{\lambda}_1 \geq \hat{\lambda}_2 \geq \cdots \geq \hat{\lambda}_{k_{\max}} \geq 0$ are the ordered eigenvalues of $\widehat{\boldsymbol{M}}_R$ and $\widehat{\boldsymbol{M}}_C$. Based on the initial loading matrix estimators, the initial estimation of the k_1 and k_2

$$\hat{k}_1 = \arg\max_{1\leq j\leq k_{\max}}\frac{\hat{\lambda}_j(\widehat{\boldsymbol{M}}_R)}{\hat{\lambda}_{j+1}(\widehat{\boldsymbol{M}}_R)}, \hat{k}_2 = \arg\max_{1\leq j\leq k_{\max}}\frac{\hat{\lambda}_j(\widehat{\boldsymbol{M}}_C)}{\hat{\lambda}_{j+1}(\widehat{\boldsymbol{M}}_C)} \tag{4}$$

Based on the loading matrix estimators $\widehat{\boldsymbol{R}}$ and $\widehat{\boldsymbol{C}}$, we obtain the projection loading matrix estimator, the matrix factor estimator and the signal matrix estimator as follows:

$$\widehat{\boldsymbol{F}}_t = \frac{1}{pq}\widehat{\boldsymbol{R}}^\top\boldsymbol{Y}_t\widehat{\boldsymbol{C}} \tag{5}$$

$$\widehat{\boldsymbol{S}}_t = \widehat{\boldsymbol{R}}\,\widehat{\boldsymbol{F}}_t\widehat{\boldsymbol{C}}^\top \tag{6}$$

3. Empirical analysis of Provincial commodity retail index

3.1. Data collection and interpretation

In this section, we collected retail data for 16 product metrics across 31 provinces in China (excluding China Hong Kong, China Macau, and China Taiwan), spanning 36 months from January 2020 to December 2022. In studying the retail metrics of various commodities across China's 31 provinces. Thus it can be expressed in the form of a matrix time series $\boldsymbol{Y}_t \in \mathbb{R}^{16\times 31}, t = 1, \dots, 36$. Figure 1 shows the time series of 16 commodity indicators in 31 provinces.

The selection of these 16 commodity types is strategic. This assortment covers essential consumer sectors such as food, beverages, apparel, and home appliances, reflecting everyday necessities. It also spans from basic needs like fuel to luxury items like jewelry and cosmetics, demonstrating the diverse consumption patterns across different income levels and preferences. Additionally, the inclusion of modern technological and cultural products such as home electronics, office supplies, and digital publications highlights the demand for tech and cultural goods. Categories like transport and communication goods and building materials serve as indicators of economic activities and development. Finally, the choice of health and leisure products like medicines and sports goods underscores spending trends in health and recreation, providing a comprehensive view of market dynamics and socio-economic trends in the provinces. The specific product type selection categories are shown in Table 1. Next, we use matrix time series for modeling.

Table 1: Product selection criteria and name.

Criteria category	Commodity name
Basic needs covered	Food
	Beverages and Tobacco
	Apparel and Footwear
	Textiles
	Home Appliances and Audio-Video Equipment
	Fuel
	Daily Goods
Diversified consumption	Jewelry
	Furniture
	Cosmetics
Technology and culture	Office and Cultural Supplies
	Books, Magazines, and Digital Publications
Economic activity	Transportation and Communication Goods
	Building Materials and Hardware
Health and leisure	Medicines and Healthcare Products
	Sports and Leisure Goods

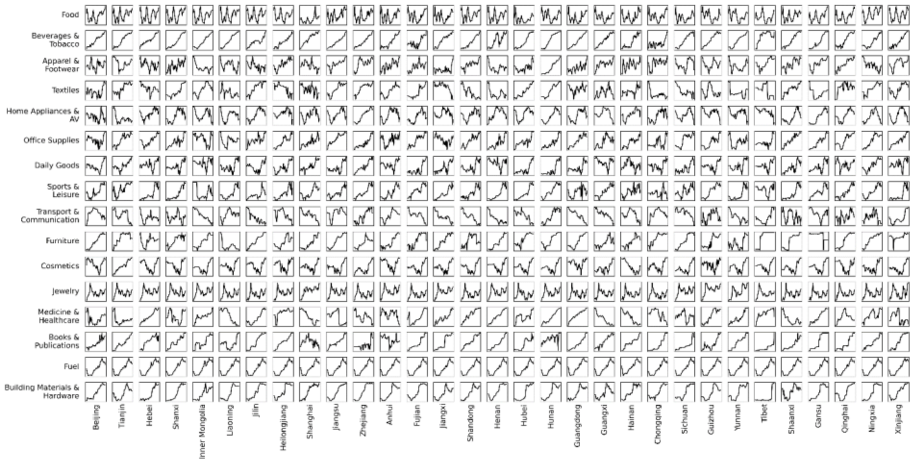

Figure 1: Time series chart of $\boldsymbol{Y}_t \in \mathbb{R}^{16\times 31}, t = 1, \ldots, 36$.

3.2. Result analysis

We use formula (1) to decompose $\boldsymbol{Y}_t$, and then use the estimation method in Section 2.2 to estimate the loading matrices $\boldsymbol{R}$ and $\boldsymbol{C}$. Estimating the number of factors k_1 and k_2, we get $\hat{k}_1 = 2$, $\hat{k}_2 = 2$.

Thus, we can obtain that $\widehat{\boldsymbol{R}} \in \mathbb{R}^{16\times 2}$, the i column of $\widehat{\boldsymbol{R}}$ represents the impact of factor i on the

16 commodity retail indicators, and $\widehat{\boldsymbol{C}} \in \mathbb{R}^{31\times 2}$,the i column of $\widehat{\boldsymbol{C}}$ represents the impact of factor i on the overall retail indicators of 31 provinces. In order to be able to explain well, we perform maximum variance rotation on the calculation results of $\widehat{\boldsymbol{R}}$ and $\widehat{\boldsymbol{C}}$, multiply them by 30 and round them, and then draw a heat map for study.

3.2.1. Analysis of the loading matrix *R*

Figure 2 show the heat map of estimated results of loading matrix $\boldsymbol{R}$ and clustering results by factors.

In analyzing the impact of Factor 1 on the retail indices of 16 types of commodities across China's 31 provinces from January 2020 to December 2022, we must consider the unique economic fluctuations marked by the COVID-19 pandemic. Commodities such as building materials and hardware (loading of 46), fuel (loading of 45), and office supplies (loading of 41) exhibit high positive loadings, indicating their strong sensitivity to macroeconomic policies and market conditions. These high loadings suggest that sectors like construction and energy significantly benefit from governmental infrastructural investments and increased energy demands during economic recoveries.

Conversely, commodities with negative loadings such as cosmetics (-6) and jewelry (-11) reflect consumer restraint in spending on non-essential items during economic downturns. This shift in consumer behavior affects retail markets heavily reliant on discretionary spending and highlights the need for businesses in these sectors to innovate and adapt strategies to maintain consumer interest and spending. Fluctuations in the positively loaded commodities directly impact financial markets, as they are often linked to broader economic indicators such as construction output and energy consumption. This correlation necessitates vigilant risk management and strategic planning by financial market participants to anticipate and mitigate potential market volatilities. Furthermore, understanding these loading scores helps in evaluating the effectiveness of government economic policies during the pandemic. The positive impact seen in critical sectors underlines the importance of targeted fiscal stimuli and regulatory support to bolster economic stability and growth.

Overall, Factor 1's diverse effects on various commodities—ranging from infrastructure-related materials to luxury goods—underscore the interconnectedness of consumer behavior, economic policy, and market dynamics. This comprehensive perspective is crucial for policymakers, businesses, and investors aiming to navigate the complexities of the market and formulate strategies that leverage economic opportunities while managing potential risks effectively.

Analyzing the impact of Factor 2 on the retail indices of 16 commodity types across China's 31 provinces from January 2020 to December 2022 offers insights into another dimension of market dynamics. Factor 2's loadings vary significantly, highlighting diverse responses to economic stimuli, consumer preferences, and sectoral shifts during this period. Commodities like cosmetics (63), jewelry (47), and daily goods (45) show high positive loadings, indicating that these sectors are highly responsive to changes associated with Factor 2, which may include shifts in consumer confidence, luxury spending, and essential daily purchases. The strong performance of cosmetics and jewelry might reflect a rebound in luxury and discretionary spending as markets recover or adapt to new norms post-pandemic. The significant positive loading for daily goods suggests an increased emphasis on products that cater to everyday needs, possibly driven by a rise in health and safety concerns. Conversely, commodities such as home appliances and audio-video equipment (-43) and transport and communication goods (-40) exhibit substantial negative loadings. This downturn could indicate reduced consumer spending in these sectors due to economic contractions, shifts towards savings rather than spending, or perhaps due to supply chain disruptions that affected product availability and consumer purchasing patterns. Other commodities like food (22), office supplies (6), and medicine and healthcare products (18) display moderate positive loadings, suggesting a stable demand or gradual recovery in these sectors. These areas may have benefited from consistent demand irrespective of broader economic conditions, reflecting their essential nature. On the flip side, apparel and footwear (-8), textiles (-20), and furniture (-7) show negative loadings, potentially pointing to consumer cautiousness in spending on non-essential, higher-cost items during uncertain economic times. The variation in loadings across different commodities suggests that multiple factors influence consumer behavior and sectoral performance. For policymakers, understanding these subtleties is crucial in tailoring economic policies that support recovery in negatively impacted sectors while stabilizing those with volatile gains. For businesses, these insights into factor loadings can guide strategic adjustments—ramping up marketing efforts in booming sectors, exploring new distribution channels, or innovating product lines in areas experiencing downturns.

Overall, Factor 2's loadings reveal how different commodity sectors react to a complex interplay of economic, social, and possibly geopolitical factors during the examined period. For investors and financial analysts, these insights are valuable for risk assessment, portfolio management, and identifying growth opportunities in a post-pandemic economic landscape. Understanding these dynamics enables a proactive approach to capitalizing on emerging trends and cushioning against potential setbacks in more volatile or negatively impacted markets.

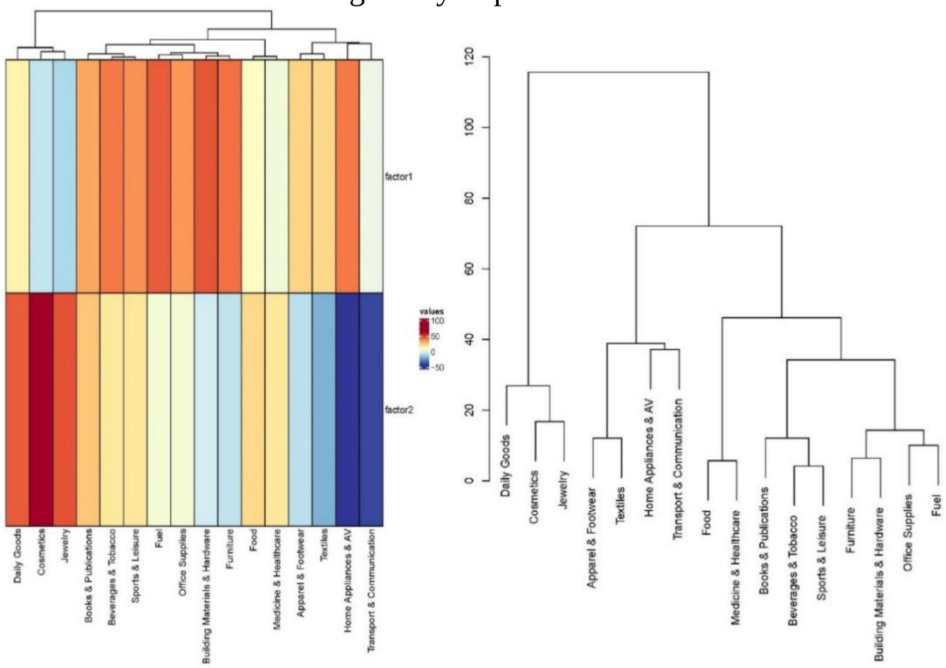

Figure 2: Heat map of estimated results of loading matrix $\boldsymbol{R}$ and clustering results by factors.

The analysis of Factor 1 and Factor 2 loadings for various commodity types provides crucial insights for macroeconomic policy and financial risk management. For policymakers, it is essential to balance support between sectors positively correlated with economic stimuli (Factor 1) and those sensitive to changes in consumer behavior (Factor 2). As shown in the clustering results from Figure 2 based on Factors 1 and 2, by identifying clusters such as "Daily Goods" and "Cosmetics," policymakers can tailor economic stimuli to cater to consumer elasticity, while financial managers can hedge risks by recognizing related vulnerabilities (e.g., between "Fuel" and "Building Materials"). Financial analysts should focus on diversifying investments and developing commodity-specific risk mitigation strategies responsive to these factors, ensuring stability and capitalizing on opportunities within a dynamic economic landscape.

3.2.2. Analysis of the loading matrix $\boldsymbol{C}$

Based on the calculation of $\boldsymbol{C}$, Figure 3 shows the heat map of the impact of Factor 1 and Factor 2 on the commodity retail indicators in 31 provinces in China.

Analyzing the Factor 1 loadings from January 2020 to December 2022 across China's 31 provinces offers a detailed insight into the interplay of financial risks, macroeconomic environments, and geographical positions. During this period, marked by the COVID-19 pandemic and its varied economic repercussions, regional disparities in economic resilience and financial stability became pronounced. Coastal Provinces: Regions such as Shanghai (-26), Jiangsu (-53), Zhejiang (-59), and Guangdong (-11) are typically engines of China's economic growth, heavily reliant on manufacturing and export-oriented industries. The negative loadings observed here reflect these provinces' heightened sensitivity to global trade disruptions and international market volatility during the pandemic. The decline in international demand, coupled with supply chain interruptions, severely impacted these areas, underlining their financial risk exposure in global downturns. Western and Inland Provinces: Provinces like Qinghai (-39), and Gansu (-7), known for their less developed infrastructures and reliance on traditional industries, also showed negative loadings. These indicators suggest that these regions faced significant challenges due to internal economic slowdowns and reduced investments. Their geographical isolation and limited industrial diversification may exacerbate financial risks during times of broader economic stress, highlighting the need for targeted fiscal policies and infrastructure development to enhance economic resilience. Central and Resource-rich Provinces: Surprisingly, some central provinces such as Henan (8) and regions rich in natural resources or tourism like Shaanxi (7) and Yunnan (15) demonstrated positive loadings. These positive values could indicate that these regions, possibly due to local economic policies, agricultural bases, or domestic tourism, managed to maintain or even increase their economic activities relative to others. Their positive financial performance during this period might suggest a buffer against macroeconomic shocks, driven by local consumption and diversified economic activities that are less dependent on global markets.

From a financial risk management perspective, the analysis suggests that coastal and economically advanced regions need robust strategies to hedge against global economic fluctuations. This might include enhancing technological innovation, improving supply chain resilience, and developing new markets beyond traditional geographies. For the western and inland provinces, the focus should be on risk diversification, perhaps by fostering new industries, upgrading infrastructure, and improving access to financial services to stimulate local economies. Policymakers should consider these regional disparities when designing economic stimulus packages and financial support measures. Strengthening financial institutions and market structures in vulnerable regions can help mitigate the adverse effects of global financial shocks, while investment in human capital and technological capabilities can foster long-term economic stability.

Overall, the detailed analysis of Factor 1 loadings from 2020 to 2022 highlights the importance of tailored financial strategies that consider the unique economic compositions and geographic nuances of each province, ensuring a balanced approach to economic recovery and sustainable growth in the post-pandemic era.

The analysis of Factor 2 loadings across China's 31 provinces provides a distinctive viewpoint from Factor 1, revealing different dimensions of economic and financial characteristics of each region during January 2020 to December 2022. Here's a deeper dive into how Factor 2's impact diverges from Factor 1, emphasizing unique financial and economic aspects. High Negative Loadings: Provinces like Jiangxi (-54), Shandong (-46), Henan (-55), and Yunnan (-58) show significant negative loadings under Factor 2, suggesting vulnerability to factors possibly distinct from those represented by Factor 1. While Factor 1 might capture the broader economic sensitivity to global trade or manufacturing prowess, Factor 2 could be more closely related to internal financial pressures such as consumer debt levels, housing market instability, or regional banking vulnerabilities. These high negative loadings highlight areas that might be experiencing acute financial distress or are heavily influenced by domestic economic policies and consumer confidence. Moderate to Low Negative Loadings: Urban economic powerhouses such as Beijing (-20), Tianjin (-15), and Guangdong (-37) display less severe negative loadings compared to their Factor 1 loadings, indicating that while they are impacted by national and global economic shifts, they also face challenges specific to urban economic structures, like real estate volatility and metropolitan debt levels. Positive Loadings: Contrasting Factor 1, where positive loadings were rare, Factor 2 shows several provinces like Jiangsu (6), Hainan (14), and Shaanxi (3) with positive effects, suggesting that these areas might be benefiting from domestic economic policies, or they possess resilient sectors that thrive independent of external economic shocks, such as local tourism, technology industries, or agriculture.

Implications for Financial Risk Management and Economic Policy: High Negative Loadings: These regions require targeted financial oversight and possibly intervention to manage high levels of risk associated with real estate, consumer credit, and regional banks. Positive Loadings: These areas provide potential opportunities for investors looking for regions less affected by external shocks and more driven by domestic consumption and internal economic strengths. Neutral Loading: Monitoring and maintaining the economic balance in such regions could be crucial to ensuring stability in face of national economic fluctuations.

Overall, Factor 2 highlights the importance of understanding internal economic pressures and regional financial structures separate from the global economic influences captured by Factor 1. For policymakers and financial strategists, differentiating these factors is crucial for crafting responsive, region-specific economic policies and risk management strategies that cater to the unique challenges and strengths of each province. This tailored approach is vital for mitigating risks and leveraging potential growth areas within China's diverse economic landscape.

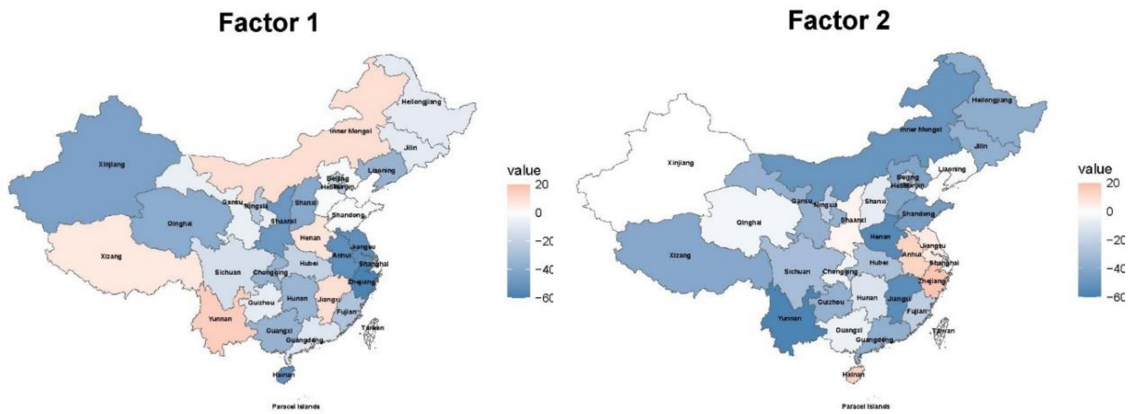

Figure 3: The heat map of the impact of Factor 1 and Factor 2 on the commodity retail indicators

Combining insights from Factor 1 and Factor 2 across China’s provinces, financial and economic policies should be finely tuned to regional characteristics. Provinces negatively impacted by both factors require targeted economic support and risk management strategies to mitigate financial vulnerabilities, especially in sectors like real estate and manufacturing. Conversely, provinces with positive loadings under Factor 2 present investment opportunities and should be encouraged to capitalize on their robust domestic markets and sectors insulated from global disruptions. Tailored fiscal policies and financial oversight are essential to foster regional economic resilience and sustainable growth, aligning local strengths with national economic goals.

4. Conclusion

This research provides significant contributions to macroeconomic financial risk management through the application of matrix factor models to analyze commodity retail price indicators across

Chinese provinces. By effectively managing high-dimensional data, this approach has unveiled intricate relationships and dependencies within regional markets, offering a comprehensive view of economic dynamics that are crucial for informed decision-making. The insights garnered from this study enable policymakers and financial strategists to develop more targeted and effective economic policies and risk management strategies. Specifically, it aids in identifying sectors and regions that are potentially vulnerable to economic shocks, allowing for the implementation of preemptive measures to mitigate risks. Additionally, the detailed analysis of commodity price fluctuations across provinces informs the crafting of region-specific interventions that can enhance financial stability and promote sustainable economic growth. This research not only advances the theoretical framework of financial risk analysis but also serves as a valuable tool for practical applications in macroeconomic planning and policy formulation.

References

[1] Liu, X., Wang, J., & Chen, Y. (2020) Urbanization and Its Impact on Retail Sales and Financial Stability. Journal of Urban Economics, 34, 123-145.

[2] Zhang, H., Li, S., & Xu, W. (2019) The Influence of Regional Policies on Economic Performance and Risk. Regional Studies, 53, 789-812.

[3] Xu, Q., Zhao, L., & Tang, M. (2018) Regional Consumption Differences and Economic Resilience. Economic Research Journal, 45, 332-348.

[4] Wang, L., Sun, Y., & Liu, Z. (2021) Local Economic Conditions and Financial Environments. Journal of Financial Studies, 29, 215-230.

[5] Wang, D., Liu, X., & Chen, R. (2016) Factor Models for Matrix-Valued High-Dimensional Time Series. Journal of Econometrics.

[6] Chen, E. Y., & Chen, R. (2019) Modeling Dynamic Transport Network with Matrix Factor Models: with an Application to International Trade Flow. arXiv: Econometrics.

[7] Tang, C., & Shi, Y. (2021) Forecasting High-Dimensional Financial Functional Time Series: An Application to Constituent Stocks in Dow Jones Index. Journal of Risk and Financial Management.

[8] Davis, C. (1963) The Rotation of Eigenvectors by a Perturbation. Journal of Mathematical Analysis and Applications, 11, 20-27.