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Hai WANG
Singapore Management University, haiwang@smu.edu.sg

Tian LU

Yingjie ZHANG

Yue WU

Yiheng SUN

See next page for additional authors

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Last Digit Tendency: Lucky Numbers and Psychological Rounding in Mobile Transactions

Hai Wang[a,+], Tian Lu[b,+], Yingjie Zhang[c,+,*], Yue Wu[d,+], Yiheng Sun[d], Jingran Dong[d], and Wen Huang[d]

[a]School of Computing and Information Systems, Singapore Management University, Singapore 178902
[b]W. P. Carey School of Business, Arizona State University, Tempe, AZ 85287
[c]Guanghua School of Management, Peking University, Beijing, China 100871
[d]Tencent Weixin Group, Shenzhen, China 518054
[*]Corresponding author: yingjiezhang@gsm.pku.edu.cn
[+]These authors contributed equally to this work

ABSTRACT

The distribution of digits in numbers obtained from different sources reveals interesting patterns. The well-known Benfords law states that the first digits in many real-life numerical data sets have an asymmetric, logarithmic distribution in which small digits are more common; this asymmetry diminishes for subsequent digits, and the last digit tends to be uniformly distributed. In this paper, we investigate the digit distribution of numbers in a large mobile transaction data set with 835 million mobile transactions and payments made by approximately 460,000 users in more than 300 cities. Although the first digits of the numbers in these mobile transactions follow Benfords law, the last digit has a strong tendency to be a lucky number or be influenced by psychological rounding. This lucky number tendency is more significant in transactions that are more strongly connected to social interactions, such as money sent as gifts or as “red envelopes” (a traditional method of gift-giving during Chinese holidays), and in transactions by individuals with potentially greater emotional needs, such as during COVID-19 outbreaks and natural disasters. This psychological rounding tendency is more common in online e-commerce payments, in-store purchases, and money transfers between individuals. These findings are key for understanding the last digit tendency and its psychological and emotional mechanisms, which could be used as an indicator of public sentiment or in methods of detecting fraudulent business activity.

Keywords: Last Digit; Lucky Number; Psychological Rounding; Mobile Transaction

1 Introduction

The distribution of digits in numbers obtained from different sources has interesting patterns. The frequency of digits from 1 to 9 is well-known to follow a nonuniform distribution. Benfords law, also known as the Newcomb-Benford law, was originally observed in [1] and described more precisely in [2, 3, 4, 5]. The law states that the first digits of numbers from widely divergent sources have a logarithmic distribution. Specifically, although this phenomenon is not universal, the frequency of a given first digit p $(p = 1, 2, , 9)$ in many real-life numerical data sets is approximately equal to $\log_{10}(p+1)/p$; that is, first digits have a strong tendency to be small digits. Benfords law also predicts that this asymmetry diminishes for the second, third, and subsequent digits, and the last digit tends to occur with equal frequency in a uniform distribution.

Digit distributions that follow Benfords law have been observed in a wide variety of data sets, including those on newspaper readership counts, electricity bills, stock prices, income tax, population numbers, death rates, elections votes, the lengths of notes in classical music, the magnitude of image gradients, physical and mathematical constants [6], and numbers in the natural sciences, in general, [7]. The asymmetric distribution of digits has been applied in various contexts, such as the analysis of psychological pricing [8]; image forensics [9]; volcanology [10] and marsquakes [11]; the identification of irregularities in electoral data [12, 13, 14]; and the detection of accounting fraud [15, 16], campaign finance irregularities [17], international trade fraud [18], anomalies in COVID-19 numbers [19], crypto wash trading [20], and fraud in other economic [21] and scientific data [22].

In the era of big data and with the rapid development of information technology, Internet-of-things devices, and advances in analytics and computing methods, numerous new types of data have been generated, recorded, collected, and analyzed in various contexts. Among these, innovative technologies for mobile transactions and payments, which emerged in the 2010s, are widely used and have generated enormous and rich data sets regarding e-commerce, in-store, and private payments. In this paper, using a large mobile transaction data set from Tencent mobile payment in China (i.e., WeChat Pay), we investigate the digit distribution and tendency of the numbers in mobile transactions and payment. For commercial transactions, we investigated online e-commerce purchases and in-store purchases; for social payments, we investigated inter-individual money transfers and red envelopes. The patterns in the digit distribution could reveal certain tendencies and preferences of digits, as well as the possible psychological and emotional causes behind.

Specifically, we find that, while the first digit of numbers in mobile transactions follows Benfords law in both commercial and social-related categories, the last digit has a strong tendency in favor of lucky numbers and psychological rounding, which is very different from what Benfords law predicts. Lucky numbers were more frequently used in transactions closely related to social interactions and were associated with individuals who potentially had greater emotional needs. Psychological rounding was more common in commercial transactions, including in-store purchases and e-commerce purchases, and in money transfers between individuals. On the basis of these findings and their underlying psychological and emotional mechanisms, mobile transaction digit distributions can be used as a mirror of public sentiment and as a possible detector of fraudulent business activity.

The contributions of this study are three-fold. First, we determined the last digit distribution in both commercial and social mobile transactions. This distribution diverged from the prediction of Benford's law, which was previously widely presumed to be true. We theorized two mechanisms to explain this tendency: preference for lucky numbers and psychological rounding. Second, prior studies on price endings or rounded pricing have focused on commercial transactions; we extended the literature to cover social behavior by using rigorous statistical tools and empirical evidence. Third, we proposed possible methods of using this last digit tendency for practical applications. The frequency of lucky numbers as the last digit in social payments reflects how people have emotional needs; specifically, they desired to support each other and maintain social connections during disasters. By contrast, we also discussed the practical value of using the last digit tendency to detect fraudulent business activity, such as fake promotions.

2 Data

2.1 Mobile Transaction Data Set

The Tencent Weixin (WeChat) Group granted us access to a large-scale mobile transaction data set. WeChat Pay is a digital wallet service integrated into WeChat, China's most popular messaging app, and has accumulated over 900 million users in 2021 [23]. Unlike in the United States, in which the primary modes of payment are cash and credit cards, mobile payment is the main payment method in China with a penetration rate as high as 95.1% at the end of 2021 [24]. WeChat Pay enables two types of payments: (1) commercial transactions in online and offline channels that cover various retailers, products, and services, and (2) social-related payments (hereafter "social payments"). Social payments fall into two categories. The first is peer-to-peer money transfers, similar to transfers on Venmo, for everyday needs, such as splitting bills and paying rent. The second is for "red envelopes," a term indicating traditional gifts or "compensations" of money that are part of Chinese culture. Red envelopes are applied in various scenarios, such as offering apologies for lateness to a meeting or providing a penalty for losing a game. They can be sent to individuals or groups, commonly known as "group red envelopes." Specifically, the transfer of a red envelope typically involves sending money as a gift to commemorate holidays, weddings, joyful occasions, or as a special expression of gratitude. [1]

Our complete transaction data set covers a long period from January 2018 to June 2021. Because we sought to compare the distributions of different digits in transactions, we removed data on transactions amounting to less than CNě10 (∼US$1.6) because these transfers may have confounding information between the first and last digits.[2] The final data set contains the records of 835 million transactions made by approximately 460,000 users in over 300 cities in China. Users in this data set were randomly selected from the nationwide user pool to guarantee sample representativeness. Such user sample affords our analyses to be made on a sufficiently large size while avoiding huge computational cost. We observed granular information on every transaction record, including user ID and user demographics (e.g., age, gender, and education level), and transaction attributes, such as the timestamp, amount, city of the transaction, and type. Note that, it is reported that WeChat Pay and Alipay collectively account for over 96% of the mobile payment market in China in 2022.[3] Furthermore, recent scholarly research suggests similar transaction patterns and purposes between the two providers [25]. Given these factors, we assert that the randomly-selected sample data from WeChat Pay can effectively capture the overall (commercial and social) transaction characteristics in China, and the findings derived from our sample are generalizable to Chinese society.

The transaction amount in our data set has at most two decimal digits, namely an integer (e.g., CNě18), or being with one decimal digit (e.g., CNě18.1) or two decimal digits (e.g., CNě18.12). The digit 0 is removed if it is in the last digit of a decimal, that is, no cases of CNě18.0 or CNě18.10 are included. For the transaction amounts CNě18, CNě18.1, and CNě18.12, we count their last digit as 8, 1, and 2, respectively. Commercial transactions composed 88.52% of the data set; these transactions had an average amount of CNě204.96 (∼US$32), and social payments composed 11.48% of the data set, with an average amount of CNě416.04 (∼US$65). In the user sample, 62.18% were male. These focal users are randomly sampled by Tencent and the ratio between genders actually reflects that of the nationwide sample of WeChat Pay users. A plausible reason might be the inherently larger proportion of male WeChat Pay users and the broader transactions scenarios for male users than female users in daily life. [4] The average user age was 33. We collected data on all of these users' transactions during the time window. For more details, please refer to Supplementary Table **??** in the online supplementary information.[5] Our analyses were implemented using Python 3.7 and conducted on Tencent's Machine Learning Platform with 128 GB of RAM.

2.2 Distributions of Percentages of Digits

The large-scale data set contained high-resolution information on a crucial slice of the everyday life of the population. We investigated the digit distribution and overrepresentation or underrepresentation of numbers in mobile transactions and payments. Patterns in the digit distribution could reveal preferences for certain digits as well as possible psychological and emotional mechanisms affecting payment amounts.

Because of the potential effects of the COVID-19 pandemic on mobile transactions, we first focused on the time window between January 2018 and December 2019. Fig.1 reports the distributions of the first, second, third, and last digits in commercial transactions and social payments separately. Note that, to better present our results and rule out potential interference, we applied the following rules for all our subsequent analyses: (1) As mentioned before, to keep a consistent definition of the last digit, we guaranteed that all transaction amounts with one or two decimals in our data set were not ended by digit 0. Digit 0 in these cases was removed; (2) Because for amounts less than CNě100 (CNě1,000), their second (third) digit was also their last digit, to avoid confounding effects from this overlap, they were removed when analyzing the second (third) digit distribution.

We observed from Fig.1 that in both commercial and social transactions, the first digit generally followed an approximately logarithmic distribution; this asymmetry diminished to approach uniformity for the second and third digits of numbers, similar to the findings of [22]. The last digits, however, exhibited unique patterns in the data set, such as high frequencies of 5 and 8. This non-uniform distribution of last digits diverged substantially from Benford's law. It also contradicted with the predicted uniform distribution of the last digits if data is generated from an absolutely-continuous random variable [26] or under a

[1]In practice, red envelopes sent to individuals could either be a convenient method of performing a money transfer or could be gifts. Given that we cannot empirically differentiate between these motivations, the following analyses of red envelopes are conducted on the "group red envelopes".

[2]We also report the numbers and statistics of the transactions of different types that are less than CNě10 in the Supplementary Information. We find that the distributions of transactions below CNě10 are comparable to those above CNě10, indicating the robustness of our findings regardless of the inclusion or exclusion of transactions below this threshold.

[3]`https://www.enterpriseappstoday.com/stats/alipay-statistics.html`. Accessed on June 28, 2023.

[4]`https://ecommercechinaagency.com/guide-wechat-marketing-strategy`. Accessed on June 28, 2023.

[5]This article contains online supplementary information. The data set in the article was sampled appropriately and used only for testing purposes and included no confidential commercial information. All users' sensitive (personally identifiable) information was removed. Our analyses were conducted in China on Tencents server with its employees, who strictly followed data protection regulations. According to Tencent data regulation, the original data set used in this study cannot be published. We can offer an anonymized subsample upon request. We will also make the used code public.

few relatively mild conditions [27].[6] In particular, the distribution of the last digits had a strong tendency to be affected by *psychological rounding* or be a *lucky number*.

3 Empirical Strategies and Results

3.1 Lucky Number and Psychological Rounding

The effects of price endings on consumer behavior have long been investigated in the literature [29, 30, 31, 32]. Previous studies have compared "just-below" and round prices and examined the potential mechanisms for their effects on consumers. Although round numbers offer price convenience by reducing the time and effort of transactions, just-below prices (i.e., pricing in the nines, such as $2.99) influence consumer perceptions of price because people tend to compare or remember the leftmost digits [29, 33, 34]. Researchers have theorized that the latter phenomenon has level effects and image effects [32, 35]. By leveraging large-scale mobile transaction records, we verified the existence of this trade-off and demonstrated that the two psychological pricing strategies could be effective and were widely adopted in different channels: online versus offline commercial channels (Figs. 2(a) and 2(b)). In particular, in offline shopping, price convenience was a relatively more important factor for either comparing products or prices or for closing a transaction. Thus, round numbers (i.e., 0 and 5) were favored. By contrast, in online shopping, this price convenience was less important due to real-time price calculations and the fact that digital payments were exact and thus required no change; this resulted in a tendency to have prices with non-round number (e.g., 9) to strengthen price level effects [32]. Note that although we could not observe item prices directly but only total amount for each transaction, we believe that our analyses based on a large-scale transaction set can still show the overall patterns.

As indicated in Fig.2(a), the digit 8 was strongly favored as the last digit in online commercial transactions. This phenomenon was primarily driven by a belief in lucky numbers; 8 has long been regarded as the luckiest number in Chinese culture. Its pronunciation in Mandarin, "Ba," sounds similar to the character "Fa"—to become wealthy—and also connotes prosperity, success, and high social status [36]. This finding was consistent with experimental studies in the literature. For example, [37] found that superstition-based pricing with lucky numbers signaled a certain level of price attractiveness and created a more positive brand attitude. This effect could be intensified for some Chinese consumers who are attuned to superstitious beliefs about lucky numbers [38, 39].

The preference for psychological rounding or lucky numbers was not only observed in the last digits of commercial transactions but also in social payments. Fig.2(c) revealed that the digit 8 was significantly more common as the last digit of red envelope payments. Giving red envelopes is a Chinese tradition of exchanging envelopes of money ("lucky money") with friends and family members during the holidays. As noted by [40], people believe in luck for various reasons, including a desire to be optimistic; moreover, situational factors, such as special events, or objects that are related to luck can increase the tendency for individuals to choose lucky numbers. Moreover, although the digit 5 showed up frequently in social payments, Fig.2(d) revealed that 5 also had high frequency in normal money transfers between individuals. Studies [41, 42, 43] have suggested that the tendency to choose the number 5 also reflects the user's need for psychological rounding. Studies [41, 43] have found that people are inclined to be generous and kind to improve their self-image. This can explain prosocial behavior, such as high tips and donations. In the context of money transfers (especially among friends or relatives), users tend to round their payment numbers (e.g., rounding $24.6 to $25) to improve their self-image by appearing generous.

In order to verify our theoretical conjectures, we followed the prior literature (e.g., 36, 43) to design a survey wherein we devised several psychological rounding- and lucky number-related constructs and corresponding question items. We conducted this survey with the help of a professional survey company, targeting the randomly-chosen nationwide survey subjects who are WeChat Pay users. We checked the validity of the proposed survey constructs and applied the structural equation model to assess the relationships among different constructs. Generally, the survey results offer sound theoretical relevance of WeChat Pay users' transaction patterns in different (e.g., commercial and social) types and the underlying psychological mechanisms, which pave the way to motivate and interpret our empirical analyses with the secondary data. We report all of the survey details and results in the Supplementary Information.

3.2 Empirical Modeling

We employed a logit model to quantify the aforementioned findings. Eq.1 presents a comparison of digit distributions between channels among commercial transactions. We ran regressions at the transaction level. In the equation, the subscripts i and t indicate the transaction and day, respectively. The dependent variable Y_{it} is a dummy that indicates whether the last digit of transaction i on day t is a particular number from 0 to 9. We tested all digits from 0 to 9 but only reported the results for four digits (i.e., 0, 5, 8, and 9) which either were lucky numbers (8) or used in psychological rounding (0, 5, and 9). The

[6] Furthermore, we generated distributions of various digits in commercial transactions similar to Fig.1 using an additional data set of e-commerce transactions on Taobao.com and JD.com (refer to [28] for data details). These distributions (reported in Supplementary Fig.**??**) exhibited comparable patterns aligning closely with Fig.1, This consistency reinforces the generalizability of our research findings.

Table 1. Logit estimation results

	Eq. [1]			
Variables	DV: *Digit 0*	DV: *Digit 5*	DV: *Digit 8*	DV: *Digit 9*
Offline	**0.4426****** (0.0048)	**0.4130****** (0.0063)	**-0.7182****** (0.0056)	**-1.0171****** (0.0058)
Cum_trans	Yes	Yes	Yes	Yes
Demo_chars	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes
Log likelihood	-2.202×10^6	-1.541×10^6	-1.049×10^6	-8.545×10^5
#Obs.	3,622,645	3,622,645	3,622,645	3,622,645
	Eq. [2]			
Variables	DV: *Digit 0*	DV: *Digit 5*	DV: *Digit 8*	DV: *Digit 9*
RedEnvelope	**-0.1318****** (0.0031)	**-0.1982****** (0.0058)	**0.8441****** (0.0053)	**-0.2592****** (0.0113)
Festival	**0.1945****** (0.0060)	**-0.3940****** (0.0122)	**0.2345****** (0.0090)	**-0.2118****** (0.0227)
Cum_trans	Yes	Yes	Yes	Yes
Demo_chars	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes
Log likelihood	-2.570×10^6	-1.135×10^6	-8.808×10^5	-3.995×10^5
#Obs.	5,417,209	5,417,209	5,417,209	5,417,209

Because of the large sample size, we randomly chose 1/100 of the data to run the logit model estimations for Eq.1 and 1/10 of the data for Eq.2, respectively, to avoid the large sample size fallacy [44]. In both equations, dependent variables (DVs) are dummies indicating whether the last digit of the mobile transaction was 0 (or 5, 8, 9). The variables in bold are focal dummy variables, which indicate whether a commercial transaction was made offline (*Offline*), a social payment was made with red envelopes (*RedEnvelope*), or a social payment occured during the Spring Festival (*Festival*). *Cum_trans*, *Demo_chars*, and *Time* are historical cumulative transaction-related, demographic, and time-related control variables, respectively. Cluster standard errors by user are in parentheses. $^{***}p < 0.001$.

dummy $Offline_{it}$ is the focal variable, which indicates whether transaction i was made in an offline channel. We also included three control variables. The first is a vector of historical transaction characteristics, Cum_trans_{it}, of the user corresponding to transaction i until day t; this vector comprises the cumulative transaction frequency, the average amount of past transactions, and cumulative frequencies of each digit (0–9) appearing in a transaction amount's last digit. The second is a vector of demographic characteristics $Demo\_chars_i$ of age, gender, education level, and the level of development of the city in which transaction i occurred. The third is time effects $Time_t$; this is represented as a vector of dummies that describe whether a transaction occurred on a weekday or national holiday, whether the transaction occurred in a given month (ranging from 1 to 24, which corresponds to the months in the 2-year time window) to capture the time trend. Finally, ε_{it} is the error term. Supplementary Table ?? reports the statistics for the variables.

$$Y_{it}\mid_{logit} = \beta_0 + \beta_1 \cdot Offline_{it} + Cum\_trans_{it} \times \beta_2 + Demo\_chars_{it} \times \beta_3 + Times_t \times \beta_4 + \varepsilon_{it}, \tag{1}$$

When the models were fitted to the data, as shown in Table 1, significant positive coefficients of *Offline* were obtained on the digits 0 (coefficient = 0.4426, $p < 0.001$) and 5 (coefficient = 0.4130, $p < 0.001$) and significantly negative coefficients of *Offline* were obtained on the digits 8 (coefficient = -0.7182, $p < 0.001$) and 9 (coefficient = -1.0171, $p < 0.001$). Supplementary Tables ?? and ?? present the complete estimation (marginal) results of the focal variables and all controls for Eqs. 1 and 2. Compared with online transaction amounts, offline transaction amounts had a 9.27% and 5.34% higher probability of ending with the digits 0 and 5, respectively, and 5.61% and 6.16% lower probability of ending with the digits 8 and 9, respectively. These results suggested that, consistent with Figs.2(a) and 2(b), compared with online channels, offline transaction amounts tended to have the digits 0 and 5 rather than the digits 8 and 9 for convenience. Moreover, we observed that the digit 8 appeared significantly more frequently (coefficient = 0.8441, $p < 0.001$) as the last digit of a red envelope than of a money transfer, with an absolute increase of 3.27%. This finding implied a preference for lucky numbers in red envelopes sent for social reasons. Note that the number 6 also holds significance in Chinese culture as another lucky number, similar to 8. To validate this, we conducted regressions as outlined in Table 1 and presented the results in Supplementary Table ??. These findings reinforce the robustness of our observations regarding the lucky number phenomenon.

3.3 Lucky Number during Holidays

We then deepened our analyses by investigating lucky number preference during holidays. We examined data on the Spring Festival (typically lasting 1 week), which marks the beginning of a new year on the traditional lunar calendar and is the most important festival in China. The Spring Festival occurred between February 15 and 21 in 2018 and February 5 and February 11 in 2019. We compared the distribution of the last digits in social payments before, during, and after the Spring Festival in Fig. 3(a). Supplementary Fig. ?? presents a more granular plot that decomposes the biweekly proportions of the digit 8 as the last digit in red envelopes in 2018 and 2019. The proportion of the digit 8 during the Spring Festival verified the finding that a lucky number, which one alluded to as part of a prosocial behavior, caused the uneven distribution of last digits.

We further confirmed this Spring-Festival-driven pattern in Eq. 2 with the dummy variable, *Festival*. Eq.2 details the digit distributions of different types of social payments (i.e., red envelope vs. money transfers) for comparison. We performed regressions at the payment level. We considered identical dependent variables Y_{it} by using Eq.1. In the equation, one focal variable is the dummy variable $RedEnvelope_{it}$, which indicates whether a payment is made using a red envelope (= 1) or a money transfer (= 0). $Festival_{it}$ is a binary indicator of whether the payment occurred during the Spring Festival. Eq.2 also had similar control variables, specifically historic payment characteristics, demographic characteristics, and time effects, as Eq.1.

$$Y_{it}\,|_{logit} = \beta_0 + \beta_1 \cdot RedEnvelope_{it} + \beta_2 \cdot Festival_{it} + Cum\_trans_{it} \times \beta_3 + Demo\_chars_{it} \times \beta_4 + Times_t \times \beta_5 + \varepsilon_{it}. \quad (2)$$

The estimate, shown in the lower panel of Table 1, again revealed that people tended to send more red envelopes with amounts ending with the digit 8 to express their best wishes to family members and friends during the Spring Festival (coefficient = 0.2345, $p < 0.001$).

Potential confounders remain. For example, an alternative explanation for the frequency of the digit 8 other than its status as a lucky number might exist. For example, the digit 8 may be preferred simply because it is close to the digit 9 and is also related to psychological rounding. To rule out this alternative, we leveraged the heterogeneity of lucky numbers among different people because different ethnic groups have different lucky numbers. For example, although 8 is considered to be a lucky number in Han culture in China, 2 and 4 (and even numbers in general) are preferred in Miao culture (in China's southern provinces) [7] and 1, 3, and 9 (and odd numbers in general) are favored in Mongolian culture. We then examined cities that had a high population of Miao or Mongolian people and compared them with similar cities in which Han people were the majority. Cities with a high Miao population included Qiandongnan and Xiangxi; we compared these with Wuzhou, Ziyang, Kiamusze, and Wuwei, which had a Han Chinese majority. Similarly, cities with a high Mongolian population included Tongliao and the Xing'an League; we compared these cities with the Han-majority cities of Hulunbuir, Ulanqab, Loudi, and Qingyang. The level of economic development of cities was used as a proxy for their similarity. Supplementary Table **??** presents the proportion of the Miao or Mongolian people in the population of these cities as well as key city characteristics (e.g., total population and GDP per capita in 2019). Figs. 3(b) (c) present the distributions of the last digit during the Spring Festival among different ethnic groups. These results demonstrated that a preference for lucky numbers drove unique patterns in the last digits of transactions.

4 Case Analyses

Considering the aforementioned findings that the last digits tended to be numbers that are considered lucky or used in psychological rounding, we then analyzed two real-world cases to explore the potential implications of these two mechanisms.

4.1 Lucky Number Tendency: Behavioral Divergence during Disasters

Previous studies have noted that people tend to support each other, express opinions, and engage in emotional coping during disasters [45] to satisfy the need to maintain social connections [46]. Considering these human behaviors in our context, disasters may cause people to express their concern in any way possible, including transmitting "luck" to the people in need. We thus investigated the distribution of the last digits in user social payments to identify the correlations between user desires to deliver "luck" and the presence of disasters, including COVID-19 outbreaks and floods. In specific, the COVID-19 pandemic has served as a crucial event for studying and analyzing the behavioral changes that occur in response to disasters, providing valuable insights into human adaptability, resilience, and collective behavior during times of crisis. Recent studies have documented how COVID-19 influenced the social network structure [47], emoji usages on social media [48], and preferences of consuming products [49]. On a more general basis, other pioneering works have also investigated human behavioral changes (e.g., communications and mobility patterns [50], movement trajectories [51]) in response to disasters.

First, we analyzed data obtained during outbreaks of COVID-19. Despite strict pandemic prevention policies in China, COVID-19 transmission still occurred briefly in a few cities over the past 2 years. We considered three sets of treatment (with outbreaks) and control cities (with local similarities but without outbreaks during the same periods). These treatment cities were large cities in China, and their COVID-19 outbreaks continued for approximately 2 months. This natural experiment allowed us to clearly identify the tendency to use lucky numbers during and after the outbreaks.

- Treatment City 1: Shanghai, from November 2, 2020 to January 3, 2021. Control cities (near the Yangtze River Delta): Wuxi, Nanjing, Yangzhou, Ningbo, and Taizhou.

[7] Refer to Supplementary Table **??** for all of the information sources used in this paper.

Table 2. Difference-in-difference estimation results

Variables	DV: *Digit 8*
TreatCity	-0.0487 (0.0251)
During	0.0389 (0.0268)
Post	0.1622*** (0.0170)
TreatCity·During	**0.1412***** (0.0422)
TreatCity·Post	**0.1373***** (0.0281)
Cum_trans	Yes
Demo_chars	Yes
City_chars	Yes
Log likelihood	-1.032×10^5
#Obs.	408,242

Due to the large sample size, 1/10 of the data were randomly chosen for Eq.3 to avoid the large sample size fallacy. The dependent dummy variable indicates whether the last digit of the red envelope payment was 8. The variables in bold are the focal dummy variables ($TreatCity \cdot During$ and $TreatCity \cdot Post$), which indicate whether red envelope payments were made in the cities impacted by COVID-19 ($TreatCity$), during ($During$) and after the outbreak ($Post$), respectively. Treatment cities ($TreatCity$ = 1) are Shanghai, Shenzhen, and Chengdu. Control cities and the periods before, during, and after the outbreak are as aforementioned. Cum_trans, $Demo\_chars$, and $City\_chars$ are historical cumulative transaction-related, demographic, and city-related control variables, respectively. Cluster standard errors by city are in parentheses. ***$p < 0.001$.

- Treatment City 2: Shenzhen, from November 9 to December 27, 2020. Control cities (near the Pearl River Delta): Zhuhai, Zhongshan, Foshan, Fuzhou, and Quanzhou.
- Treatment City 3: Chengdu, from November 2 to December 27, 2020. Control cities (in central and western China): Mianyang, Nanchong, Changsha, Xi'an, and Jinan.

For each set of cities, we calculated the change in the percentage of the digit 8 as the last digit of social payments during and after COVID-19 outbreaks compared with the preoutbreak period. The duration of each outbreak was approximately two months; thus, we defined both the preoutbreak and postoutbreak period as approximately two months. Details are provided in the online supplementary information. As expected, Figs. 4(a)–(c) revealed a significant increase in the use of the ultimate digit 8 in treatment cities, implying that people in cities during COVID-19 outbreaks were much more likely to deliver "luck"; thus, the last digit distribution of payments can serve as a measure of public sentiment.

We further applied a difference-in-differences (DiD) specification to identify the effects of COVID-19 on social interactions as reflected by social payments whose transaction amounts had the lucky number 8 as the last digit. The DiD model is commonly used and has demonstrated its popularity for causal inference in the recent literature [52, 53]. In Eq.3, the dependent variable Y_{it} is a dummy variable that indicates whether the last digit of payment i on day t is 8. Shanghai, Shenzhen, and Chengdu were treatment cities (i.e., the dummy $TreatCity_i$=1), which had a relatively severe COVID-19 outbreak during the studied periods. We used the dummy variable $During_t$ and $Post_t$ to indicate whether the data were for during or after the outbreak (1 for yes and 0 otherwise), respectively. In the DiD analysis, the parameters of interest were β_4 and β_5, which corresponded to the interactions between $TreatCity_i$ and $During_t$ or $Post_t$ and captured the effects during and after an outbreak, respectively. As done for Eqs.1 and 2, we controlled for historical cumulative payments (Cum_trans_{it}), demographic characteristics ($Demo\_chars_i$), and time effects ($Time_t$). Moreover, we included city characteristics ($City\_chars_i$), such as the population in 2019 and the city-level COVID-19 infection rate and recovery rate to control for basic characteristics and COVID-19 severity across cities. ε_{it} is the error term. We used the logit model and cluster standard errors by city to estimate parameters. Table **??** presents the statistics for the variables.

$$\begin{aligned} Y_{it}\,|_{logit} = {} & \beta_0 + \beta_1 \cdot TreatCity_i + \beta_2 \cdot During_t + \beta_3 \cdot Post_t + \beta_4 \cdot TreatCity_i \cdot During_t + \beta_5 \cdot TreatCity_i \cdot Post_t \\ & + Cum\_trans_{it} \times \beta_6 + Demo\_chars_i \times \beta_7 + City\_chars_i \times \beta_8 + Time_t \times \beta_9 + \varepsilon_{it}. \end{aligned} \tag{3}$$

Before the estimation, we conducted a relative time model [54], the results of which corroborate the assumption of parallel trends in the pre-treatment period. Refer to Fig. **??** for details. Table 2 reports the DiD estimation results. Table **??** demonstrates a complete version of the estimation results. The coefficients of both $TreatCity \cdot During$ and $TreatCity \cdot Post$ were significantly positive (0.1412 and 0.1373, $p < 0.001$ for both), suggesting that people were more likely to use a lucky number during COVID-19 outbreaks to deliver wishes of "luck" to other people; this tendency persisted in the postoutbreak period.

We then analyzed data from a natural disaster, a summer flood, in a similar manner. Three summer floods in China in 2018 were identified, and three sets of treatment and control cities were identified, which are described as follows. Because the three floods all lasted for approximately 2 weeks, a 2-week time window was used for both the predisaster and postdisaster periods. Fig. 4(d) revealed the tendency for lucky numbers to be used both during and after the summer floods in different focal regions. Consistent with our findings in the context of COVID-19, in all three treatment cities, a significant increase in the use of the digit 8 as the last digit of social payments was observed during the summer flood.

- Treatment City 1: Shantou, from August 20 to September 2, 2018. Control cities: Other cities in Guangdong Province.
- Treatment City 2: Gannan, Dingxi, Longnan, Tianshui, Pingliang, and Qingyang from July 2 to July 15, 2018. Control cities: Other cities in Gansu Province.
- Treatment City 3: Chengdu, Mianyang, and Guangyuan from July 2 to July 15, 2018. Control cities: Other cities in Sichuan Province.

The tendency to use lucky numbers in social payments suggested that if this pattern could be identified at an early stage using a tool that processes large-scale mobile transaction data in real-time, the emotional needs of the population could be recognized quickly before the effects of local disasters or other unexpected events become obvious. The tendency would serve as an indicator or a mirror of public sentiment.

4.2 Psychological Rounding Tendency: Detection of Fake Discount Promotions

As described, the tendency for psychological rounding is significant in commercial transactions and has been discussed theoretically in the literature. An examination of the last digit distribution in payments could be used to detect fraudulent business activities, such as fake promotions.

Specifically, the observed distribution of the last digit in commercial transactions could potentially reveal whether a retailer is truly offering a promotion as advertised. To verify this claim empirically, we compared the last digit patterns of the commercial transactions of two retailers, denoted as retailers A and B, which sold similar products in the same city and at similar price levels. Both retailers claimed to offer “a CNě6 discount for the first CNě100 you pay” from August 3 to 9, 2020. However, retailer B modified (specifically, increased) the original price during the promotion, and retailer A did not. Fig. 5 presents the last digit distribution before, during, and after the promotion of the two retailers. We observed that distributions for the two retailers had similar patterns before and after the promotion. In the case of the real promotion for retailer A (i.e., no modification of the original price), the last digit distribution during the promotion differed between before and after the promotion; a significant increase was observed in payments ending in the digit 4. The digit 0 was the most common last digit of the original prices; thus, the application of the CNě6 discount resulted in an increase in digit 4. By contrast, the last digit distribution of retailer B remained unchanged during the promotion, revealing the modification of the original price. This pattern thus indicates that the promotion was fraudulent (or at least not as advertised). Another example with a different promotion is presented in Fig.**??**.

This comparison suggests that only partial information on the last digit of transaction records is adequate for an analyst to exploit the psychological rounding tendency of the last digit to track the marketing behavior of retailers or merchants. Additionally, it is crucial to note that for any tendency of the last digit, a genuine promotion will likely change its distribution and hence lead to a distinct pattern. The detection of fake discount promotion relies fundamentally on the fact that the last digit in commercial transactions exhibits certain discernible patterns, which herein include the psychological rounding tendency observed in the provided data.

5 Conclusion

In summary, we investigated the last digit distribution for different mobile transactions using rigorous statistical tools and empirical evidence. For commercial transactions, we investigated online e-commerce purchases and in-store purchases; for social payments, we investigated inter-individual money transfers and red envelopes. We also compared the last digit distribution before, during, and after the Spring Festival for several ethnic groups with different lucky numbers and before, during, and after disasters. Lucky numbers were more frequently used in transactions closely related to social interactions and were associated with individuals who potentially had greater emotional needs. Psychological rounding was more common in commercial transactions, including in-store purchases and e-commerce purchases, and in money transfers between individuals. On the basis of these findings and their underlying psychological and emotional mechanisms, mobile transaction digit distributions can be used as a mirror of public sentiment and as a possible detector of fraudulent business activity.

Declaration of Competing Interest

The authors declare that they have no conflict of interest in this work.

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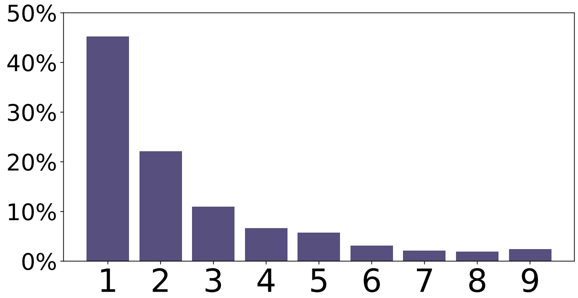
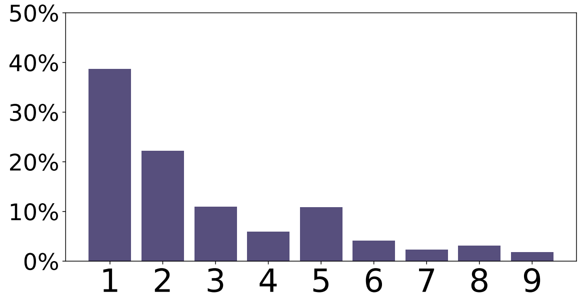
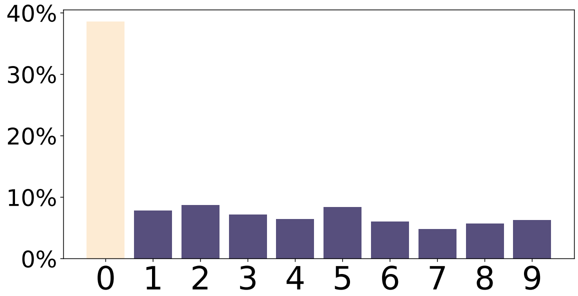


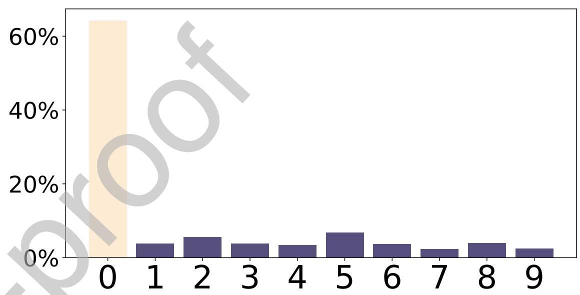
(a) Distribution of the first digit in commercial transactions



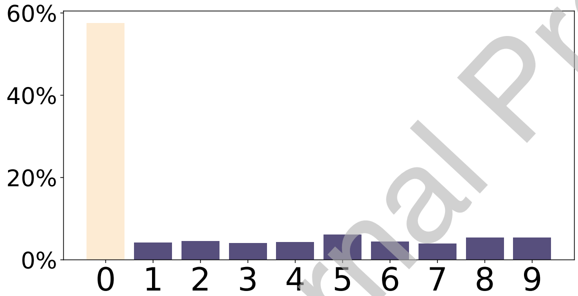
(b) Distribution of the first digit in social payments



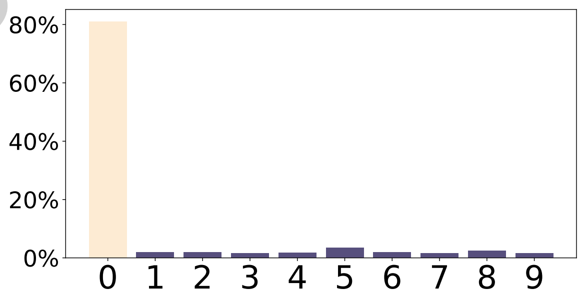
(c) Distribution of the second digit in commercial transactions



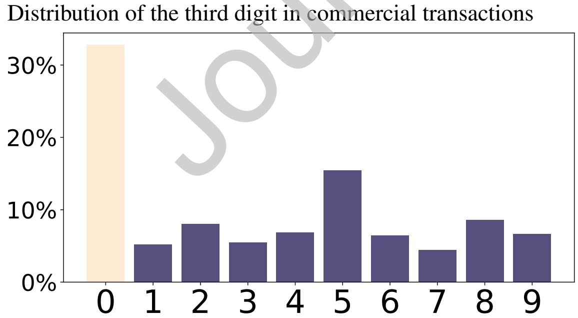
(d) Distribution of the second digit in social payments



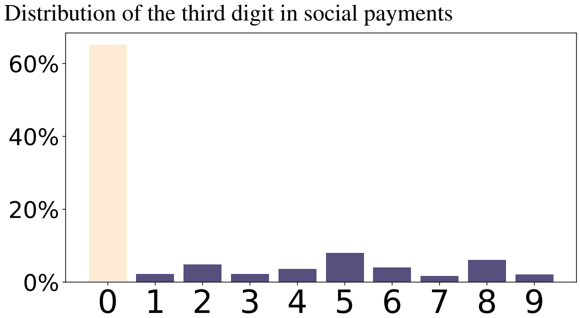
(e) Distribution of the third digit in commercial transactions



(f) Distribution of the third digit in social payments

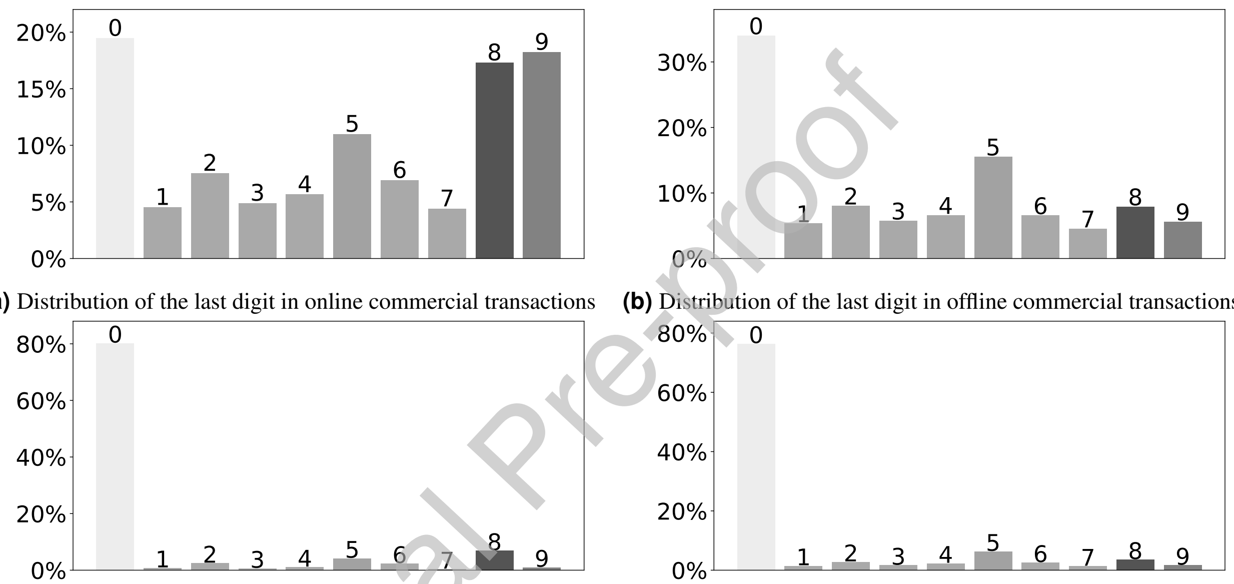


(g) Distribution of the last digit in commercial transactions



(h) Distribution of the last digit in social payments

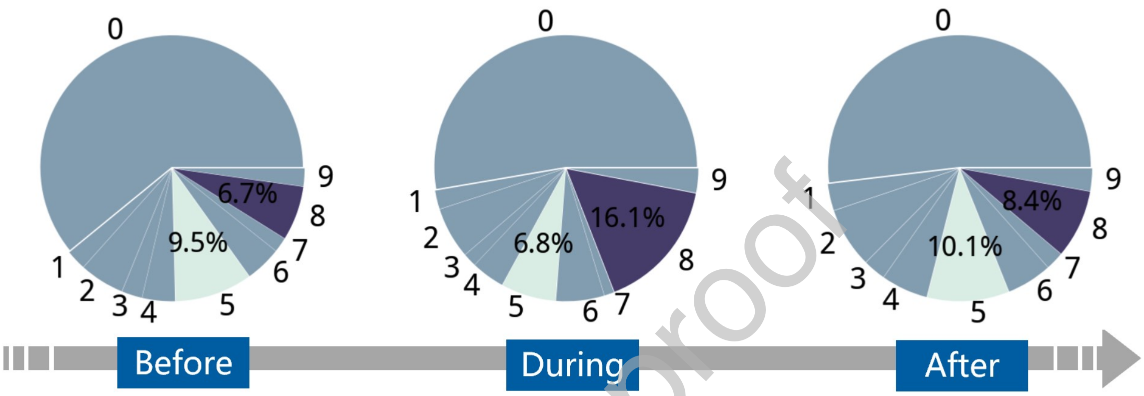
Figure 1. Distributions of the first, second, third, and last digits in mobile transactions in 2018 and 2019. Social payments were more frequently rounded than commercial transactions; thus, the percentage of the digit 0 was relatively higher (corresponding to an even lower total number of all other digits) in social payments.



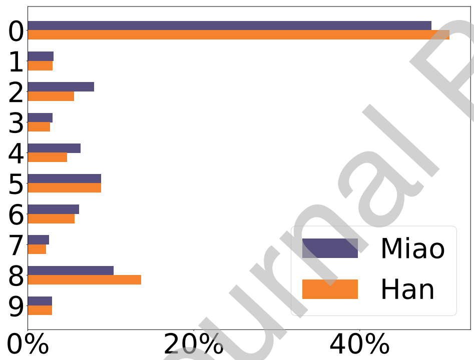
(a) Distribution of the last digit in online commercial transactions **(b)** Distribution of the last digit in offline commercial transactions

(c) Distribution of the last digit in red envelope social payments **(d)** Distribution of the last digit in money transfer social payments

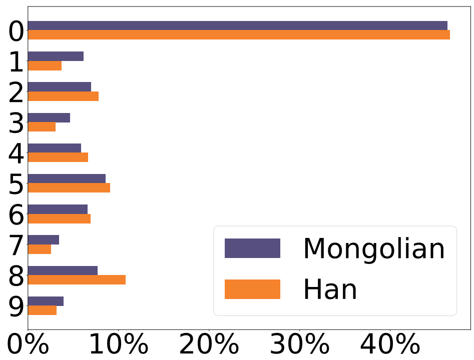
Figure 2. Tendency to choose lucky numbers or for psychological rounding. The time window was between January 2018 and December 2019. In (a), online transactions mostly occurred on e-commerce platforms and stores; offline transactions included spending in restaurants, groceries, and malls. For commercial transactions, online transactions accounted for 9.50% of all transactions with an average amount of CNě94.73; offline transactions accounted for 90.50% with an average amount of CNě216.52. For social payments, red envelopes accounted for 20.34% with an average amount of CNě40.83; money transfers accounted for 79.66% with an average amount of CNě849.48.



(a) Distribution of the last digit in social payments before, during, and after the Spring Festival

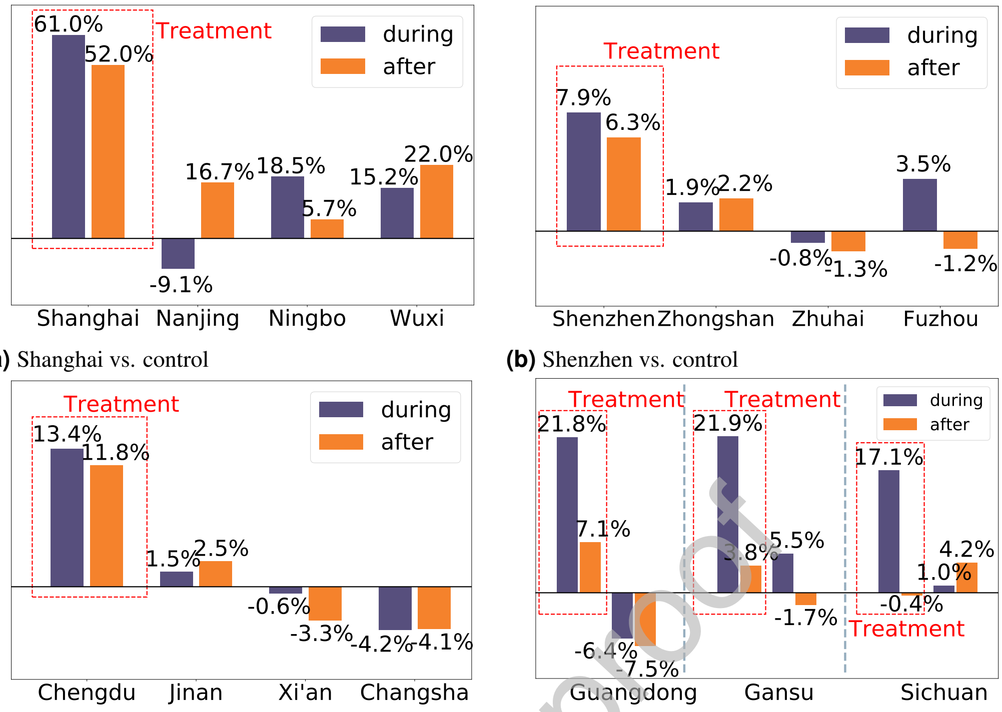


(b) Distribution of the last digit in social payments during the Spring Festival (Miao vs. Han), in descending order of (%by Miao–%by Han)



(c) Distribution of the last digit in social payments during the Spring Festival (Mongolian vs. Han), in descending order of (%by Mongolian–%by Han)

Figure 3. Lucky number tendency during the Spring Festival. Statistics in figures are the average values of year 2018 and 2019.



(a) Shanghai vs. control **(b)** Shenzhen vs. control

(c) Chengdu vs. control **(d)** Treatment (flood) vs. control

Figure 4. Tendency to use lucky numbers during disasters. (a), (b), and (c) present percentage change of the digit 8 in the last digit of social payments during and after a COVID-19 outbreak and (d) presents the results for a summer flood. Baselines in the figures are the values in the predisaster periods (approximately 2 months for COVID-19 and 2 weeks for floods). % change = (during − pre)/pre or (post − pre)/pre. Treatment cities are represented using dotted frames.

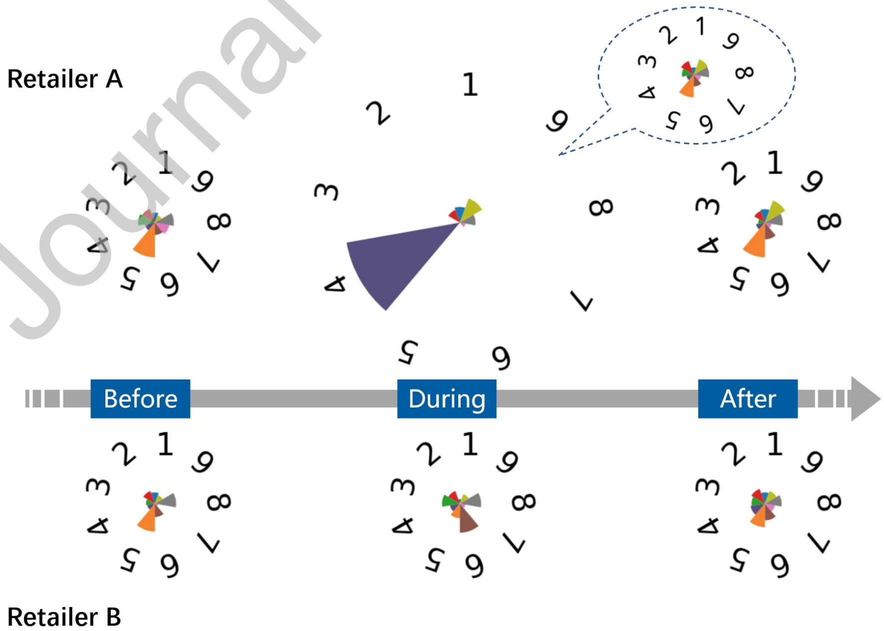


Figure 5. Distribution of the last digit in the commercial transactions of two retailers before, during, and after a promotion. Both retailers are located in Chengdu and sold digital accessories at an average price of CNě60. Both retailers claimed to offer “a CNě6 discount for the first CNě100 you pay” promotion from August 3 to 9, 2020.

Last Digit Tendency: Lucky Numbers and Psychological Rounding in Mobile Transactions

Highlights:

- We investigate the digit distribution of numbers in a large mobile transaction dataset.
- Although the first digit of numbers in transactions follows Benford's law, we find that the last digit has a strong tendency to be a lucky number or be influenced by psychological rounding.
- This lucky number tendency is more significant in transactions that are a key part of social interactions, such as money sent as gifts or as "red envelopes" during holidays, and in transactions with potentially greater emotional needs, such as during COVID-19 outbreaks and natural disasters.
- This psychological rounding tendency is more common in payments between individuals.
- This tendency could be used as an indicator of public sentiment or in methods of detecting fraudulent business activity.

Declaration of interests

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

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Last Digit Tendency: Lucky Numbers and Psychological Rounding in Mobile Transactions

First author: Hai Wang

Dr. Wang is an Associate Professor (with tenure) in the School of Computing and Information Systems at Singapore Management University and a visiting faculty at the Heinz College of Information Systems and Public Policy at Carnegie Mellon University. He received B.S. from Tsinghua University and Ph.D. in Operations Research from MIT. His research focuses on methodologies of analytics and optimization, data-driven decision-making models, machine learning algorithms, and their applications in a general context of smart cities. He has published in leading journals such as American Economic Review P&P, Transportation Science, M&SOM, and Transportation Research Part B/C. He serves as Associate Editor for INFORMS journals Transportation Science and Service Science, Special Issue Editor for Transportation Research Part B, Part C, and Service Science, and Editorial Board Member for Transportation Research Part C and Part E. Dr. Wang was selected as Chan Wu & Yunying Rising Star Fellow, received Lee Kong Chian Research Excellence Award, was nominated for MIT's top Graduate Teaching Award, and won the Excellent Teaching Award at SMU. During his Ph.D. studies at MIT, he served as the co-President of the MIT Chinese Students & Scholars Association and as Chair of the MIT-China Innovation and Entrepreneurship Forum.

Corresponding author: Yingjie Zhang

Yingjie Zhang is an assistant professor of Marketing at Guanghua School of Management, Peking University. Before joining PKU, she was an assistant professor of Information Systems at the University of Texas at Dallas. She received her B.S. degrees in Computer Science and Economics from Tsinghua University and her Ph.D. degree in Information Systems and Management from Heinz College, Carnegie Mellon University. Her research interests center on FinTech, mobile and sensor technologies, big data and smart city, user-generated content, and sharing economy, using interdisciplinary methodologies including structural modeling, machine learning, field experiment, econometrics, and analytical models in IS and marketing. Her research work has been published in the Information Systems Research, Transportation Research Part C, and ACM Transactions on Intelligent Systems and Technology. She is the winner of the Best Paper Award at the International Conference on Information Systems (ICIS 2019) and the winner of the INFORMS ISS Nunamaker-Chen Dissertation Award (2019). She recently received the Best Published Paper Award Runner-up of Information Systems Research in 2020.

Contact:
Email: yingjiezhang@gsm.pku.edu.cn
Postal address: No.5 Yiheyuan Road, Haidian District, Beijing, China