

Should Low-Frequency-High-Consumption Enterprises Add Online-to-Offline Platforms? An Empirical Study Using the VAR Model

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Abstract This study investigates the impact of online-to-offline (O2O) platforms, such as Ele.me and Meituan, on offline sales in low-frequency-high-consumption industries, specifically a mid-to-high-end liquor distribution chain. Using data from 77 offline stores in Beijing collected during 2019–2022, the study employs a VAR model to analyze the relationship between offline sales and the use of O2O platforms. The results reveal a long-term equilibrium between the two, with most indicators showing a positive impact of O2O platforms on offline sales. The research provides valuable insights for low-frequency-high-consumption enterprises in making multi-channel decisions and quantifies the impact of O2O platforms on offline sales.

Keywords O2O platform; low-frequency-high-consumption; liquor distribution chain enterprise; store sales; VAR model

Received March 4, 2023, accepted June 27, 2023

Supported by the National Natural Science Foundation of China (72172146, 71772169, 72272140); the Fundamental Research Funds for the Central Universities (E3E40802X2) and the China Scholarship Council (202004910235)

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1 Introduction

An Online-to-offline (O2O) platform is a mobile phone application that enables consumers to purchase local life services, such as catering, supermarket shopping, flowers, and medicine, which are then delivered directly to their homes to meet their immediate consumption needs^[1]. O2O platforms have two defining characteristics: They are platform-type applications and typically provide high-frequency, low-consumption local life services. Examples of typical O2O platforms include Meituan, Ele.me, Doordash in the US, Just Eat in the UK, and Delivery Hero in Germany. The COVID-19 pandemic has accelerated the global popularity of O2O platforms, with transaction volumes reaching \$5.15 billion in China, \$2.65 billion in the US, and \$1.89 billion in Europe^[2].

However, the development of O2O platforms has not been smooth sailing. Mainstream media, such as the New York Times, Wall Street Journal and BBC, have reported a lot about the tension between physical commerce and O2O platforms: most physical stores intuitively believe that the launch of O2O platforms will erode offline sales.

Existing studies of the impact of O2O platform on offline stores mainly focus on the impact of the launch of O2O in high-frequency-low-consumption enterprises^[1]. But there is still a lack of empirical evidence on the impact of adding O2O platforms on low-frequency-high-consumption enterprises (e.g., high-end wine). Since the epidemic spread, many enterprises in China have been severely affected^[3]. In order to survive and develop under the epidemic, enterprises have sought new sales channels^[4, 5]. O2O platforms are one way to sell. However, should low-frequency-high-consumption enterprises go online on O2O platforms? The existing literature cannot answer this question.

This paper presents a unique dataset comprising 36,355 observations collected from 77 stores of a mid-to-high-end liquor distribution enterprise in Beijing, covering the period from June 2017 to June 2022. The enterprise added Meituan, Ele.me, and JD O2O platforms between 2019 and 2022. Mid-to-high-end liquor distribution enterprises are low-frequency-high-consumption businesses, which makes them an excellent case study for examining the impact of O2O platforms on offline sales before and during the pandemic. The research findings indicate that in low-frequency and high-consumption industries, the expansion of O2O platform channels may initially lead to a decline in offline store sales. However, in the long term, it is expected to have a positive impact on offline sales. The findings of this study will provide valuable insights for channel decision-making for mid-to-high-end liquor distribution enterprises and other low-frequency-high-consumption businesses.

2 Literature and Background

2.1 Literature Review

Most channel addition literature (see Zhang, *et al.*^[1]) was limited to firms adding firms own online sales channels, such as their own websites or apps, to their traditional offline sales channels. Geyskens, *et al.*^[6] studied the impact of adding the Internet channel on stock market returns, and find that it generally has a positive impact on stock returns, but it may lead to financial crises in the short term. Some other studies have begun to investigate the impact of adding offline channels on online sales. These studies have found that although the new channel

may erode the existing customers of the online store in the early stage of channel introduction, it could bring new users to the original channel at a faster speed and increase the number of repeat customers in the middle and late stages^[7].

There is also emerging literature studying platform channel addition such as O2O platform. The advantage of this channel stems from two aspects. Firstly, the popularization of mobile payment has broadened the range of consumption scenarios and made purchasing more convenient for consumers. Additionally, payment data generated by the platform allows companies to track consumer behavior for personalized customization. Secondly, the O2O platform's unique fast delivery mode (30 minutes) can satisfy customers' real-time needs to a great extent, differ from traditional e-commerce platforms such as JD.com or Taobao^[8].

Existing literature on introducing O2O platform channels has mainly focused on high-frequency and low-consumption industries such as fast food and groceries. For example, Zhang, et al.^[1] studied the fast-food industry and found that although the O2O platform may erode physical stores' sales in the short term, it produces a synergy effect on offline sales and profits in the long run. He, et al.^[9] delved into when physical stores should adopt an O2O platform strategy. Lee and Yoon^[10] further explored the factors affecting the application of O2O platforms by small enterprises in the food sales and life service industries. However, there is limited literature discussing whether low-frequency and high-consumption industries (such as high-end wine companies) are suitable for adding O2O platforms. Therefore, this study aims to analyze the impact of adding O2O platforms on offline sales in low-frequency and high-consumption industries to provide insight into the potential effectiveness of O2O platforms for such industries.

2.2 Theoretical Background

According to the Channel Capability Theory, the addition of a new channel will erode the sales volume of an existing channel if the new channel's capability is very similar to or greatly exceeds that of the existing one^[7]. Conversely, if the new channel provides complementary capabilities, it will generate synergistic effects with the original channel^[11]. Zhang, et al.^[1] proposed that O2O channels have a "super power" compared to traditional channels, which is reflected in three aspects: 1) O2O channels can reach more consumers than traditional offline channels since regular customers of physical stores are usually within 1KM while O2O channels can reach 5KM; 2) O2O channels provide fast and cheap home services, saving consumers time and offering more convenience than traditional channels; and 3) hundreds of consumers can order food on the O2O platform simultaneously, whereas the traditional 400-phone number can only accommodate a limited number of consumers at the same time. According to this theory, the super power of O2O channels will attract most consumers in physical stores to the O2O platforms, producing an erosion effect on offline channels.

Historically, O2O platforms were predominantly associated with daily necessities and fast-moving consumer goods. However, as technology advances and consumer preferences evolve, there is a noticeable trend toward low-frequency-high-consumption industries/enterprises introducing O2O platforms. For instance, on May 13th, Ele.me officially announced that over 500 authorized Apple stores across the country will gradually join Ele.me. During Mother's Day, users who have a demand for purchasing digital products such as iPhones, iPads, and Apple

Watches will have access to a new shopping channel¹.

This paper argues that the super power of O2O platforms is weakened in low-frequency-high-consumption enterprises since consumers tend to believe that “seeing is believing” for consumption with low-frequency-high-unit price, and convenience has a lower effect on low-frequency consumption. Therefore, the conclusions drawn based on high-frequency-low-consumption enterprises may not be applicable to low-frequency-high-consumption enterprises. This paper further emphasizes the theoretical value and practical significance of studying the impact of O2O platforms on low-frequency-high-consumption enterprises.

3 Methodology

This study utilizes 36,355 data points from 77 stores of a mid-to-high-end liquor distribution enterprise in Beijing to quantify the impact of online-to-offline (O2O) platforms on offline sales. The data used for our research is first-hand data obtained through a collaborative effort with a liquor distribution company. This dataset includes sales data from 77 of the company’s stores that utilized online O2O platforms such as Ele.me, Meituan, and JD from June 29, 2017, to June 30, 2022. Following Racicot and Théoret^[12], Kim^[13], and Lee and Kim^[14], this paper employs VAR model to analyze the relationship between the use of O2O platforms and offline sales^[15].

3.1 The Selection of Influence Indicators

Before examining the impact of the online-to-offline (O2O) platform of the enterprise on offline sales during the epidemic, it is crucial to understand the factors that cause fluctuations in offline sales. The selection of impact indicators plays a significant role in determining the results^[16], thus a factor analysis method is employed to objectively identify the influence indicators. The process is as follows:

Step 1: This study selects indicators related to the O2O platform that may impact offline sales based on the principle of index selection, using relevant materials, literature, and periodicals as references^[17]. The final six indicators were selected among the following 21 indicators: O2O platform order volume, O2O platform customer unit price, conversion rate, O2O platform user retention rate, O2O platform user activity, product sales, O2O platform promotion effect, O2O platform merchants’ settled number, O2O platform merchant service quality, O2O platform supply chain management efficiency, logistics delivery timeliness, return and exchange rate, review rating, promotion input cost, brand awareness, O2O platform popularity, O2O platform product information reliability, O2O platform network payment security, O2O platform operation experience, O2O platform personalized service, and O2O platform infrastructure construction.

Step 2: Using the selected primary indicators, data is collected from the operation of n O2O

¹Baidu Baijiahao. “Mother’s Day allows buying an iPhone on Ele.me! Apple’s authorized flagship store lands on Ele.me,” Nancn.com, Baidu Baijiahao. “Mother’s Day allows buying an iPhone on Ele.me! Apple’s authorized flagship store lands on Ele.me,” Nancn.com, <https://baijiahao.baidu.com/s?id=1765928766752504559&wfr=spider&for=pc>, (May 25, 2023).

platforms used by n enterprises to form the sample observation matrix, as follows:

$$A = \begin{pmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{mn} \end{pmatrix}. \quad (1)$$

In Formula (1), A represents the sample observation matrix; n is the number of samples; m represents the number of influence indicators.

Step 3: Standardize each component data in A with the following processing formula:

$$\hat{a}_{ij} = \frac{a_{ij} - \tilde{a}}{\tilde{a}}. \quad (2)$$

In Formula (2), a_{ij} and \hat{a}_{ij} represent the j -th influence indicator of the O2O platform used by the i -th enterprise before and after processing; \tilde{a} and \tilde{a} represent the mean and standard deviation of the index.

Step 4: Establish the standardized matrix, denoted as \hat{A} , based on each standardized \hat{a}_{ij} .

Step 5: Use \hat{A} to obtain B .

$$B = \begin{pmatrix} b_{11} & \cdots & b_{1n} \\ \vdots & \ddots & \vdots \\ b_{m1} & \cdots & b_{mn} \end{pmatrix}. \quad (3)$$

In Formula (3), B is the correlation coefficient matrix; b_{ij} represents the correlation coefficient.

Step 6: Solve B , and then obtain the eigenvalue $C_1 \geq C_2 \geq \cdots \geq C_m \geq 0$ and eigenvector $D = \{D_{1j}, D_{2j}, \cdots, D_{1m}\}$.

Step 7: Calculate the cumulative contribution rate, denoted as E_j .

Step 8: Select k common factors whose $E_j \geq 85\%$ and transform them orthogonally^[18].

After the above process, six influence indicators are selected, as shown in Table 1 below. As can be seen in Table 1, the overall popularity and usage of the O2O platform is 92.36%; the reliability of the product information provided on the O2O platform is as high as 91.23%; A high-security payment rate (91.12%) means that most customers feel safe and secure when making payments on the platform; the overall user experience on the O2O platform is 90.85%, including ease of use, user-friendly interface, and efficient operation; the level of personalized service provided on the O2O platform is slightly lower as of 89.32%. The underlying infrastructure of the O2O platform, including technology, systems, and processes. The O2O platform infrastructure construction is 87.11%, which means that the platform is able to efficiently and effectively handle relatively high levels of traffic and transactions.

Table 1 Cumulative contribution rate of influence indicators

Indicators	Cumulative contribution rate/%
O2O platform popularity	92.36
O2O platform product information reliability	91.23
O2O platform network payment security	91.12
O2O platform operation experience	90.85
O2O platform personalized service	89.32
O2O platform infrastructure construction	87.11

3.2 The Determination of Dependent Variables

In addition to the independent variable index in Table 2^[19], the impact analysis also needs the reference of another dependent variable index^[20]. According to the research theme — the impact of an enterprise’s online O2O platform on offline sales, offline sales are taken as the dependent variable^[21]. The formula for calculating offline sales is as follows:

$$Y' = \frac{P}{1 + G}. \quad (4)$$

Among it,

$$P = (g \cdot \bar{L}) (1 + G), \quad (5)$$

where Y' represents annual offline sales in monetary value; P stands for sales including tax; G is for tax rate; g represents annual offline sales in units; \bar{L} represents the average price.

This study analyzed 77 stores in Beijing that use Ele.me, Meituan, and JD as their on-line O2O platforms. These 77 stores are spread across 15 districts in Beijing. Among them, Fengtai District and Chaoyang District have a higher concentration of stores, accounting for approximately 50% of the total number of stores. The distribution of stores in other districts is relatively more evenly spread. The earliest recorded open date is in 2012, and the latest is in 2022. The average number of stock keeping units (SKUs) for the stores is 399, and the average store size is 115 square meters (see Table 2).

Table 2 Store overview

Variable	Mean	Std. Dev.	Min	Max	Observations
open date	2018.948	1.645537	2012	2022	$N = 77$
SKU	399.9221	278.1211	50	1359	$N = 77$
store size (m ²)	115.4152	56.5341	30	400	$N = 77$

The sample enterprises were mainly engaged in the sale of mid-to-high-end Baijiu, red wine, and foreign wine, with Baijiu being the most sold product and customers having a high average purchase price. The panel data has 36,355 observations and recorded the daily sales (excluding returns) of the 77 stores in Beijing from June 29, 2017 to June 30, 2022, a total of 1,828 days. There were 140 days during this period when no sales were recorded due to stock shortages or holiday closures. The descriptive statistics of the data are presented in Table 3.

Table 3 Descriptive statistics

Variable	Mean	Std. Dev.	Min	Max	Observations
sale	11812.640	59327.650	0	2964600	$N = 36355$
add_ELM	0.480	0.500	0	1	$N = 36355$
add_MT	0.473	0.499	0	1	$N = 36355$
add_JD	0.313	0.464	0	1	$N = 36355$
after_covid19	0.680	0.466	0	1	$N = 36355$
holiday	0.066	0.249	0	1	$N = 36355$
Pre-holidays	0.060	0.237	0	1	$N = 36355$
Day of the week	4.029	1.988	1	7	$N = 36355$

add_ELM: If the store was launched on Ele.me that day, add_ELM = 1, otherwise add_ELM = 0; add_MT: If the store was launched on Meituan that day, add_MT = 1, otherwise add_MT = 0; add_JD: If the store was launched on JD that day, add_JD = 1, otherwise add_JD = 0; after_covid19: On January 20, 2020, the National Health Commission issued Notice No. 1: The novel coronavirus pneumonia is included in the management of notifiable infectious diseases, so if the data are from January 20, 2020 and later, after_covid19 = 1, if the data are before January 20, 2020, after_covid19 = 0; holiday: If that day is Chinese legal holidays (e.g., New Year's Day, Spring Festival, Tomb Sweeping Day, Labor Day, Dragon Boat Festival, Mid-Autumn Festival, National Day), holiday = 1, otherwise holiday = 0; pre-holidays: Consider tobacco and alcohol as holiday gifts, are often consumed in advance, so three days before the holiday are introduced, pre-holidays = 1, otherwise pre-holidays = 0; day of the week: If the day is Monday (Tuesday, Wednesday, Thursday, Friday, Saturday, Sunday), the value of week is 1 (2, 3, 4, 5, 6, 7). As after_covid19 is 0.68, which is a moderate size, it shows that the sample is relatively balanced before and after the outbreak. The highest online rate of Ele.me is 0.48, followed by Meituan's 0.47 and JD's 0.31.

3.3 Model

The regression model was used to establish the mapping relationship between the selected independent and dependent variables, in order to analyze the changes in offline sales that result from the use of O2O platforms^[22]. To identify the dynamic impact of channel addition on sales, we use the vector autoregressive (VAR) model, which was selected to predict the dynamic relationship between the independent and dependent variables. The basic structure of the model is described as follows:

$$Y_t = \prod_1 Y_{t-1} + \prod_2 Y_{t-2} + \cdots + \prod_k Y_{t-k} + U + h_t. \quad (6)$$

Among it, Y_t is the dependent variable that represents the offline sales time series of $n \times 1$, and Y_{t-k} represents the offline sales vector of each store after a lag of k periods, as shown in (7):

$$Y_{t-k} = (y_{1t-k}, y_{2t-k}, \cdots, y_{nt-k}). \quad (7)$$

where k represents the maximum lag period, and n represents the number of stores. The above variable interpretations also apply to the following formulas.

U is the constant term column vector of $n \times 1$, as shown in (8):

$$U = (u_1, u_2, \dots, u_n), \quad (8)$$

$\prod_j, j = 1, 2, \dots, k$ is the independent variable parameter matrix of the O2O platform of $n \times n$, and its specific formula is shown in (9):

$$\prod_j = \begin{bmatrix} \pi_{11j} & \pi_{12j} & \cdots & \pi_{1nj} \\ \pi_{21j} & \pi_{22j} & \cdots & \pi_{2nj} \\ \vdots & \vdots & \vdots & \vdots \\ \pi_{n1j} & \pi_{n2j} & \cdots & \pi_{nnj} \end{bmatrix}, \quad j = 1, 2, \dots, k. \quad (9)$$

Finally, h_t represents the random error column vector of $n \times 1$ ^[23].

Since this study is conducted under the epidemic situation, in order to ensure the accuracy of the analysis model of influence relationship, the error correction item is added, namely the epidemic impact degree^[24].

The following three aspects are tested through the constructed analysis model of influence relationship, as shown in Table 4 below.

Table 4 Test of influence relationship model

Methods of test	Explanations
Johansen co-integration test	Test of long-term relationship between independent and dependent variables
Granger test	Test of short-term relationship between independent and dependent variables
Impulse response function analysis	Describing the dynamic interaction between each independent variable and dependent variable and its effect

4 Results and Discussion

After completing the theoretical analysis^[25], the impact of enterprises' online O2O platform on offline sales under the epidemic situation is specifically analyzed.

4.1 Johansen Co-Integration Test

Using the software "Eviews", the co-integration relation formula is established as follows:

$$Y'' = 3.6252 + 0.1524x_1 + 0.2010x_2 + 0.0530x_3 + 0.2524x_4 + 0.1127x_5 + 0.1364x_6 + 0.038x_7, \quad (10)$$

where $x_1, x_2, x_3, x_4, x_5, x_6, x_7$ represent the value of the independent variable seven days in a week respectively, Y'' represents offline weekly sales.

Calculate its goodness of fit, and the calculation formula is as follows:

$$R^2 = 1 - \frac{V}{Q} = 0.9255, \quad (11)$$

where V represents the sum of squares of deviations, Q represents the sum of the total squares.

From the above formula, we can see that the final goodness of fit reaches above 0.9, indicating that the equation is well fitted. There is a long-term equilibrium relationship between the offline sales of mid-to-high-end liquor distribution enterprises and the use of O2O platform online in their stores.

4.2 Granger Test

In order to obtain the short-term equilibrium relationship between offline sales and the use of O2O platform of enterprise stores, a Granger test was conducted using a random sample of 5 stores out of the total 77 stores in Beijing. Random assignment of the sample helps ensure representative selection while minimizing the impact of sample distribution^[26]. The stores are named as Store 1, Store 2, \dots , Store 5 respectively, the test results are shown in Table 5 below.

Table 5 Granger test results

Time/Phase	F -Statistic value of test				
	Store1	Store2	Store3	Store4	Store5
1	1.5263	1.7452	2.1792	1.7864	3.9864
2	1.5522	1.7656	2.2285	1.8645	4.0920
3	1.6452	1.7655	2.4895	1.8712	4.1826
4	1.6541	1.9854	2.5860	1.9123	4.2987
5	1.7125	2.8654	2.7852	2.0323	4.4213
6	1.4532	1.4624	2.3122	1.7132	4.0215
7	1.4025	1.3651	2.2222	1.7032	3.5421
8	1.3240	1.2012	2.0122	1.4264	2.1422
9	1.3065	1.0414	1.2527	1.2645	1.3214
10	1.2032	0.5622	0.7465	1.0652	-0.4652
11	-0.0522	-0.1842	-1.1233	0.8531	-1.5612
12	-0.1456	-1.8945	-1.8742	-0.8642	-2.6565

Table 5 shows the results of a Granger causality test, which is a statistical test used to determine the relationship between two time series variables. The test is used to determine if one time series is useful in predicting the other time series.

In the table, each row represents a different time or phase, and each column represents the F -statistic value of the test for a specific store. Phases 1~12 in the table are divided by month, that is, January is phase 1, February is phase 2, and so on. The F -statistic value is a measure of the strength of the relationship between the two time series variables. A high F -statistic value indicates a strong relationship between the two time series variables and suggests that one

time series is useful in predicting the other time series. As shown in Table 5, the results of the Granger causality test provide insights into the short-term impact of the online O2O platform on the offline sales of enterprise stores during the epidemic. The following can be observed:

1) During the first five phases, the F -statistic test values are positive and show an increasing trend. This indicates that during this period, the use of the O2O platform led to positive growth in offline sales. This suggests that the O2O platform has a positive impact on the offline sales.

2) In the later stages of Phases 6~12, the F -statistic test values gradually decrease and become negative. This suggests that the offline sales were negatively impacted by the online O2O platform.

In conclusion, the results from Table 5 demonstrate that the impact of the online O2O platform on the offline sales was initially positive, but became negative over time.

4.3 Impulse Response Function Analysis

In order to further analyze the short-term dynamic relationship between the impact of enterprise stores' online O2O platform and offline sales under the epidemic situation, impulse response function is used to calculate the impulse response value, and the results are shown in Figure 1 below.

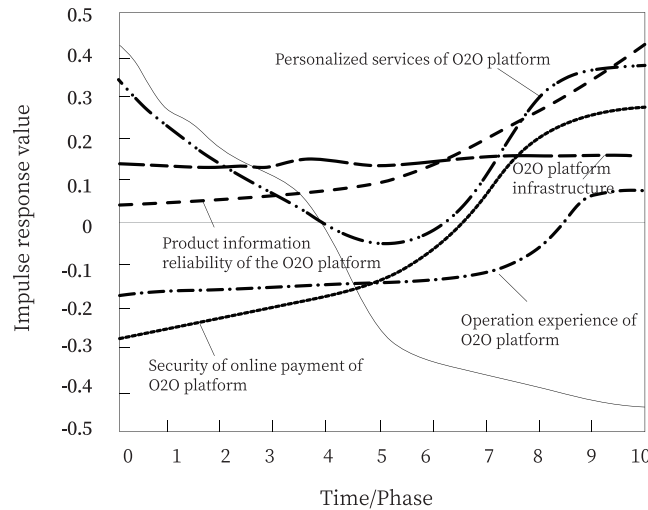


Figure 1 Impulse response values

The following six points can be seen from Figure 1:

1) The results of the impact analysis model showed that after a shock to the popularity of the O2O platform, the overall trend was downward. In the first phase, the impulse response was at its peak, while in the last phase, it was at its lowest value. Over this period, the positive impact changed to negative impact, becoming increasingly significant. This suggests that fluctuations in the popularity of online platforms could result in fluctuations in sales volume.

2) The results showed that when the reliability of product information on the O2O platform was impacted, the impulse response value curve remained in a positive impact. During the first 5 phases, the positive value curve gradually increased, then rose significantly and had a long-

lasting impact. This indicates that a higher level of reliability in the product information on the O2O platform is more conducive to boosting the growth of offline sales.

3) The results showed that when the security of online payments on the O2O platform was impacted, the impulse response curve transitioned from negative to positive, with an increasingly rapid increase. This indicates that the negative impact weakened as the security of online payments improved. The improvement in online payment security strengthened people's trust in the platform, thus driving the growth of offline sales and playing a positive role in promoting sales.

4) The results showed that after a shock to the operation experience of the O2O platform, the impulse response changed from negative to positive and then stabilized. This indicates that the initially inadequate operation and construction of the platform had a negative impact on offline sales, as it was not recognized by consumers. However, as the platform improved over time, the negative impact diminished and the platform's ability to attract customers through online shopping contributed to the growth of offline sales, ultimately reaching a positive and stable state of influence.

5) In the case of an impact on personalized services on the O2O platform, the impulse response between the online platform and offline sales showed a decline followed by an increase. This response showed a noticeable lag, which was attributed to people's long-standing offline consumption habits that gradually changed over time.

6) The results of the analysis show that when the O2O platform infrastructure is impacted, the impulse response value remains positive and stable. This suggests that changes to the infrastructure of the O2O platform will not significantly affect offline sales.

Upon completion of the analysis of the short-term dynamic relationship between the online O2O platform of enterprise stores and offline sales during the epidemic, the overall impact of the O2O platform on offline sales is analyzed by quantitatively calculating the above independent variable indexes to obtain a comprehensive value.

Present the pulse response curves demonstrating the impact of stores' O2O platform on offline sales, depicted in Figure 2.

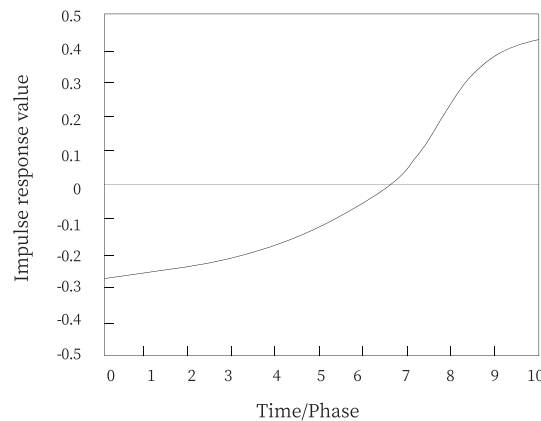


Figure 2 Impulse impact curves of the online O2O platform of enterprise stores on offline sales

As can be observed from Figure 3, the initial impact of enterprise stores using the online O2O platform on offline sales is negative in the short term. However, after a certain period, the impact transitions to a positive one, indicating that in the long run, the benefits of using the online O2O platform will outweigh the drawbacks of single offline sales. In other words, the short-term development disadvantages are outweighed by the advantages in the long term. To further analyze the impact of enterprises' online O2O platform on offline sales during the epidemic, the erosion of Ele.me, Meituan, and JD platforms on store offline sales is evaluated, and the impulse impact curves are depicted in Figure 3.

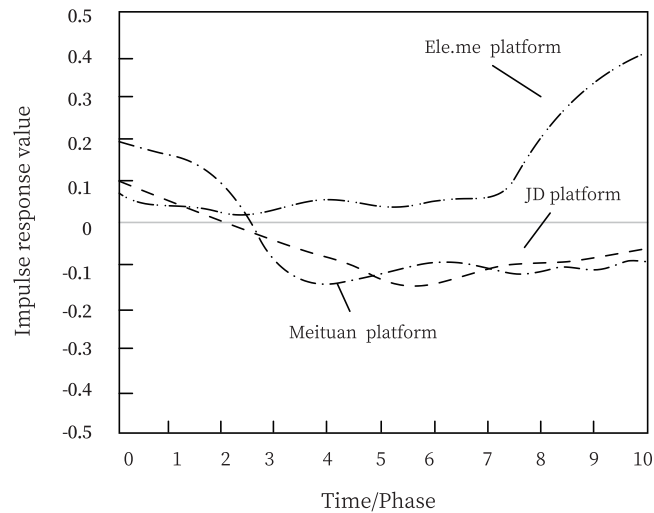


Figure 3 Impulse impact curves of different platforms on offline sales of enterprise stores

As shown in Figure 3, the impact of the Ele.me platform on the offline sales of enterprise stores is visible. During the initial stage, a slight erosion was observed, which stabilized in the mid-stage, while the impulse response value significantly increased in the later stage. This indicates that the sales volume of enterprise stores rose at this time. This is due to Ele.me's main focus being in Shanghai, with a user group that is not well-aligned with the original sample enterprise stores and limited products that meet the unit price demands of customers. Thus, when the enterprise stores receive takeout orders on the Ele.me platform, most of these orders become additional income for the enterprise stores. Both the Meituan and JD platforms show some erosion of enterprise stores, with the impulse response value declining to a certain extent and remaining relatively stable in the later phase. The curves indicate that the erosion degree is relatively low. The reason for this is that Meituan has a large user base in Beijing, high user attributes, many orders, and prominent individual enterprise stores, leading to high overlap in customer behavior. In contrast, JD offers authentic products that align with the loyalty business philosophy of the enterprise stores, has consistent online and offline customer identity, and similar commodity prices and usage scenarios. As a result, platform takeout presents the phenomenon of eroding the sales of offline enterprise stores.

4.4 Discussion

The empirical results presented above show that, for low-frequency and high-consumption enterprises, the addition of O2O platform channels may erode the sales of offline stores in the short term. However, as time passes, the introduction of O2O channels can have a positive impact on offline sales. Our result is consistent with the previous research results that show how companies increase their offline channel sales by adding O2O platforms^[1, 6, 7], and we extend this line of research on the addition of O2O platform channels in low-frequency and high-consumption enterprises.

As digital technology continues to develop, people's consumption patterns are changing, and more and more customers are choosing home delivery services. However, most high-frequency and low-consumption enterprises (such as high-end liquor) are uncertain whether they should go online on the O2O platform. For instance, in the liquor industry, the prices of the same product vary significantly in different consumption scenarios due to its unique layered agency nature, and it is challenging to establish a unified pricing model. Liquor enterprises may be interested in introducing O2O platform channels, but they may hesitate due to uncertainty regarding the effectiveness of O2O platforms in low-frequency, high-consumption scenarios, and concerns about potential brand erosion resulting from their implementation. The findings of this study precisely address this issue by providing quantifiable empirical evidence to support low-frequency-high-consumption enterprises should confidently launch O2O platform. It also suggests enterprises prepare for short-term erosion though.

5 Conclusion

The spread of COVID-19 seriously affects the stores of mid-to-high-end liquor distribution enterprises. In response to the situation, many enterprises begin to introduce O2O business models and develop new sales channels with the help of O2O platform in order to solve the problem. However, are low-frequency-high-consumption enterprises also suitable for online O2O platforms?

This study analyzed 36,355 data collected from Chinese mid-to-high-end distribution enterprises that operate through an online O2O platform, covering the period both before and after the epidemic. The factor analysis method was employed to identify key indicators, establish dependent variables, and construct an impact analysis model utilizing the VAR model. The results of the empirical analysis showed that in the short term, the O2O platform had a detrimental effect on offline sales for enterprise stores, but in the long term, it had a positive impact.

6 Limitation and Future Research

While this article strives for rigor, there are still areas that require further enrichment and development in future research.

It's important to acknowledge that the data in this article is derived solely from a single company with stores located exclusively in Beijing. The absence of regional comparisons and heterogeneity analysis may limit the generalizability of the findings. Future research could address this limitation by collecting data on stores from various provinces and cities within a

specific industry.

Furthermore, low-frequency and high-consumption industries encompass not only high-end retail sectors such as the liquor industry but also traditional service industries like home decoration and wedding services. Therefore, it would be valuable to investigate whether the conclusions drawn in this paper hold true for the broader spectrum of low-frequency, high-consumption industries, specifically discussing the potential for traditional service industries to integrate into the O2O platform.

Future research could also benefit from incorporating data from both high-frequency-low-consumption and low-frequency-high-consumption enterprises as moderating variables into the model. Additionally, a deeper exploration of online O2O platform indicators for enterprises and an expansion of the influence indicators would provide further insight.

By addressing these gaps, future research can contribute to a more comprehensive understanding of the O2O landscape, incorporating diverse geographic regions and a wider range of industries, ultimately enhancing the validity and applicability of the findings.

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