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Does time of day affect consumers' price sensitivity?

Sha Zhang [1,2]✉, Xiting Wu [1], Yonggui Wang [3]✉ & Peiqi Jiang [1]

In the current economic downturn, consumers are showing increased price sensitivity. With mobile technology enabling anytime connection, understanding daily price sensitivity fluctuations is crucial. This study analyzes transaction data from two companies, covering both offline and online scenarios. Additionally, an online experiment was conducted to further reveal the causal relationship between time-of-day and consumers' price sensitivity. The studies indicate that price sensitivity is highest in the morning, decreasing by approximately 0.5% per hour. These findings are interpreted using the circadian rhythms theory. This research deepens our understanding of how price sensitivity changes over time, offering invaluable insights for businesses to tailor their pricing and promotional strategies throughout the day.

[1] School of Economics & Management, University of Chinese Academy of Sciences, Beijing, China. [2] MOE Social Science Laboratory of Digital Economic Forecasts and Policy Simulation at UCAS, Beijing, China. [3] School of Business Administration, Zhejiang Gongshang University, Hangzhou, Zhejiang, China. ✉email: zhangsha@ucas.ac.cn; ygwang@zjsu.edu.cn

Introduction

In the post-pandemic era, many countries globally are facing an economic downturn, with companies cutting costs and consumers curbing spending (Joyce 2023). Indeed, consumption patterns worldwide are increasingly focused on price sensitivity (McKinsey's Consumer Pulse Surveys in 2023). In the U.S., 66% of consumers are pursuing cheaper goods, an increase of 4% from 2022 (Aull et al. 2023); 79% of consumers have traded down shopping behaviors, purchasing less-expensive alternatives (Baum et al. 2023). Nearly 80% of European consumers prefer switching to cheaper products, while 10% would also switch to lower-priced retailers and brands. "Fewer" and "smaller" have become the features of purchases. (Moulton et al. 2023). In China, consumers are pursuing a lower cost via different platforms, or by adjusting the quantity or pack size in their purchases (Zipser 2023).

In response to these changes, JD.com, a leading e-commerce giant in China, has changed its positioning strategy in 2023. Moving away from its traditional focus on high-value customers, JD has adopted a "low-price strategy" to attract price-sensitive consumers (Fan 2023). Leveraging the power of mobile technology, e-commerce platforms like JD.com can foster intimate consumer relationships by reaching customers at any time of day (Phang et al. 2019), and consumers can purchase at any time (Park and Yi 2023). This technological advantage underscores the importance of understanding the temporal variations of consumer price sensitivity within a day. Thus, we propose the research question: Does time-of-day affect consumers' price sensitivity? Answering this question by exploring the general temporal trends in consumer price sensitivity is of great importance to help enterprises make price-related strategic adjustments and conduct different promotions throughout the day.

Price sensitivity is defined as the relative change in consumers' likelihood or willingness to pay after a price change (Wakefield and Inman 2003). Price sensitivity has attracted considerable attention in marketing research (Bijmolt et al. 2005). Contrary to the initial idea of price sensitivity being a fixed characteristic of consumers, recent research acknowledges that it is influenced by various situational factors, especially physical surroundings and the social surroundings perspective (Li et al. 2017, Gao et al. 2021, Zhou et al. 2009), but lacking the temporal perspective. For example, Wakefield and Inman (2003) find that consumers tend to be more price-sensitive in group settings compared to when they are alone. Sudhir et al. (2005) showed that time-of-year affects consumer price sensitivity in the film industry, with sensitivity tending to be higher in the first three quarters of a year, peaking in the first quarter, and decreasing in the fourth quarter. This research highlights the temporal aspect is influential in consumers' price sensitivity, but no study has examined whether consumer price sensitivity changes throughout the day.

We conducted three studies to explore the relationship between time-of-day and price sensitivity. Studies 1 and 2, representing offline and online scenarios respectively, utilize real-world data from two different companies. In particular, Study 1 focuses on offline consumption scenarios and measures price sensitivity through consumer's discount-seeking behavior by analyzing 21,280 offline purchase records. It was found that the discount percentage is higher in the morning than in the afternoon, and the lowest in the evening, indicating that consumers' price sensitivity decreases over time. Study 2 utilizes 506,409 consumer online food delivery data made by 196,421 consumers, with consumers' switching behavior on different online food delivery platforms (comparing prices across different platforms) is used as a proxy for price sensitivity. The results showed that, compared with the afternoon and evening, more consumers switch platforms in the morning, confirming decreasing price sensitivity. Additionally, Study 2 verified the moderation effect of sunlight duration on the relationship. In general, we find that in both online and offline consumption scenarios, price sensitivity decreases by approximately 0.5% per hour. Study 3, using online experiments ($N = 180$), directly measured consumers' price sensitivity by asking consumers' purchase intention after price increase and was carried out in the morning, afternoon, and evening. Study 3 also ruled out possible confounding factors such as variety-seeking. Our results remained consistent.

This research contributes to price sensitivity literature by using "big" and "small" data to quantify that consumers' price sensitivity decreases 0.5% per hour, deepening our understanding of how price sensitivity changes over time. From the practical perspective, our results demonstrate the necessity for dynamically adjusting prices and promotions throughout the day.

The remainder of this study is organized as follows: Section 'Literature review' summarizes existing studies on price sensitivity and the time-of-day effect. Section 'Theoretical background and hypotheses' introduces the concept of circadian rhythm and develops hypotheses based on this theory. Section 'Method' describes the research methodology used in the three studies and reports the results of each study. Section 'Discussion' summarizes the results, presents the theoretical contributions and managerial implications, and discusses the limitations of this study along with directions for future research.

Literature review

Price sensitivity. Price sensitivity refers to how consumers react to price levels and to price changes (Goldsmith et al. 2005), which has been widely studied in marketing (Bijmolt et al. 2005). Compared with consumers with lower price sensitivity, highly price-sensitive consumers tend to pursue more competitive prices (Natarajan et al. 2017). Previous studies believed that individual-level price sensitivity may exhibit a degree of stability and could measure individual differences (Natarajan et al. 2017). A consumer who is price-sensitive to Category A is also likely to be price-sensitive to Category B (Duvvuri et al. 2007). However, subsequent studies found that consumers' price sensitivity would be affected by situational factors and varies within individuals. Consumers' price sensitivity tends to be affected by the consumption occasion and varies among different categories (Wakefield and Inman 2003, Cortiñas et al. 2008).

Situational variables, as originally categorized by Belk (1975), encompass five distinct groups: physical surroundings, social surroundings, temporal perspective, task definition, and antecedent states.

Physical surroundings include factors related to geographical and institutional location, sounds, aromas, weather, visible configurations, and surrounding materials. In this perspective, the purchase occasion, the shopping channel, the distance to competitors, and the weather (Wakefield and Inman 2003, Chu et al. 2008, Hoch et al. 1995, Li et al. 2017) have been explored. For instance, customers exhibit lower price sensitivities when they shop online than offline, with households' price sensitivities negatively related to how far the households are located from the physical stores (Chu et al. 2008). Apart from the distance from physical stores, the distance from competitors will also make a difference (Hoch et al. 1995). Weather-related variables have been explored. Purchase responses to promotions are found to be higher and faster in sunny weather relative to cloudy weather, while lower and slower in rainy weather (Li et al. 2017).

The second group of situational variables is social surroundings, including the characteristics and roles of other persons, as well as interpersonal interactions occurring. In this perspective, Wakefield and Inman (2003) show that price sensitivity is lower

Table 1 Literature review on situational variables affecting price-sensitivity.

Author	Classification	Variables	Methods	Finding
Hoch et al. (1995)	Physical Surroundings	distance to competitors	Empirical research	Isolated stores display less price sensitivity than stores located close to their competitors.
Wakefield & Inman (2003)	Physical Surroundings Social Surroundings	consumption occasion social situation	Questionnaire, interview, & empirical research	Consumers' price sensitivity is attenuated by both hedonic (v.s. functional) and social consumption situations (companion).
Chu, Chintagunta & Cebollada (2008)	Physical Surroundings	shopping channel distance to physical stores	Empirical research	Households exhibit lower price sensitivities when they shop online than offline. Households' price sensitivities are inversely related to how far they are located from the physical stores
Zhou, Vohs, & Baumeister (2009)	Social Surroundings Antecedent States	interpersonal rejection physical pain	Experiment	Interpersonal rejection and physical pain caused desire for money to increase.
Li, Luo, Zhang, & Wang (2017)	Physical Surroundings	weather	Field experiment from a company	Purchase responses to promotions are higher and faster in sunny weather relative to cloudy weather, whereas lower and slower in rainy weather.
Wang & Lans (2018)	Task Definition	gift-giving uncertainty	Experiment	Reduced price sensitivity is a source of the deadweight loss of gift choice, especially when givers are uncertain about receivers' preferences.
Gao, Wang, & Bailey (2021)	Social Surroundings Temporal Perspective	public recognition temporal distance	Experiment	Public recognition significantly reduces price sensitivity to green products. Independent self-construal consumers' price sensitivity to green products between initial purchase and a subsequent purchase appears as an inverse U-shaped curve by temporal distance matching from present to near future (7 days later) and then to distant future (15 days later).
Sudhir, Chintagunta & Kadiyali	Temporal Perspective	time of year (quarter)	Empirical research	Price sensitivity in Quarter 1 is higher than in other quarters. Consumers have higher price sensitivity in Quarters 1–3 compared to Quarter 4.
This paper	Temporal Perspective	Time-of-day effect	Empirical research	Customer price sensitivity decreases as the day wears on, i.e., customers are more price sensitive in the morning than the rest of the day. Sunlight duration will positively moderate the negative time-of-day effect on price sensitivity.

in social settings (e.g., consuming with others), compared to nonsocial settings (e.g., consuming alone). Zhou et al. (2009) also found that interpersonal rejection will cause the desire for money to increase.

The third group is task definition. Task definition represents an intent or requirement to select, shop for, or obtain information about a general or specific purchase, which may reflect different buyer and user roles anticipated by the individual. For instance, Wang and Lans (2018) explored customers' price sensitivity in the special task of gift-giving.

The fourth group of situational variables is antecedent states, comprising momentary moods (e.g., acute anxiety) and momentary conditions (e.g., illness). Research from Zhou et al. (2009) demonstrates that physical pain can intensify the desire for money, potentially influencing consumers' price sensitivity.

Lastly, the temporal perspective pertains to time-related factors, such as time of day and season of year. Sudhir et al. (2005) found that consumers have the highest price sensitivity in quarter 1 and lowest price sensitivity in quarter 4, but they studied a highly seasonal product (i.e., film). Gao et al. (2021) investigated a moderated-moderation effect of temporal distance on price sensitivity. To be exact, when green purchases are publicly recognized, the price sensitivity between the initial purchase and the subsequent purchase for highly independent self-construal consumers appears as an inverse U-shaped curve by temporal distance matching from present to near future and to distant future. Moreover, although these two studies explore the temporal perspective of situational variables, they are still not the focus.

In conclusion, among the five categories of situational variables, the direct impact of physical surroundings and social surroundings on price sensitivity has been explored. However, the exploration of price sensitivity from a temporal perspective still has a large number of gaps in terms of direct influencers, intrinsic mechanisms, and boundary conditions (see Table 1).

Time-of-day effect. Temporal variables have been widely explored, including both natural time nodes and critical event time nodes. Dai et al. (2014) found the fresh start effect in which temporal landmarks will motivate aspirational behavior. The explored temporal landmarks cover a wide range, including the outset of a new week, month, year, or semester, as well as the first workday after a holiday and months since the last birthday. The study showed that people are more likely to tackle their goals, such as adjusting diets and visiting gyms, immediately following salient temporal landmarks, as these landmarks demarcate the passage of time, create new mental accounting periods, and relegate past imperfections to a previous period.

In recent decades, the effect of time within a day has gradually attracted researchers' attention. Kouchaki and Smith (2014) found that unethical behavior (e.g., lying and cheating) is more likely to occur in the afternoon than in the morning. Besides, lower self-control in the afternoon or evening will also increase consumers' purchase of unhealthy products (Yang et al. 2022) and push consumers to shift away from virtue content to vice content (Zor et al. 2022). Variety seeking is also highly related to the time of day (Gullo et al. 2019, Roehm and Roehm, 2004). Gullo et al. (2019) found that consumers' variety-seeking is lower in the morning than at other times of day, while Roehm and Roehm (2004) found that more variety-seeking will occur during times of day when people are experiencing arousal lows (e.g., morning) rather than arousal peaks. Research also explored the effect of the time of day on consumers' views on different product values and found that consumers prefer utilitarian value in the morning and hedonic value in the afternoon (Phang et al. 2019). Consumers' attitudes toward different kinds of online sales promotions (Park and Yi 2023) and products with specific name characteristics (Collinson et al. 2020) are influenced by the time of day as well. Consumer attributes, such as creativity (Kühnel et al. 2022) and vigilance against manipulation (Hossain and Sain, 2013), will also change over time.

Among the related research, the time-of-day effect has a wide range of effects, mainly in the form of the fresh start effect. Although, similar to the fresh start effect, Sudhir et al. (2005) found the highest price sensitivity in the first quarter of the year, no study has explored the changes in price sensitivity from the micro-view of the time effect within a single day.

Theoretical background and hypotheses

The circadian rhythm. The circadian rhythm functions as an internal biological clock, regulating the timing of bodily functions (Hofstra, De Weerd (2008), Park and Yi 2023). The circadian rhythm is maintained in many physiological processes, including the sleep/wake cycle, heart rate, body temperature, blood pressure, and synthesis and secretion of several hormones (Baehr et al. 2000, Adan et al. 2012, Hofstra, De Weerd (2008)). It is also closely related to psychological processes and will affect various cognitive tasks (Schmidt et al. 2007), including attentional capacities (e.g., psychological arousal, selective attention, divided attention, and sustained attention), executive functioning (e.g., shifting, planning, and inhibition), and memory (e.g., working memory, episodic memory, and semantic memory).

The circadian rhythm fluctuates over 24 h. Represented by the arousal level, it is lower in the morning (Kleitman 1987, Thayer 1978) and increases throughout the day. What's more, both internal factors and external factors will influence the circadian rhythm, including age, gender, and health state, as well as the sunrise duration, weather, light, and temperature (Collinson et al. 2020, Park and Yi 2023, Bass 2012, Schmidt et al. 2007, Eilam 2019). Therefore, it can be said that the time of day is a proxy for the circadian phase (Park and Yi, 2023), which allows a richer understanding of consumers' physiological and psychological processes.

Hypothesis. Consumers' circadian rhythms in physiological and psychological processes are different within the time of day (Thayer 1978). Individuals usually have a low level of physiological arousal in the morning and gradually a higher level of arousal as the day goes by (Kleitman 1987), where psychological arousal is internal stimulation. According to Zuckerman (1979), each consumer has an ideal level of stimulation, which is the amount of stimulation a person generally prefers from all possible internal sources and external sources. Consumers may engage in the exploration of the environment to satisfy the need for the optimal stimulation level (Menon and Kahn 1995). In other words, when consumers feel low psychological arousal and obtain low internal stimulation in the morning, they might compensate by choosing more external stimulation to reach their optimal stimulation level. Price is a kind of external information and external stimulus. Comparing different prices from different platforms is a process of searching, selecting, and analyzing information from the external world, thus obtaining external stimulation. When consumers have less internal stimulation in the morning, they may obtain more external stimulation by collecting price information or comparing prices to achieve the optimal level of stimulation. In this case, consumers are more likely to have high price sensitivity in the morning, such as repeatedly comparing the price of the same product on different platforms or paying attention to the discounts and promotions of the product. As time passes by, consumers' psychological arousal level and internal stimulation increase, thus the demand for external stimulation decreases. As a result, consumers' price sensitivity decreases over time. Therefore, we propose H1:

H1: Customer price sensitivity decreases as the day wears on, i.e., customers are more price sensitive in the morning than the rest of the day.

Furthermore, the circadian rhythm, as an internal mechanism, will also be affected by external factors, such as sunlight (Gullo et al. 2019, Collinson et al. 2020). The sunlight duration is often affected by the season and weather, changing accordingly. For the same time on different days, when the sunlight duration is longer, the psychological arousal level of consumers is higher and the internal stimulation is more, so the demand for external stimulation is lower, and consumers' price sensitivity declines. Conversely, when sunlight duration decreases, despite being at the same time of day, consumers' price sensitivity will increase. Therefore, we propose H2:

H2: Sunlight duration will positively moderate the negative time-of-day effect on price sensitivity – the increase in sunlight duration will weaken the erosion of price sensitivity by time-passing in a day.

Method

Study 1

Data. Study 1 examines orders from chain catering company A, recorded between January 2022 and February 2022, across 18 stores in Beijing, China. We analyzed 21,280 purchase records from the CRM system, tracking details like order number, product information, purchase time, original price, and actual payment, using phone numbers as consumer identifiers. Company A utilized promotion activities such as discounts and coupons. Most of these promotions take place on a weekly basis, and the number and type of promotions do not change within a single day. For detailed discount strategies, please refer to Appendix A. To evaluate consumer price sensitivity, we calculated both the absolute discount amount and the discount rate. Consumers with higher price sensitivity tend to pursue lower prices and higher discount rates. Price sensitivity is indicated by the percentage of discount in the original price (PDOP), a more objective measure than absolute discount amounts, as PDOP is less influenced by original price. For instance, a PDOP of 0.3 for Consumer A versus 0.2 for Consumer B suggests higher price sensitivity in Consumer A. Further, we calculate the time effect on the PDOP to test whether consumers' price sensitivity varies by time of day.

Model-free evidence. Figure 1 and Table 2 reveal the model-free evidence of the time effect on the price sensitivity. The line chart in Fig. 1 shows a peak in consumers' PDOP during morning hours, followed by a gradual decline. Table 2 shows the payment information during various times of day, including the average original price, the average actual payment, the average discount amount, and the average PDOP. T-test is further conducted to examine the differences between PDOP during different times. Specifically, the morning average PDOP is 0.2959, significantly exceeding the afternoon ($\beta = 0.2701$, $t = 4.5570$, $p < 0.001$) and evening values ($\beta = 0.2328$, $t = 11.1039$, $p < 0.001$), while the PDOP in the afternoon was also significantly higher than that in the evening ($t = 8.7564$, $p < 0.001$). This indicates that customers' price sensitivity (interested in pursuing discounts) is notably higher in the morning and lowest in the evening.

Model specification. To determine the effect of time of day on price sensitivity, we use the following Ordinary Least Squares (OLS) regression model:

$$\mathrm{PDOP}_i = \alpha + \beta_1 Hour_i + \beta_2 Month_i + \beta_3 Week_i + \beta_4 Hol_i + \beta_5 Rainsnow_i + \beta_6 Temp_i + \varepsilon_i$$

where i designates the purchase record. PDOP_i is the percentage of discount in the original price of the purchase record i, measuring consumer's price sensitivity. $Hour_i$ is the independent variable, the hour-of-day continuous variables. People may have different spending habits on weekdays and non-weekdays, so we control the day-of-week variable. The holiday variable is introduced for the same reason. The day of the week and month when the order is generated are also taken into consideration. $Week_i$ is a categorical variable, with Monday as the reference base. $Month_i$ takes the value 0 for data from January and 1 for data from February. Hol_i is a dummy variable, which is 1 if the date of order is on holiday, and 0 otherwise. Climate and environmental factors can also affect people's consumption behavior, so we take weather conditions and temperature into account. $Rainsnow_i$ is a dummy variable, which is 1 if the weather on order day is rain or snow, and 0, otherwise. $Temp_i$ is a continuous variable, representing the average daily temperature.

Results. Table 3 shows the results of the OLS regression model. The PDOP decreases significantly ($\beta = -0.0055$, $p < 0.001$) as the day progresses, indicating higher consumer price sensitivity when it is earlier in the day. Particularly, consumers' price sensitivity in an offline consumption scenario decreases by 0.55% per hour. Thus, H1 is supported.

We opt for PDOP as our focal model to eliminate the influence of absolute quantity and to more accurately reflect the price sensitivity of consumers. The other three models, with actual payment, original price, and discount amount as dependent variables, are presented in columns 2–4 in Table 3, complementing the results of PDOP. The actual payment refers to the final amount the customer is required to pay for an order after all applicable discounts have been applied. The original price refers to the price of an order prior to the application of any discounts or promotional reductions. The discount amount represents the monetary value subtracted from the total price, calculated as the difference between the total price and the actual payment made by the consumer. The coefficients on time-of-day are significantly negative in original price model ($\beta = -0.4655$, $p < 0.001$) and discount amount model ($\beta = -0.3963$, $p < 0.001$).

Other variables also have significant effects on PDOP and price sensitivity. Consumers' price sensitivity is significantly higher during holidays than on ordinary days. In this offline consumer scenario, bad weather will also reduce price sensitivity.

Study 2. Study 2 aims to replicate the findings of Study 1 using a different company's actual purchase data, and employ platform switching as another proxy of price sensitivity. Additionally, it extends the investigation by examining how sunlight duration functions as a moderator.

Data. Study 2 utilizes data from 506,409 takeout orders made by 196,421 customers over 6 months, sourced from three food delivery platforms linked to 27 Beijing stores of fast-food chain B. This data includes details such as order time, size, store, platform, and customer phone numbers. By tracking phone numbers, we can observe individual customer purchase patterns over time, including platform-switching behaviors. As low prices often motivate platform switching (Ryu et al. 2023), this behavior serves as an indicator of higher price sensitivity, with customers more likely to switch platforms seeking lower prices.[1] Thus, platform switching is used as a proxy for price sensitivity in study 2.

Table 4 shows the descriptive analyses of all the variables.

Model-free evidence. We first present model-free evidence and found that the more platforms customers use, the lower their average consumption will be. The average spending is 33.76 yuan for single-platform customers, 31.25 yuan for dual-platform customers, and 29.00 yuan for three-platform customers. Categorizing dual-platform customers and three-platform customers as multi-platform customers, the average consumption for this group is 30.98 yuan, which is significantly lower than that of single-platform customers ($p < 0.001$). Therefore, it is valid to use platform switching to approximate price sensitivity. The occurrence (vs. non-occurrence) of switching behavior aligns with higher price sensitivity.

Additionally, a variance analysis was adopted to explore the changes in the platform switching across time of day. We considered the platform-switching rate (the ratio of switched orders to total orders) instead of absolute numbers, due to its dependence on order quantity. The results, as presented in Table 5, unveil that the platform-switching rate is 0.043 in the morning, significantly higher than that in the afternoon ($M = 0.039$, $p < 0.001$) or evening ($M = 0.041$, $p < 0.01$). This indicates higher price sensitivity during morning hours compared to later times.

Model specification. Because the dependent variable platform switching is a dummy variable, Study 2 uses the Logistic regression model to test the main and moderating effects. Equations (1) and (2) examine the main effect. Equation (1) focuses on time-of-day and platform switch, while Eq. (2) adds control variables. Equation (3) and Eq. (4) examine the moderating effect, with control variables added to Eq.(4).

$$switch\ likelihood_i \equiv P\left(\mathrm{Platswitch}_i = 1, |Hour_i\right) = \frac{Exp\left(U_i\right)}{Exp\left(U_i\right) + 1}$$

$$U_i = \alpha + \beta_1 Hour_i + \varepsilon_i \tag{1}$$

$$switch\ likelihood_i \equiv P\left(\mathrm{Platswitch}_i = 1, |, Hour_i, Freq_i, Month_i, Week_i, Hol_i, Rainsnow_i, Temp_i\right) = \frac{Exp\left(U_i\right)}{Exp\left(U_i\right)+1}$$

$$U_i = \alpha + \beta_1 Hour_i + \beta_2 Freq_i + \beta_3 Month_i + \beta_4 Week_i + \beta_5 Hol_i + \beta_6 Rainsnow_i + \beta_7 Temp_i + \varepsilon_i \tag{2}$$

$$switch\ likelihood_i \equiv P\left(\mathrm{Platswitch}_i = 1, |Hour_i, Sundur_i, Hour_i * Sundur_i\right) = \frac{Exp\left(U_i\right)}{Exp\left(U_i\right)+1}$$

$$U_i = \alpha + \beta_1 Hour_i + \beta_2 Sundur_i + \beta_3 Hour_i * Sundur_i + \varepsilon_i \tag{3}$$

$$switch\ likelihood_i \equiv P\left(\mathrm{Platswitch}_i = 1, |Hour_i, Freq_i, Month_i, Week_i, Hol_i, Rainsnow_i, Temp_i, Sundur_i, Hour_i * Sundur_i\right) = \frac{Exp\left(U_i\right)}{Exp\left(U_i\right)+1}$$

$$U_i = \alpha + \beta_1 Hour_i + \beta_2 Freq_i + \beta_3 Month_i + \beta_4 Week_i + \beta_5 Hol_i + \beta_6 Rainsnow_i + \beta_7 Temp_i + \beta_8 Sundur_i + \beta_9 Hour_i * Sundur_i + \varepsilon_i \tag{4}$$

where i designates the order. U_i, the dependent variable, denotes the latent utility of making a platform switch. $Platswitch_i$ is a dummy variable representing the occurrence of switching behavior, where 1 indicates that the order was placed through a different platform than the one the customer used previously, and 0 otherwise. We have purchase records of consumers on three delivery platforms for stores of company B. Each record shows the consumer's purchase time and platform. If a consumer's ordering platform differs from the last one, $Platswitch_i$ is coded as 1. If the platform is the same, $Platswitch_i$ is coded as 0. The independent variable, $Hour_i$, is the hour-of-day continuous variable. Consumers' frequency of using delivery platforms may influence the platform-switching behavior. Frequent consumers are more likely to use multiple platforms and pursue lower prices. Therefore, we controlled $Freq_i$, which is consumers' number of times of purchasing the focal brand on all the delivery platforms during the data period. Consumers may have different spending habits on weekdays versus non-weekdays and from month to month, so we controlled for the day-of-week and the month variables. $Week_i$ is the same as in Study 1, and $Month_i$ is a categorical variable with July as the reference base. The holiday variable was introduced for the same reason. Hol_i is a dummy variable, which is 1 if the date of order is on holiday, and 0 otherwise. Climate and environmental factors can also affect consumer behavior, so we took into account weather conditions and sunshine duration. $Rainsnow_i$ is a dummy variable, which is 1 if the weather on order day is rain or snow, and 0 otherwise. $Temp_i$ equals to the average daily temperature for the day the order was placed. $Sundur_i$ is a continuous variable, representing

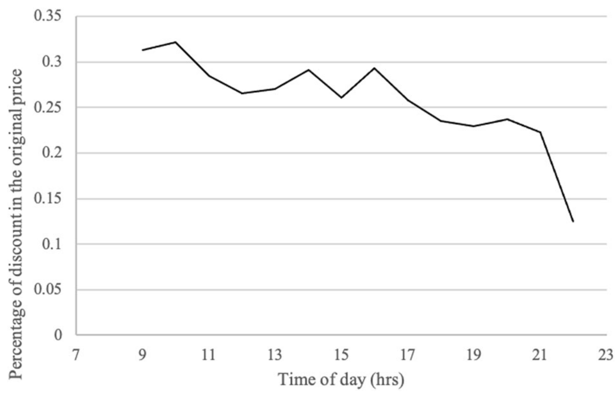

Fig. 1 PDOP varies by time of day. This figure reveals the changes in consumers' PDOP across the day.

Table 2 PDOP Varies by Time of Day.

Time of day	Percentage of discount in the original price, PDOP	Actual payment	Original price	Discount amount	Number of samples
Morning (–11:59)	0.2959	40.0376	57.5103	17.4726	4092
Afternoon (12:00-17:59)	0.2701	38.7402	53.7011	14.9609	9675
Evening (18:00-)	0.2328	36.4503	48.6865	12.2363	7513
Compare means: T-test					
Morning vs Afternoon	4.557^{***}	1.627^{*}	3.595^{***}	4.335^{***}	
Morning vs Evening	11.104^{***}	4.566^{***}	8.414^{***}	9.047^{***}	
Afternoon vs Evening	8.756^{***}	4.461^{***}	7.292^{***}	6.804^{***}	

$^{*}p < 0.1$, $^{***}p < 0.001$.

Table 3 Regression Results of Study 1.

Variable	Percentage of discount in original price (1)	Actual payment (2)	Original price (3)	Discount amount (4)
Time of day (hrs), $Hour_i$	-0.0055^{***}	-0.0692	-0.4655^{***}	-0.3963^{***}
Day of week[T.Tue], $Week_i$	-0.0010	0.7091	1.9335	1.2244^{*}
Day of week[T.Wed], $Week_i$	-0.0031	-2.3878^{*}	-3.8487^{**}	-1.4609^{*}
Day of week [T.Thur], $Week_i$	-0.0095	-1.6790	-3.1058^{*}	-1.4268^{*}
Day of week [T.Fri], $Week_i$	-0.0133^{*}	-0.4649	-1.3759	-0.9110
Day of week [T.Sat], $Week_i$	0.0037	0.3421	0.8606	0.5185
Day of week [T.Sun], $Week_i$	0.0029	0.7492	0.9962	0.2470
Month of year [T.2], $Month_i$	-0.0647^{***}	0.5034	-0.8271	-1.3305^{**}
Holiday, Hol_i	0.0174^{*}	10.2459	16.8764^{***}	6.6305^{***}
Rainy or snowy, $Rainsnow_i$	-0.0319^{***}	10.3681	11.4324^{***}	1.0643
Temperature, $Temp_i$	0.0005	0.2120	0.2104	-0.0016
Adjusted R^2	0.0179	0.0136	0.0184	0.0104

$^{*}p < 0.1$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table 4 Descriptive Statistics of Variables in Dataset ($n = 506409$).

Continuous Variables

Variables	Min	Mean	Median	Max	SD
Time of day (hrs), $Hour_i$	6.00	13.78	12.00	23.00	3.41
Sunlight duration, $Sundur_i$	9.34	11.51	11.03	14.96	1.91

Categorical Variables

Variables	N	Frequency	Accumulated frequency
Switching [0]	481963	95.17%	95.17%
Switching [1]	24446	4.83%	100.00%
Holiday [0]	485362	95.84%	95.84%
Holiday [1]	21047	4.16%	100.00%
Rainy or snowy [0]	341904	67.52%	67.52%
Rainy or snowy [1]	164505	32.48%	100.00%
Day of week [Mon]	68970	13.62%	13.62%
Day of week [Tue]	72296	14.28%	27.90%
Day of week [Wed]	76130	15.03%	42.93%
Day of week [Thur]	76126	15.03%	57.96%
Day of week [Fri]	73152	14.45%	72.41%
Day of week [Sat]	69806	13.78%	86.19%
Day of week [Sun]	69929	13.81%	100.00%
Month of year [Jul]	61932	12.23%	12.23%
Month of year [Aug]	75475	14.90%	27.13%
Month of year [Sep]	72829	14.38%	41.52%
Month of year [Octo]	79065	15.61%	57.13%
Month of year [Nov]	98666	19.48%	76.61%
Month of year [Dec]	118442	23.39%	100.00%

monthly average sunshine duration. Online promotions can also affect customers' price sensitivity, but we didn't introduce this variable because promotions on online platforms are usually long-term promotions that don't change over the course of a day.

Results. Table 6 reports the results of the four models. For the main effect, both the naive model ($\beta = -0.004$, $p < 0.01$) or the full model ($\beta = -0.005$, $p < 0.01$) indicate a decline in customers' price sensitivity throughout the day, supporting H1. Utilizing the Logit model, the odds ratio provides insight into the ratio between the likelihood of platform switching occurring and the likelihood of it not occurring. The calculated odds ratio in Eq. (2) shows that the likelihood of platform switching, indicative of price sensitivity, decreases by 0.5% with each passing hour ($\text{Exp}(\beta)-1 = -0.005$, $p < 0.01$). In other words, in such an online consumption scenario, consumers' price sensitivity decreases by 0.5% per hour. Therefore, our findings suggest that customers show higher price sensitivity in the morning, relative to the afternoon or evening.

Furthermore, the moderation effect is tested. The coefficients of the interaction between time of day and sunlight duration are significantly positive in the two models, namely 0.003 ($p < 0.01$) and 0.004 ($p < 0.01$) respectively, while sunlight duration is significantly negative to time of day ($\beta = -0.141$, $p < 0.001$; $\beta = -0.114$, $p < 0.01$). Hence, the sunlight duration is proven to have a positive moderating effect which means that the increase in sunlight duration will restrain the time-of-day effect on the switching rate. Therefore, H2 is supported and the robustness of the results is underscored.

Next, we will focus on the more detailed results of Eq. (4), mainly the changes in the odds ratio $p/(1\text{-}p)$ as the independent variable increases by one unit. When the sunlight duration is equal to 0, the odds will decrease by 4.4% ($\text{Exp}(\beta)-1 = -0.044$, $p < 0.01$) with each passing hour of the day. Furthermore, sunlight duration will weaken the main effect ($\beta = 0.004$, $p < 0.01$). For a given time of the day, as we move further away from sunrise and the sunlight duration increases, customers exhibit reduced price sensitivity.

In addition, other variables also function in line with initial expectations. From Tuesday to Friday, the odds ratios are lower than that on Monday and generally customers are less likely to switch platforms on weekends than on weekdays. On holidays, the odds ratio will increase by 10.5%, compared with ordinary times ($\text{Exp}(\beta)-1 = 0.105$, $p < 0.01$). Customers are also more likely to switch platforms during rainy or snowy conditions ($\text{Exp}(\beta)-1 > 0$, $p < 0.001$).

Study. Study 3 has three purposes. First, while Studies 1 and 2 focused on food (a hedonic product category), Study 3 aims to replicate the effects in another product category (chairs) and further establish the causal effect between time-of-day and price sensitivity through an online experiment. Second, unlike Studies 1 and 2, Study 3 directly measures price sensitivity instead of using proxies. Finally, we aim to rule out alternative explanations, such as variety seeking.

Method

Procedure: We employed a single-factor, between-subjects design via Credamo. We manipulated the time of day (morning, afternoon, and evening) when the experiment was conducted through random assignments. The questionnaire was distributed across three time periods: morning (9:00–12:00 a.m.), afternoon (2:00–5:00 p.m.), and evening (7:00–10:00 p.m.). Each questionnaire was identical across the different time periods. For each time period, we collected 60 responses, resulting in a total of 180

Table 5 Comparison of Platform Switching Rate Across Time of Day.

	Morning (6:00–12:00)	Afternoon (12:00–18:00)	Evening (18:00–24:00)	Total
Number of orders	201,889	194,513	110,007	506,409
Number of platform-switched orders	8677	7663	4515	20,855
Platform switching rate	0.043	0.039	0.041	0.041
T-test (compared with morning)		0.001***	0.01**	

**$p < 0.01$, ***$p < 0.001$.
Platform switching rate = number of switched orders/number of orders.

Table 6 Regression Results of the Logistic Models in Study 2.

Variables	Main effect		Moderation effect	
	(1)	(2)	(3)	(4)
Time of day (hrs)	−0.004*	−0.005**	−0.044***	−0.044***
Time of day (hrs) * Sunlight duration			0.003**	0.004**
Sunlight duration			−0.141***	−0.108***
Frequency		0.024***		0.024***
Day of week [Tue]		−0.046*		−0.043*
Day of week [Wed]		−0.052**		−0.050**
Day of week [Thur]		−0.050**		−0.047*
Day of week [Fri]		−0.029		−0.027
Day of week [Sat]		−0.050**		−0.049*
Day of week [Sun]		−0.091***		−0.089***
Month of year [Aug]		0.279***		0.222***
Month of year [Sep]		0.303***		0.186***
Month of year [Octo]		0.220***		0.042
Month of year [Nov]		0.470***		0.289**
Month of year [Dec]		0.314***		0.077
Holiday		0.099***		0.112***
Rainy or snowy		0.053***		0.052***
Temperature		−0.010***		−0.007***
AIC	195877	193531	195159	193520

*$p < 0.1$, **$p < 0.01$, ***$p < 0.001$.
Note: The results reported here are parameter estimates, instead of odds ratios.

samples. The sample consisted of 76% females, with 81.1% of participants aged between 21 and 40 years old. In terms of monthly disposable income, 27.2% of participants reported earning more than 10,000 yuan, 28.3% between 5000–10,000 yuan, 23.9% between 2000 and 5000 yuan, and 20.6% less than 2,000 yuan. Participants were presented with a shopping scenario involving a price increase, described as follows:

Imagine that you want to improve your study environment and have been looking for a new chair. Last week, you saw one that you liked at one of the stores in the downtown area and have decided to take a friend to see it again. Today, while you and your friend are examing the chair, you noticed on the price tag that the current price for the chair is 25% higher than the price you observed on your visit last week.

After reading the scenario, participants indicated their purchase intention for the chair at the current price, which served as the measure of price sensitivity. This measurement was adapted from Grewal et al. (1998) and included five items (see Appendix B). To rule out alternative explanations, we also measured consumers' variety-seeking behavior using the scale from Pick et al. (2016). Demographic information was subsequently collected. To ensure the quality of the sample, an attention-check question was included in the questionnaire.

Results. The Cronbach's alpha for the five price sensitivity items was 0.952, indicating a high level of reliability. The composite reliability (CR) was 0.964, and the average variance extracted (AVE) was 0.842, both exceeding the respective thresholds of 0.7 and 0.5. These values suggest a high level of validity. The five items were then averaged, where higher values indicate stronger purchase intentions after the price increase. Subsequently, we performed a reverse coding to reflect price sensitivity, with higher values indicating greater price sensitivity.

Hypothesis testing: To test the main effects between time-of-day and price sensitivity, we conduct an ANOVA to compare price sensitivity across different time periods. The results of ANOVA revealed a significant difference in price sensitivity at different times ($F = 8.186$, $P = 0.000$, $\eta^2 = 0.085$). Consistent with our expectation, participants are more price sensitive ($M = 5.59$, $F = 16.242$, $P < 0.001$, $\eta^2 = 0.084$) in the morning than in the afternoon ($M = 4.72$) or evening ($M = 4.6$). Therefore, H1 is supported.

Alternative explanation. One potential alternative explanation is that variety-seeking behavior could account for the observed effect. Consumers who are more inclined to explore a variety of options might exhibit greater price sensitivity as they compare different products. To investigate this, we tested the mediating role of variety-seeking. A bootstrapping mediation analysis with 10,000 samples revealed that variety-seeking does not mediate the relationship between time-of-day and price sensitivity ($b = -0.016$, 95% confidence interval:$[-0.093, 0.055]$, including zero). Therefore, consumers' price sensitivity is higher in the morning than in the afternoon and evening, not because they are more variety-seeking in the morning than at other times of the day.

Additional results. Comparing the results of the three studies, we also demonstrate some additional results. For one thing, although both on days off, price sensitivity on holidays shows a different trend from price sensitivity on weekends. Consumers are more price-sensitive on holidays than on ordinary days and less price-sensitive on weekends than on weekdays. The difference may be related to the length of the days off. For longer holidays, customers have more leisure time and are more willing to spend time trying different platforms; while for shorter weekends, consumers may focus on more meaningful things and get external stimulation from other sources.

For another, the effect of weather on price sensitivity differs between the online and offline scenarios. In offline consumption, bad weather, such as rainy and snowy, will reduce price sensitivity and distract consumers' attention from the discounts. The reason may be that the inconvenience of traveling in bad weather consumes energy and thus decreases the energy invested in consumption and price comparison. However, bad weather might increase customers' likelihood of switching between online platforms. In the online consumption scenario, consumers do not need to consider the impact of weather on their traveling convenience, and online platforms ease the process of price comparison between different sources.

Discussion

Summary of results. Our goals in the current research are to examine the relationship between time of day and consumers' price sensitivity, as well as the boundary conditions. Three studies were conducted and finally provided converging and robust evidence, supporting both H1 and H2.

Study 1 explored the direct purchase behavior of consumers and adopted the purchase discount as the proxy of price sensitivity. The result of the OLS regression model provides evidence that consumers' price sensitivity decreases as the day wears on. With each passing hour, consumers' price sensitivity drops by 0.55%.

Study 2 provides additional evidence that consumers' price sensitivity, represented by platform switching, diminishes within a day through the Logistic Regression Model. According to the calculated odds ratio, the likelihood of platform switching decreases by 0.5% with each passing hour, as well as the price sensitivity. Data from two different sources indicate that consumers' price sensitivity, whether in online or offline consumption scenarios, decreases by approximately 0.5% per hour. Furthermore, Study 2 shed light on the moderation effect of sunlight duration and examined that the negative price sensitivity effects will be attenuated when the sunlight duration increases. The reason may be that customers will have higher internal levels of stimulation when the sunlight duration is longer and seek less external stimulation, such as low prices, as compensation to reach their desired or optimum level (Menon and Kahn 1995).

Study 3, conducted in the morning, afternoon, and evening, directly measures consumers' price sensitivity by assessing purchase intentions after a price increase. This study provides causal evidence that consumers' price sensitivity is highest in the morning and decreases in the afternoon and evening. Additionally, Study 3 rules out the alternative explanation of variety-seeking.

Theoretical contributions. This study contributes significantly to the field in three theoretical aspects. Firstly, it uncovers a robust relationship between price sensitivity and the time of day, drawing on real-world data from two distinct sources and an experiment. Our empirical analysis demonstrates that price sensitivity decreases by approximately 0.5% per hour, a finding consistent across both offline and online scenarios. The experiment further supported the causal effect. Previous research has proven the effect of situational variables on consumers' price sensitivity from the physical surroundings perspective and the social surroundings perspective (Li et al. 2017, Gao et al. 2021, Zhou et al. 2009), while our study proves the direct influence of the temporal perspective and provides the explanation behind it using the circadian rhythm theory.

Secondly, this study sheds light on the effect of time. Previous studies have examined the effect of time from different dimensions and units, finding the existence of the "fresh start effect". This study focuses more on the impact of time changes within a single day and finds that at the beginning of the day, consumers have greater price sensitivity and consumption rationality. Consequently, our findings offer further evidence for the daily manifestation of the "fresh start effect," specifically through the lens of price sensitivity.

Finally, this study verifies the significant moderation effect of sunlight duration, linking consumers' internal physiological traits and price sensitivity to external stimuli. Sunlight duration helps us to explore the relationship through the circadian rhythm theory, as it is closely related to day-night variations, and sunlight is an important factor influencing the human biological clock.

Managerial implications. Previous studies have suggested that specific actions of firms would influence consumers' price sensitivity (Yun and Hanson 2020), which further influences consumers' repurchase intention (Graciola et al. 2018, Yi et al. 2024). This study offers several practical and effective strategies for enterprises and brands. Our findings highlight the importance of the time-of-day effect on consumer behavior in promotional activities. Companies could schedule promotions, such as price reductions and discounts, during periods of heightened price sensitivity (e.g., mornings) to leverage their pricing advantages. Notably, platforms like Taobao, Tmall, and JD.com often initiate their Double Eleven festival promotions late at night (around 20:00 or 24:00), under the assumption that most consumers have completed their workday. This strategy aligns with our empirical findings, which indicate reduced price sensitivity in consumers late at night.

Limitations and future research directions. The study also has some limitations and provide avenues for future research. First, this paper explores the effect of time on price sensitivity, focusing on food (hedonic) and chair (utilitarian) product category, which limits the scope of the product categories studied. Whether this relationship holds for other product categories requires further exploration.

Second, this study only considers the influence of objective time of day without subjective individual differences. According to previous research, consumers' circadian rhythms vary from individual to individual and result in different consumer chronotypes. Some consumers are higher on the eveningness trait, while others are higher on the morningness trait (Hossain and Saini 2013). However, due to data limitations, this study did not consider the impact of different circadian rhythm types of consumers and the matching of consumer types with time of day. Future studies can further consider the individual characteristics of consumers, and interesting conclusions may be drawn.

Finally, this study explores the moderation effect of sunlight duration, which is of limited practical significance. Although the duration of sunlight plays an important role, as a natural phenomenon, it is often not affected by individuals. Therefore, the direct application value of this variable to enterprises or brands is limited. Future studies may consider exploring other moderation variables that can be controlled or influenced by enterprises and individuals. For example, consumers with the prevention (vs. promotion) focus may have higher price sensitivity and product with different values (utilitarian value vs. hedonic value) may cause differences in price sensitivity. Future studies could further consider other temporal variables and other variables that can influence consumers' circadian rhythms as well.

Data availability

The experimental datasets generated during and/or analyzed during the current study are available from the corresponding authors upon reasonable request.

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Note

1 There are alternative explanations for platform switching, such as negative experience, variety seeking, local availability and usage scenarios (home vs work). To clarify the reasons for consumers switching platforms, we conducted a survey. Among the 130 consumers who have ever switched delivery platforms, 89 consumers cited price comparison (68.46%). Therefore, we believe seeking lower prices is the main reason for platform switching.

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Author contributions

Sha Zhang: Idea, writing, data, analysis, funding. Xiting Wu: Writing, data analysis. Yonggui Wang: Editing, new data collection, funding. Peiqi Jiang: Preliminary data analysis

Competing interests

The authors declare no competing interests.

Ethical approval

Ethical approval was not required as the study did not involve human participants.

Informed consent

Informed consent was not required as the study did not involve human participants.

Additional information

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Correspondence and requests for materials should be addressed to Sha Zhang or Yonggui Wang.

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