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Exploring Revenue Trends in Alley Commercial Areas in Seoul, Korea

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This study examines changes in sales by business category and area in Korea's small commercial districts. Unlike previous studies that focused primarily on overall sales levels before and after the COVID-19 pandemic, this paper emphasizes temporal variations in the inequality of sales distributions. Using credit-card-based data comprising 392,832 sales records aggregated by (category, area) units, the primary analysis reveals that sales distributions have recently become more dispersed across most categories, underscoring the vulnerability of less-advantaged areas in the post-pandemic period. In a secondary analysis, regression and machine learning models were applied to investigate factors influencing regional sales disparities. The findings indicate that although overall sales, which declined sharply during the pandemic, rebounded rapidly after 2021, they have shown a significant downturn in recent periods. The paper concludes with a discussion of relevant policy implications.

Key Word: Commercial Districts, Sales Growth, Distributional Inequality, COVID-19
JEL Code: L1, L8, C5

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I. Introduction

The COVID-19 pandemic has had a profound impact on local economies, with small neighborhood businesses among the most vulnerable sectors. The COVID-19 pandemic has had a profound impact on local economies, with small neighborhood businesses among the most vulnerable sectors. These businesses, often situated in the hearts of their communities, suffered significant declines in sales due to social distancing measures, mobility restrictions, and shifts in consumer behavior during the pandemic. While existing studies have documented the immediate declines in sales and the challenges faced by these businesses during the pandemic (e.g., Rhee, 2024), there is limited research on the longer-term effects, particularly concerning how the regional distribution of sales has evolved in the recent periods.

This study focuses on alley commercial areas (referred to as "Golmok Sangkwon") in Seoul, Korea, and investigates how regional disparities in sales distributions have changed in recent periods. Specifically, it aims to answer the following questions: How has the distribution of sales for small neighborhood businesses varied across different areas of the city, and what trends have emerged in the regional inequality of sales before and after the pandemic. To address these questions, we use the inter-quartile range (IQR) of the distributions under study, a frequently utilized measure of inequality (Drechsel-Grau *et al*., 2022), to quantify the changes in sales distributions across alley commercial areas.

The results reveal a concerning pattern. While overall sales for alley commercial areas have shown signs of recovery in the post-pandemic period, regional inequalities in sales distributions have worsened substantially. This suggests that the recovery has been uneven, with certain areas rebounding more strongly than others. Such disparities not only highlight the vulnerability of less-advantaged areas but also underscore the potential for long-term socio-economic divides if these trends persist.

This research is significant for several reasons. First, it fills a gap in the literature by moving beyond aggregate analyses of sales recoveries to examine regional variations. Understanding these dynamics is essential for policymakers aiming to design equitable economic recovery strategies. Second, by focusing on the periods before and after the post-pandemic period, the study provides insights into possible structural challenges facing local businesses, offering a basis for policy interventions that can promote balanced regional development.

The perspective of this paper, which examines the distribution of sales revenue across commercial districts, is novel, with few directly related prior studies. However, numerous studies have addressed the socioeconomic effects of COVID-19 in recent years. For macroeconomic implications of pandemic shocks, see Baqaee and Farhi (2022) and Guerrieri *et al*. (2022). For stock market effects, refer to Uddin *et al*. (2021) and Baker *et al*. (2020). Bloom *et al*. (2020) investigate productivity effects using firm survey data, while Alon *et al*. (2020) discuss issues related to gender equality. Brodeur *et al*. (2021) provide a comprehensive survey of the literature.

Chen *et al*. (2021) closely align with our research in terms of data types. Using credit card and scanner data from China, they revealed a substantial average decline in offline consumption during the initial phase of the COVID-19 outbreak. In the Korean context, Rhee (2024) documented the effects of the pandemic on revenue in Seoul's basic commercial districts across business categories up to 2021 through a counterfactual analysis based on the same dataset used in this paper. Additionally, Park *et al*. (2023) employed a time-series and logistic regression analysis of the period before and after the COVID-19 pandemic to classify alley commercial areas in Seoul into growing and declining districts, confirming that the geographic distribution of these districts differs significantly.

This study extends the analysis to the second quarter of 2024. Moreover, rather than focusing solely on aggregate sales levels, it examines sales inequalities across different business categories within alley districts, offering a distinct contribution. Additionally, the study utilizes a large-scale dataset with 392,832 observations, enabling a more comprehensive and data-driven assessment of regional sales recovery variations. By leveraging a machine learning model with higher predictive power, this study captures patterns more effectively than the traditional regression-based approaches used in prior research.

The structure of this paper is as follows. Section 2 introduces the structure of commercial districts in Seoul and sales data based on credit card transactions. Section 3 examines the quarterly distribution of sales by category across areas and analyzes changes in percentiles. To quantify distribution inequalities, we calculate interquartile ranges and compare the corresponding shifts over time. These results reveal a significant intensification of regional inequalities in sales distributions across most categories. Section 4 employs regression models and machine learning (ML) models to explain regional differences in sales. On the same dataset, the ML models demonstrate nearly twice the explanatory power of the regression models. Notably, to address the seasonality of quarterly sales, we analyze the predicted year-over-year changes in sales by quarter. A striking finding is that, on average across business categories, while sales in Seoul's alley commercial areas have rapidly recovered from the COVID-19 downturn, they now exhibit a sharp decline comparable to that experienced during the pandemic, reflecting the current economic slowdown. Section 5 provides a summary and concludes the study.

II. Data

The data used in this study comprise category-level quarterly sales for 1,090 alley commercial areas in Seoul, Korea, ranging from Q1 2019 to Q2 2024 (22 quarters in total). The revenue data were originally collected from card transaction records of individual stores for each quarter.[1] These figures were then adjusted to include estimated cash sales, calculated using the quarterly cash-to-card transaction ratios

[1]Card sales include both in-store and delivery sales made using personal cards, corporate cards, and debit cards. The number of individual stores included in the dataset varies slightly by quarter, but as of the fourth quarter of 2021, there are a total of 34,756 stores.

reported by the Bank of Korea (The Bank of Korea, 2019).

While the original dataset contains sales figures for individual stores, the publicly available version used in this study is aggregated at the level of business categories within each commercial area to ensure privacy protection. Although card-based sales data may not capture all transactions perfectly, such data were consistently calculated across all commercial districts and categories over the entire period. Therefore, the data are considered adequate for analyzing trends in sales changes.

Seoul's basic commercial districts are divided into a total of 1,638 geographic areas, categorized into four types of zones based on their locations and characteristics. These include tourist zones frequented by foreigners, such as "Myeongdong" and "Itaewon," traditional market zones such as "Gwangjang Sijang," developed zones concentrated around subway stations, and alley zones closest to residential areas. As of the second quarter of 2024, the alley zones analyzed in this study comprise 1,090 areas, accounting for approximately 67% of all basic commercial districts in the city.

The quarterly sales data is aggregated by commercial area and business category. With a total of 81 categories, the ideal number of records in the dataset would be $1090\times81\times22$, where 22 represents the number of quarters. However, the actual number of categories varies across areas, and sales data are missing for certain quarters in some areas. As a result, the total number of district-category pairs with complete sales records across all quarters amounts to 392,832, as summarized by year in Table 1.

Table 2 presents the number and proportion of observations for the top ten categories with the highest total sales across areas.

TABLE 1—SUMMARY OF DATA BY YEAR

Year	#Quarters	#Obs	#Areas	#Categories	Quarterly Revenue (in million KRW)	
					Mean	SD
2019	4	71424	1085	63	940.9	3379.2
2020	4	71424	1085	63	957.1	3155.5
2021	4	71424	1085	63	1006.4	3222.5
2022	4	71424	1085	63	1177.2	3430.1
2023	4	71424	1085	63	1253.7	3398.6
2024	2	35712	1085	63	1187.3	3195.2

TABLE 2—SUMMARY OF DATA BY CATEGORY

Category	No. Obs. (%)	Category	No. Obs. (%)
Korean Restaurant	22110 (5.63%)	Hof & Bar	14762 (3.76%)
Beauty Shop	19712 (5.02%)	General Clothes	13222 (3.37%)
Convenience Store	18436 (4.69%)	Pharmaceuticals	12430 (3.16%)
Coffee & Beverages	17864 (4.55%)	Auto Repair	11902 (3.03%)
Supermarket	17226 (4.39%)	Other	230230 (58.62%)
Snack Shop	14938 (3.80%)	**Total**	392832 (100%)

III. Sales Distribution Across Areas

In this chapter, we analyze temporal changes in sales distributions by business category. Figure 1 illustrates the temporal changes in the percentiles of sales distributions for the Chinese restaurant category (coded as 100002) across areas, as an example. While sales generally show an upward trend across almost all percentiles, the increase is particularly pronounced at higher percentiles, especially after the latter half of 2021, when the impact of COVID-19 began to subside. This pattern is mostly similar across categories.

From the percentiles, we calculated the interquartile ranges (IQR), the gap between the 75th percentile and the 25th percentile, as presented in Figure 2 for twelve example categories. With a few exceptions, most categories exhibit an increase in the IQR over time. When comparing the first eleven quarters (up to Q3 2021) and the latter eleven quarters (from Q4 2021), 48 out of 63 categories (approximately 76.2%) show an increase in the average IQR during the period.[2]

Figure 3 provides a further examination of the distributional changes for the same sample categories redefining the IQR as the difference between the 90th percentile and the 10th percentile. This alternative measure reinforces the robustness of the finding that the distributions have become increasingly dispersed over time.

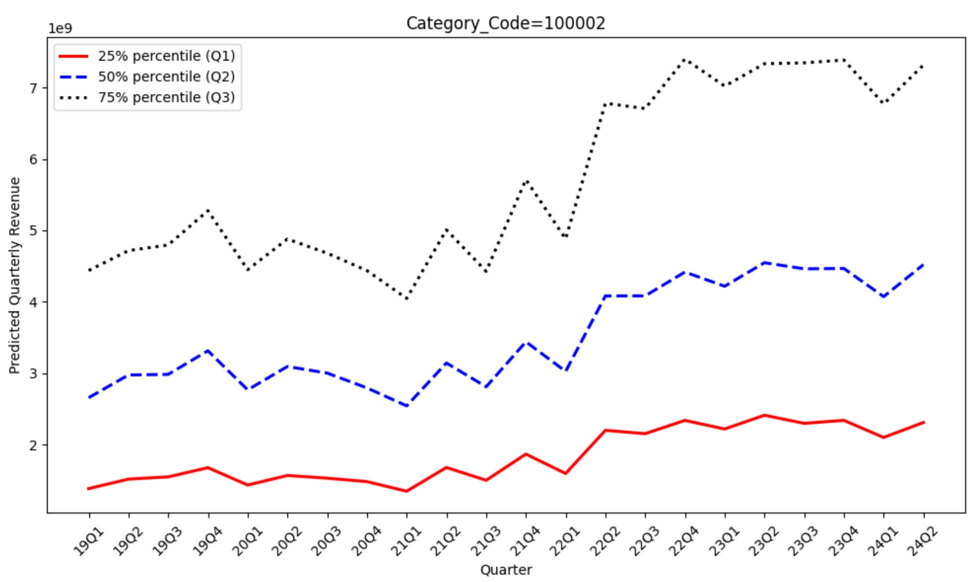

FIGURE 1. CHANGE OF SALES PERCENTILES ACROSS AREAS FOR A SAMPLE CATEGORY

[2]The average increase across all industries amounts to 98.5 million KRW. Alternative inequality measures, such as the Gini coefficient or Theil index, could also be used. When applying the Gini coefficient instead of the IQR, 44 out of 63 categories showed increased inequality over the periods, slightly different from the results presented in Figure 2.

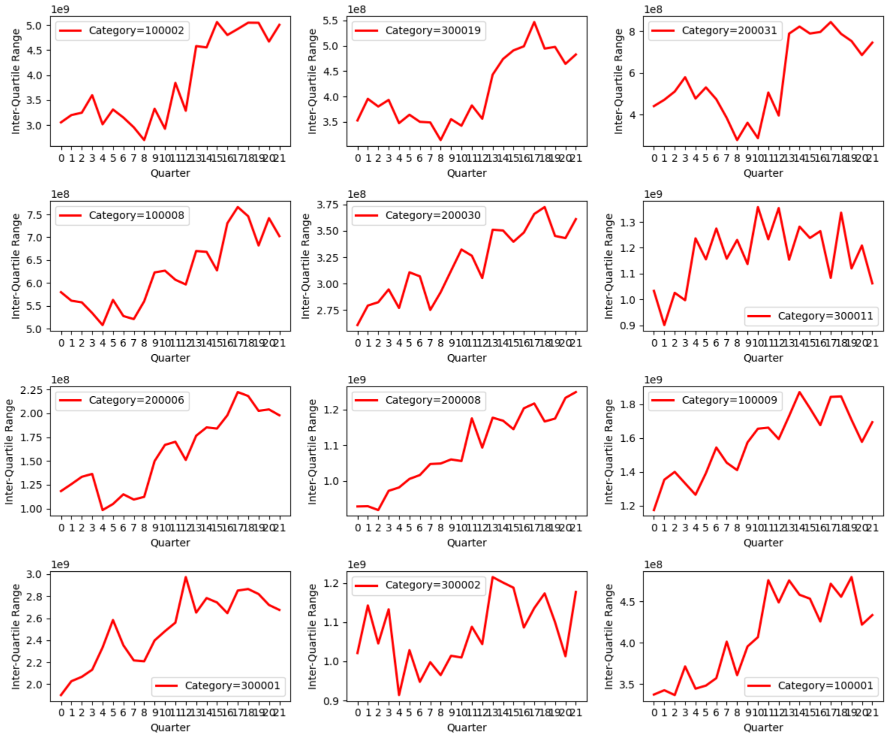

FIGURE 2. CHANGES IN INTER-QUARTILE RANGES (75TH VS. 25TH PERCENTILE)

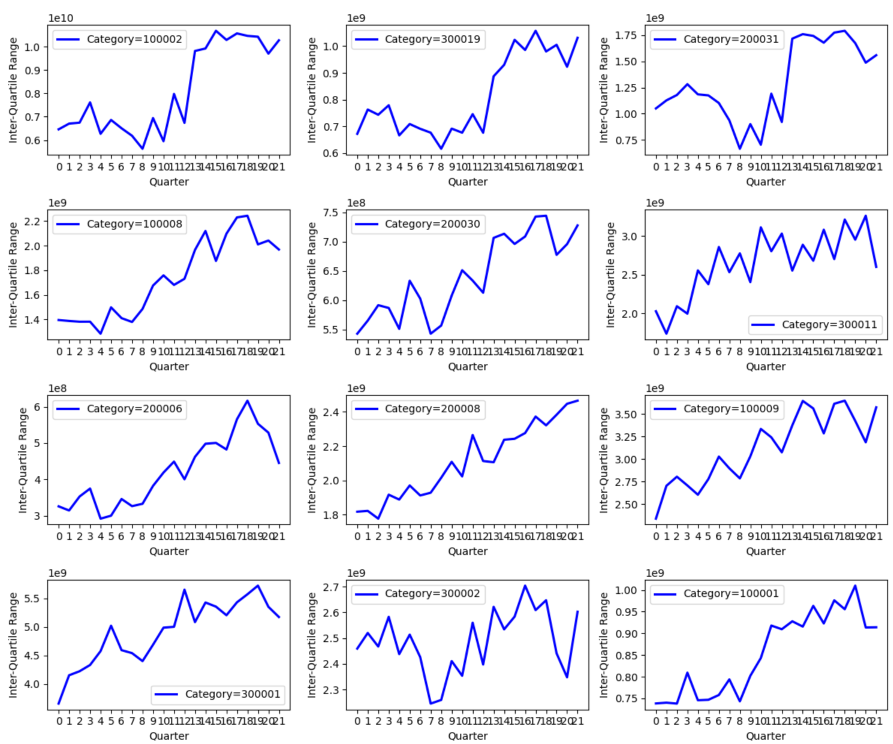

FIGURE 3. CHANGES IN INTER-QUARTILE RANGES (90TH VS. 10TH PERCENTILE)

TABLE 3—SUMMARY OF THE AUXILIARY REGRESSION OF THE IQR

	Estimates	S.E.	P-Value
Intercept	19.69	0.014	0
Quarter Index	-0.0118	0.0003	0
Quarter Index**2	0.00134	1.67e-5	0
Sales Volume (log scale)	0.00138	0.0005	0.01

To examine the pattern of the changes in the IQR over the periods more rigorously, we conducted an auxiliary regression analysis. Table 3 presents the estimation results of a regression analysis where the logarithm of 23,870 IQR values (derived from 1,085 areas over 22 quarters) is the dependent variable. The explanatory variables are the quarter index (ranging from 1 to 22), the square of the quarter index, and the logarithm of the total sales volume across all areas for each category. The R-squared value of the regression is 0.67, and all estimated coefficients are statistically significant.

Figure 4 illustrates the changes in the IQR (on a logarithmic scale) over quarters, calculated by a quadratic equation with the estimated parameters. Consistent with the previous data analysis, the results indicate an increasing trend in the IQR over time.[3] A noteworthy finding from this regression is that categories with larger sales volumes—representing categories that are more popular across many areas—exhibit higher IQR values.

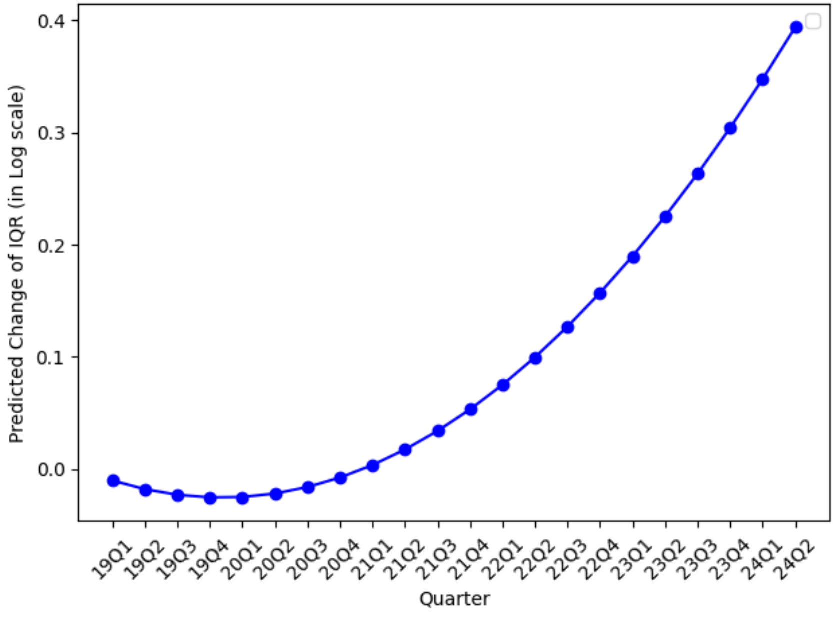

FIGURE 4. PREDICTED CHANGES IN THE IQR OVER PERIODS

[3]The analysis results remain qualitatively consistent even when using an alternative definition of the IQR, as shown in Figure 3.

IV. Analysis of Revenue Differences Across Areas

In this chapter, we explain the sales change patterns in alley districts by means of a traditional regression analysis and with currently popular machine learning models (Athey and Imbens, 2019).

A. *Regression Analysis*

The dependent variable in the regression analysis is the logarithm of sales (in 1,000 KRW), while the explanatory variables encompass dummy variables for category codes and quarters, as well as proxies for area characteristics. These proxies consist of the log values of area size (in square meters), the floating population, the average monthly income of residents in each area, and dummy variables for the administrative districts ('gu') to which each commercial area belongs (25 in total). The results of the analysis are presented in Table 4.

The explanatory power of the regression analysis, as measured by the R-squared value, was 0.503, which is not particularly high; however, all estimated coefficients

TABLE 4—SUMMARY OF REGRESSION RESULTS

	Estimates	SE	P-Value
Intercept	-12.82	0.24	0
Area Size	0.063	0.003	0
Population	0.531	0.004	0
Income Level	0.904	0.015	0
R-Squared		0.503	

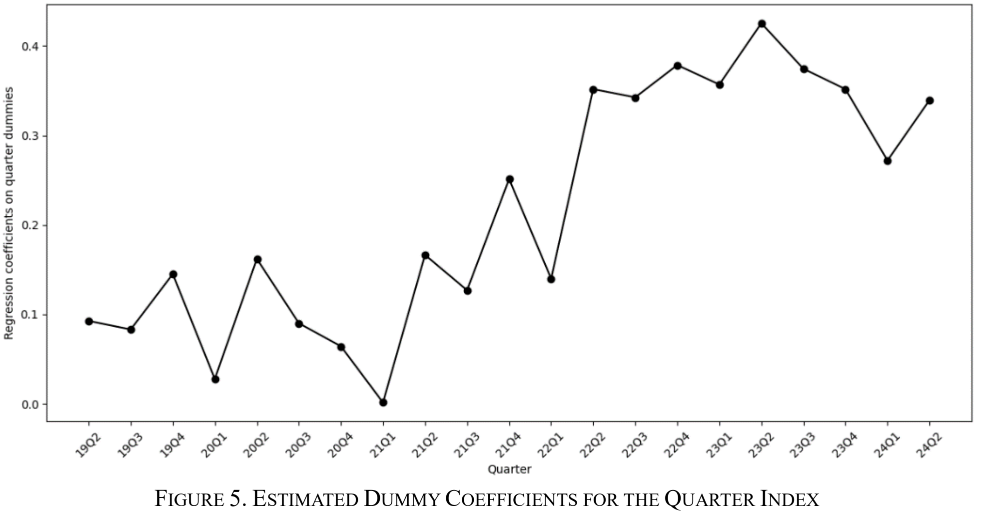

FIGURE 5. ESTIMATED DUMMY COEFFICIENTS FOR THE QUARTER INDEX

were statistically significant. Regarding the area characteristic variables, the results aligned with intuition: larger area sizes, higher populations, and greater resident income levels were associated with higher revenue levels.

Figure 5 visualizes the dummy coefficients for the quarter indices as estimated from the regression model. Assuming no omitted variables and excellent model explanatory power, this represents the overall sales changes by quarter after controlling for other factors. Similar to the data analysis in the previous chapter, the pattern reveals a rapid increase in sales following the COVID-impacted period.

Following Rhee (2024), the growth rate of sales from the same quarter in the previous year was calculated using the estimated quarterly dummy coefficients. This was done because quarterly sales exhibit strong seasonality. Formally, the growth rate of sales from t_1 to t_2 can be derived from equation (1), as follows,[4]

$$\frac{y_{it_2} - y_{it_1}}{y_{it_1}} = \frac{\exp(\beta_{t_2}) - \exp(\beta_{t_1})}{\exp(\beta_{t_1})}, \tag{1}$$

while β_t represents the dummy coefficient for quarter t.

Figure 6 presents the revenue growth rates (compared to the same quarter in the previous year) calculated using Equation (1). The negative growth rates observed from Q3 2020 to Q2 2021 are clearly attributable to the effects of COVID-19. Subsequently, revenue growth rates increased sharply up to Q1 2023. However, it is

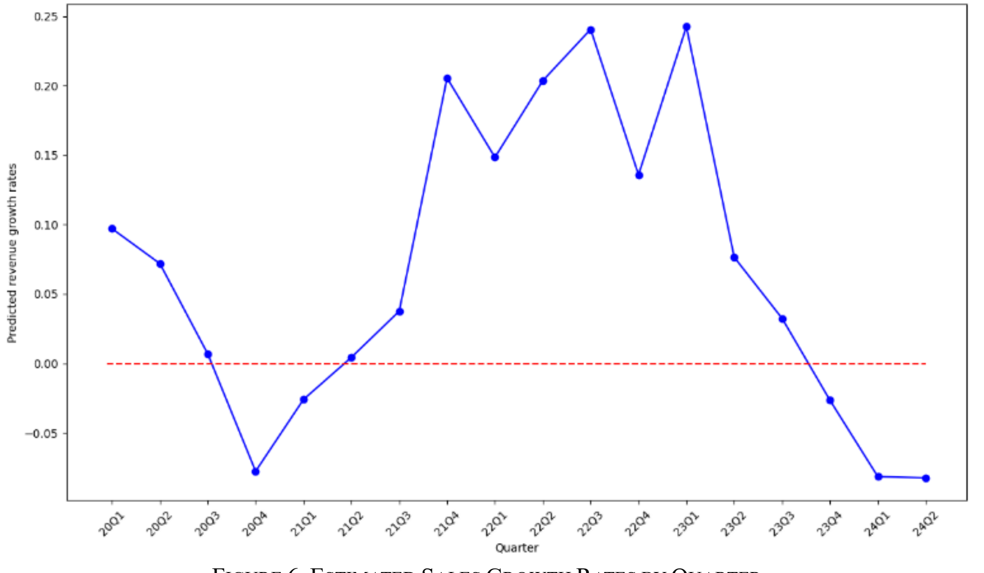

FIGURE 6. ESTIMATED SALES GROWTH RATES BY QUARTER

[4]The exponential function is applied because the dependent variable in the regression analysis was transformed to a log scale.

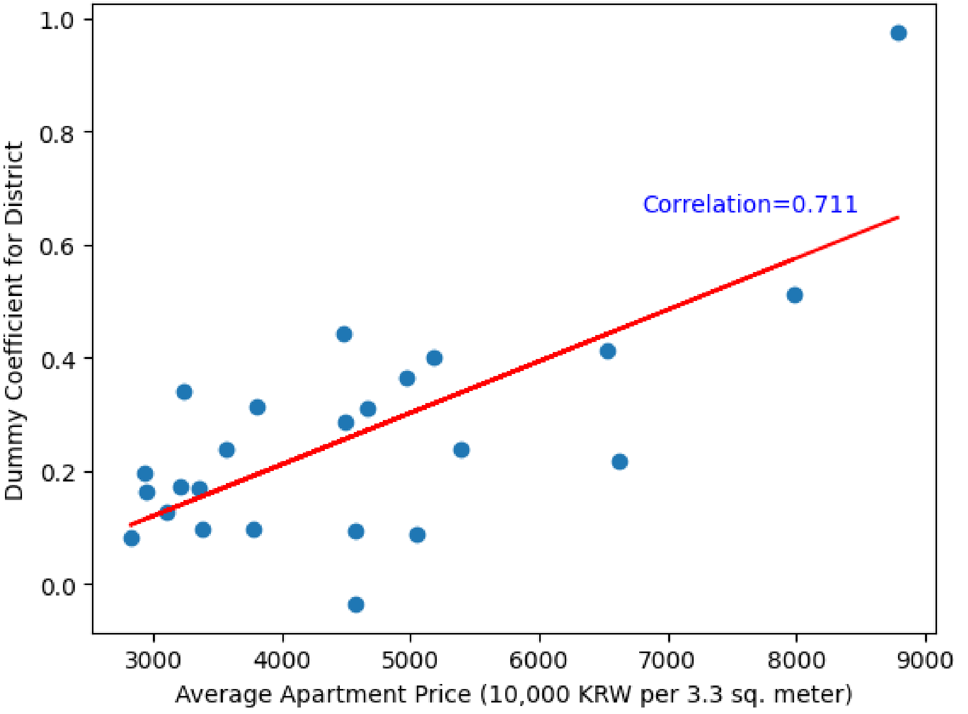

FIGURE 7. RELATIONSHIP BETWEEN DISTRICT COEFFICIENTS AND APARTMENT PRICES

notable that growth rates decelerated and then declined to levels comparable to the COVID-impacted quarters, reflecting the broader slowdown in the Korean economy in recent periods

The revenue differences across administrative districts were found to be statistically significant in most cases. To examine this difference analytically, Figure 7 illustrates the relationship between the average price, per square meter, of the apartments in each district as of February of 2024 and the regression coefficients of district dummy variables. The correlation coefficient is 0.71, indicating a pattern in which wealthier districts generally exhibit higher sales in alley commercial areas.[5]

B. *Machine Learning Analysis*

The primary purpose of incorporating a machine learning model in this section is to assess the robustness of the regression analysis and ensure that our findings are not driven by the limitations of a parametric approach. By comparing the outcomes from both models, we aim to verify whether the key patterns observed in the regression analysis remain consistent within a more flexible, non-parametric framework. If both approaches yield qualitatively similar results, it strengthens the reliability of the findings in this study.

[5]It should be noted that the pattern in Figure 7 does not imply causation and that housing prices may not necessarily have a positive effect on regional sales levels due to the potential influence of unobserved variables.

The ML model we apply in this study is the Random Forest (RF) model (Breiman, 2001b),[6] which is a popular ensemble algorithm that constructs a multitude of decision trees during training. Each tree is built using a random subset of the data (via bootstrapping) and a random subset of features. Predictions are made by aggregating the outputs of all individual trees, typically by means of averaging for regression tasks or majority voting for classification. This randomness in data and feature selection helps the model avoid overfitting and makes it robust across various data scenarios.

Figure 8 presents an example of a decision tree in the RF model. In each branch of the tree, sequential splitting occurs based on the conditions for one of the X variables ('feature'), and at the final branch, the average of the y variable ('target') is calculated for each formed group. The RF model consists of multiple such trees, and the predicted value of the y variable is obtained by taking the average of the values predicted by each tree. As shown in Figure 8, there are numerous alternatives for the cut-off points used in the splitting of the decision trees. Therefore, the RF model, which is formally nonparametric, can also be conceptualized as a model with a possibly infinite number of parameters. This characteristic enables it potentially to provide a superior predictive fit compared to a parametric model such as regression. As usual in ML models, appropriate tuning of the hyperparameters is critical when optimizing the RF model. As is typically done, we optimized the hyperparameters by a grid search over possible alternatives such that we could maximize the predictive accuracy of the model after splitting the data into training (80%) and test sets (20%).

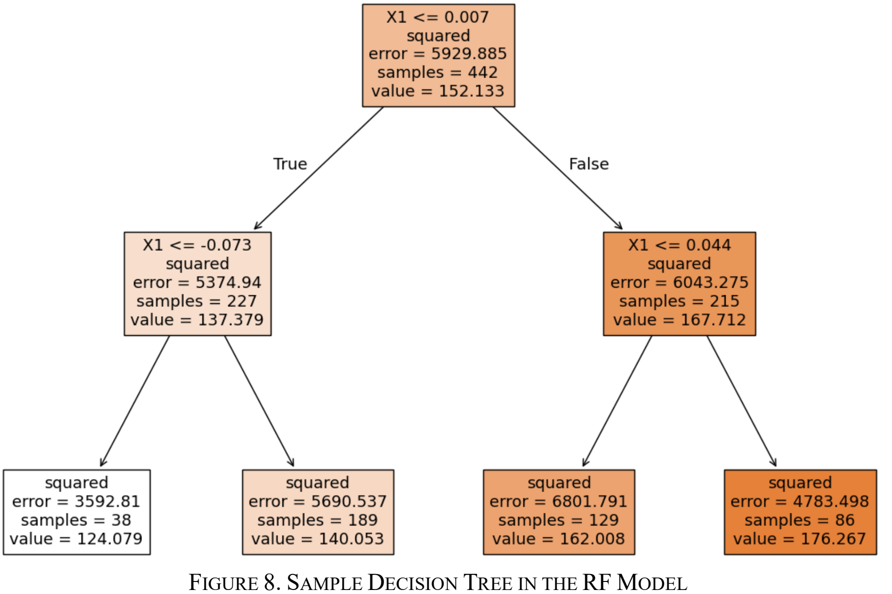

FIGURE 8. SAMPLE DECISION TREE IN THE RF MODEL

[6]Alternatively, one may use other ensemble models, such as the XGBoost model, which may offer several advantages over Random Forest, particularly with regard to feature contribution analysis, handling imbalanced data, and computational efficiency. However, because the RF model is simpler and already provides sufficiently satisfactory predictive power, we did not explore other ensemble models in this study.

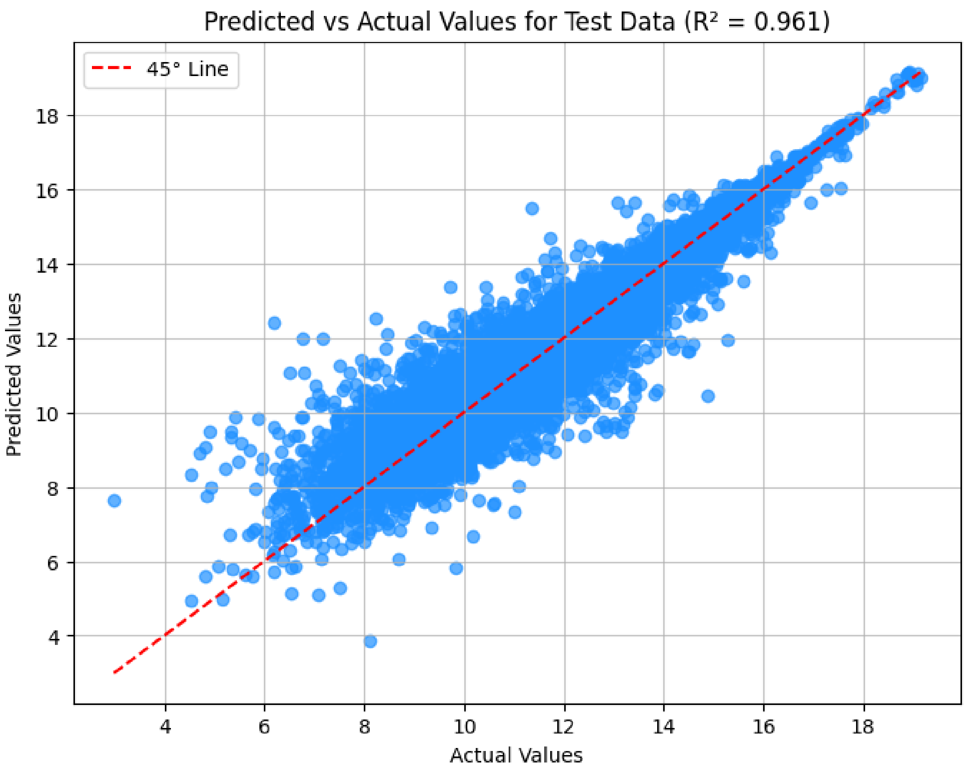

FIGURE 9. PREDICTIVE PERFORMANCE OF RF MODEL FOR THE TEST DATASET

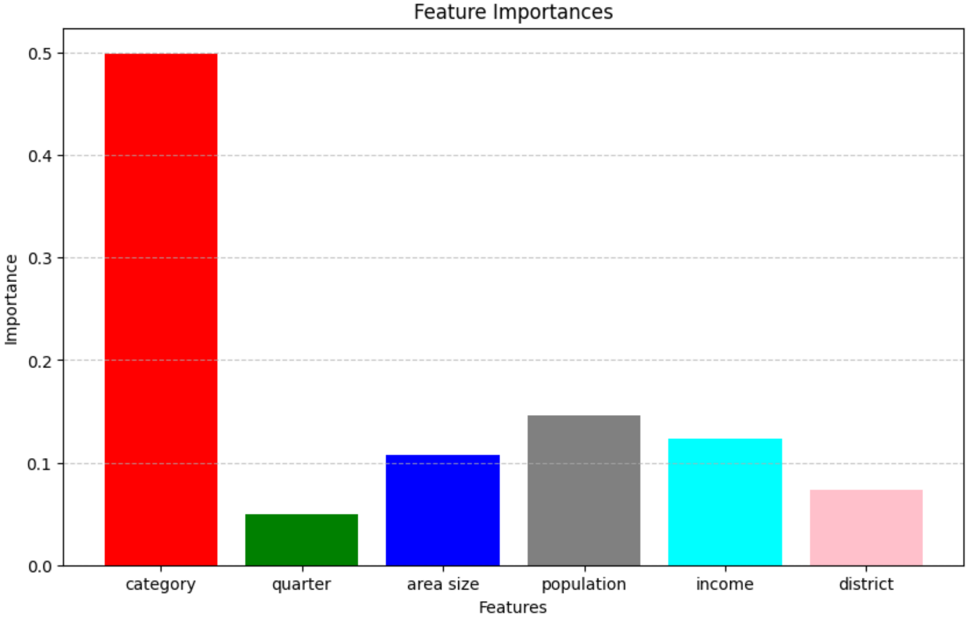

FIGURE 10. FEATURE IMPORTANCE FROM THE RF MODEL

As in the regression model, we set the model's dependent variable ('target') as the logarithm of sales revenues (in 1000 KRW), while the independent variables ('features') are the log values of the area size (in square meter), area population and the average monthly income of the residents, as well as the three sets of label-encoded values identifying 63 business categories, 22 quarter indices, and 25 administrative districts.

In Figure 9, the predictive fit of the optimized RF model is 0.96, which represents a remarkable improvement over the regression model.[7]

In machine learning models, "feature importance" measures the contribution of each explanatory variable relative to the prediction of the target variable. It is typically calculated by assessing how much each feature helps to reduce the prediction error. For example, in a RF model, feature importance is determined by evaluating how much each feature improves the model's performance at each split in the decision trees.

In Figure 10, the contribution of the category indices is the highest, accounting for approximately 50% of the variation in sales. However, when the four area characteristic variables are summed up, they contribute around 45%, emphasizing that area differences also play a significant role in explaining sales differences.[8]

To understand how individual features influence the predictions from a Random Forest (RF) model, we use a technique called Partial Dependence (PD) (Friedman, 2001; Linardatos *et al.*, 2020). This method isolates the effect of one feature by holding all other features constant. PD shows, both numerically and graphically, how changes in the chosen feature affect the predicted outcomes, making it easier to interpret the predictions of complex machine learning algorithms. The use of partial dependence plots (PDPs) would provide deeper insights into variable interactions. Machine learning models capture complex relationships among variables, making it difficult to understand their individual contributions fully, unlike in conventional parametric methods. PDPs would help illustrate how changes in individual predictors influence sales predictions while holding other variables constant.

The PDPs in Figure 11 shows significant differences in sales by category, with a pattern of increased average revenue observed for more recent quarters, larger area sizes, higher area populations, and higher average incomes.

Figure 12 clearly illustrates the partial dependence of the quarter variable after averaging out the effects of all other features. To compare with the quarterly dummy coefficients from the regression analysis (shown in Figure 5), predicted sales were adjusted to reflect the difference from sales in the reference period (Q1 2019).

There may be regional differences in the quarterly revenue profile shown in Figure 12. Figure 13 presents a separate analysis according to the administrative district,

[7]The R-squared value for the training data is as high as 0.984, even after controlling for the possibility of overfitting.

[8]As an alternative to feature importance, one may report SHAP (Shapley Additive Explanations) values, a widely recognized method for interpreting machine learning models. One key advantage of SHAP is that it provides both the magnitude and direction of each feature's effect. Although SHAP values could enhance interpretability, this study did not apply them due to computational constraints, particularly given the large dataset used. Nonetheless, the potential application of SHAP values in future research could offer valuable insights. We thank the anonymous reviewer who highlighted this point.

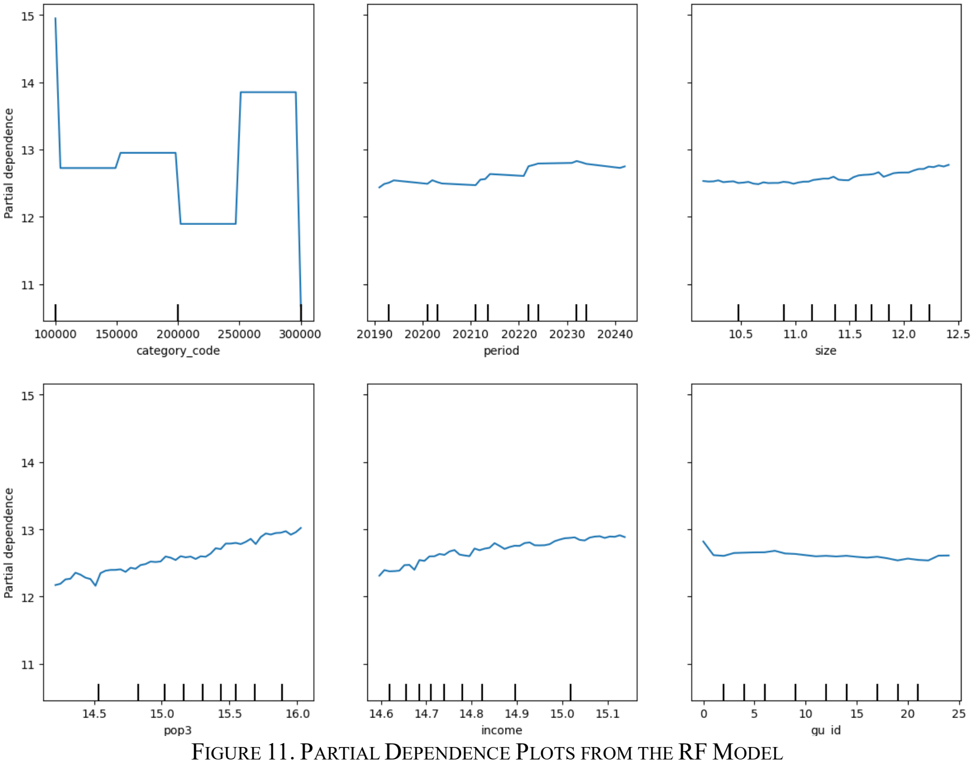

FIGURE 11. PARTIAL DEPENDENCE PLOTS FROM THE RF MODEL

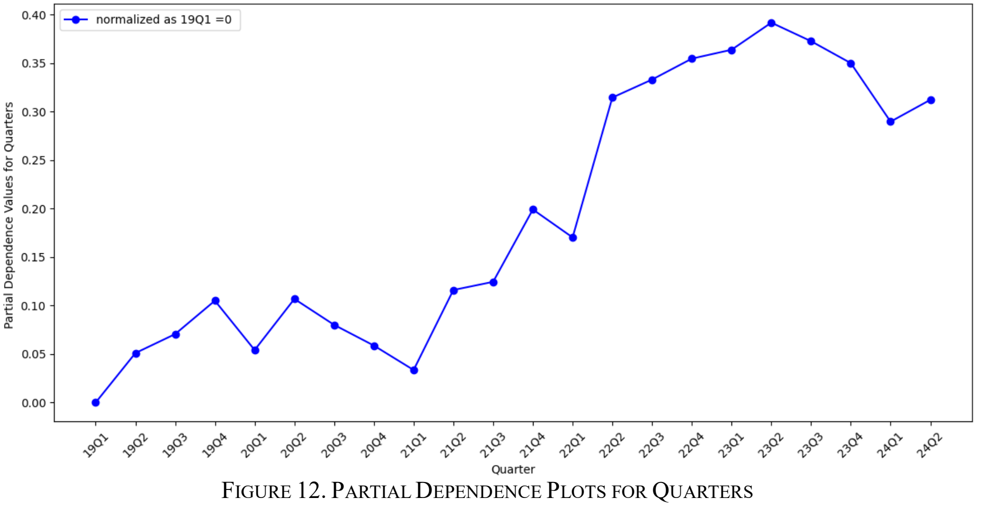

FIGURE 12. PARTIAL DEPENDENCE PLOTS FOR QUARTERS

showing the differences in the sales recovery profiles between Gangnam-gu and Eunpyeong-gu as examples. Significant differences were observed between the districts; however, due to data limitations, the determinants of these regional differences were not fully analyzed in this paper. This issue could be explored further in future research to identify appropriate policy measures.

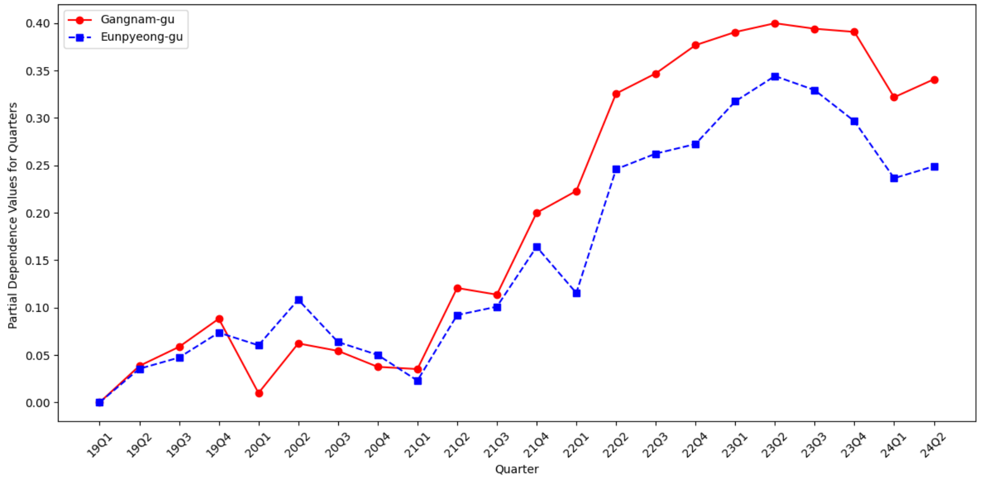

FIGURE 13. COMPARISON OF PARTIAL DEPENDENCE PLOTS FOR QUARTERS BY DISTRICT

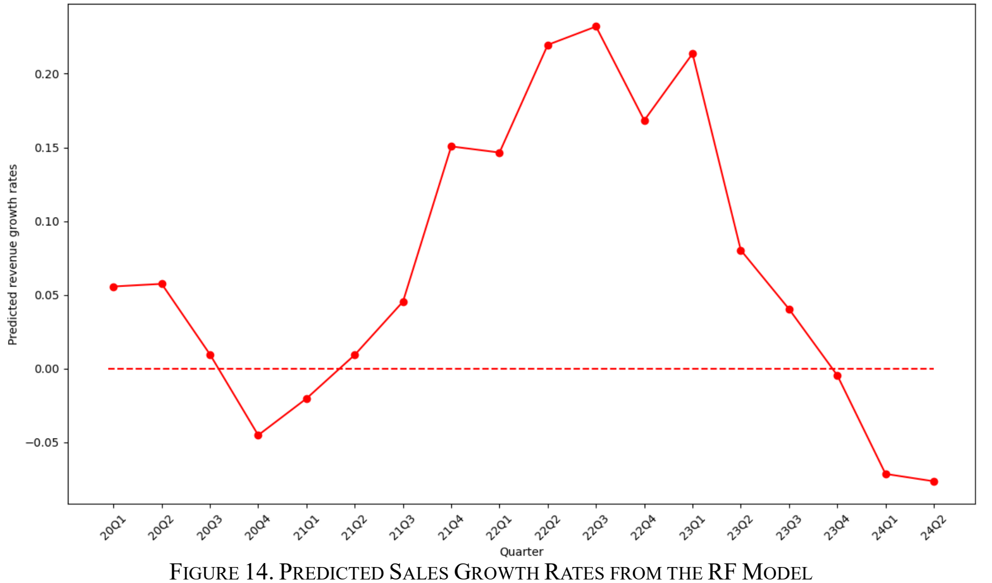

FIGURE 14. PREDICTED SALES GROWTH RATES FROM THE RF MODEL

Lastly, Figure 14 illustrates the predicted year-over-year growth rates of sales for each quarter, calculated using the partial dependence from the RF model. Similar to the regression counterpart in Figure 5, the growth rates show a rapid recovery from the initial impact of COVID-19, followed by a recent sharp decline. This pattern highlights the consistency between the RF model and the regression analysis in capturing these trends.

V. Conclusion

In conclusion, this study utilized credit card-based data comprising 392,832 sales records to explore changes in sales distributions. The primary analysis revealed that sales distributions have become increasingly dispersed across most categories, highlighting the growing vulnerability of less-advantaged areas in the post-pandemic period. A secondary analysis, employing both regression and machine learning models, identified key factors driving regional sales disparities and attempted to identify the marginal effects of periods isolated from all other features. The findings suggest that while overall sales, which had declined sharply during the pandemic, showed a rapid rebound after 2021, they have recently experienced a significant downturn.

This study has several limitations, which suggest important directions for future research. First, while we identified a pattern of increasing regional inequality of sales across most categories, the underlying causes remain unclear. Macroeconomic factors such as inflation, government support policies, and shifts in consumer sentiment may have played a crucial role in shaping these trends. Additionally, differences in commercial district types, such as tourist areas, residential zones, and traditional markets, could have contributed to the observed disparities, though our research specifically focuses on residential (“alley”) zones. A more detailed exploration of the differences between categories with increasing and decreasing levels of inequality could provide valuable insights into these causes. In addition, to address regional heterogeneity in the model specification, it may also be possible to adopt more advanced time-series methods, such as differencing techniques.

Second, we utilized machine learning models to identify a nonparametric mechanism driving disparities in sales data. However, unlike a regression analysis, ML models are designed primarily for prediction rather than explaining underlying phenomena (Breiman, 2001a), which makes them insufficient for pinpointing causal relationships. Our regression analysis, in contrast, explained approximately 50% of the variation in sales using area-specific characteristics, such as commercial area sizes, administrative districts, average resident income levels, and population levels. While this approach sheds light on correlations, it does not fully address the causal mechanisms. Discovering additional explanatory variables in subsequent analyses, including macroeconomic factors, commercial district characteristics, and shifts in consumer behavior, could improve the model’s explanatory power and inform more targeted policy measures to mitigate regional disparities in sales.

Third, we utilized credit-card-based revenue data. Given the limitations of card transaction data in terms of accuracy and transparency, policymakers should be cautious when interpreting the results. With more accurate data, more reliable conclusions could be drawn based on the methods presented in this study.

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