Chapter 9

China's consumer spending e-commerce: facts and evidence from JD's festival online sales*

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1. Introduction

China has had a fast rate of economic growth over the past four decades and has become the second largest economy in the world, following the United States. Different from other high-income countries, like the United States and Japan, China's past economic development mainly relied on investment and net exports, rather than domestic consumption (Lin, 2012; Yu, 2018). However, this pattern has reversed in recent years. According to the *China Statistical Yearbook*, in 2017, the proportion of consumption was 51%. The contribution of consumption to China's gross domestic product (GDP) growth rate accounts for 58.8%, surpassing investment (32.1%) and net exports (9.1%). Clearly, domestic consumption has started to become the locomotive of China's economic growth.

As part of domestic consumption, China's e-commerce transactions are increasing rapidly. According to the most recent *Report of China's E-Commerce*, released by China's Ministry of Commerce, in 2017, China's total e-commerce transactions reached RMB 29.16 trillion (or equivalently US$4.28 trillion). Within that amount, e-commerce goods transactions are RMB 16.87 trillion (US$2.48 trillion). The value of online retail amounts to RMB 7.18 trillion (US$1.06 trillion), with a year-to-year growth rate of 32.2%.

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Evidently, China's e-commerce, particularly, online retail, has become one of the most important components of China's booming domestic consumption. The story that remains to be told is the detailed patterns, facts, and characteristics of the development of online shopping in China, especially from the perspective of consumers.

In this chapter, we seek to understand Chinese people's consumer spending behavior via the platform of e-commerce. The analysis is carried out, thanks to the availability of micro-transaction-level e-commerce data released by the Chinese e-commerce company JingDong (JD), one of the largest online retailers in China. The JD e-commerce data cover most online transactions for the 10 most popular online shopping festivals for Chinese consumers. Overall, we have following interesting and potentially important findings.

First, Chinese consumers enjoy online shopping for Western holidays, such as Halloween and Valentine's Day, as well as the traditional Chinese festivals. Interestingly, the festival with the largest online shopping volume is not the most important festival for Chinese people—the Spring Festival—suggesting that Chinese people, to some extent, exhibit consumption heterogeneity in different festivals.

Second, the most popular products sold online at JD are cell phones, followed by food and beverages, makeup and cosmetics, digital products, and lifestyle and travel goods. These are consistent with the overall patterns suggested by aggregated data provided by the National Bureau of Statistics. The most important categories sold online are food, clothing, and lifestyle products.[1] In 2017, the year-to-year growth rates for food, clothing, and lifestyle products were 28.6%, 20.3%, and 30.8%, respectively.

Third, from the information on consumer age cohorts, we observe that consumers aged 26–35 years make up the largest share of online shopping, followed by those aged 16–25 and 36–45 years. Adding up the online spending of these three age cohorts, their aggregated online spending accounts for half of the entire online spending.

Fourth, separating China into the four economic regions—east, middle, northeast, and west—our e-commerce data show that the east region accounts for the largest share of online spending. Consumers in the east region also exhibit short-run upgrading of their online shopping packages. The shares of the top three most popular product categories—cell phone, food and beverages, and apparel and underwear—accounted for more than 70% of total online sales.

Fifth, we seek to understand the two-way nexus between online spending and regional income. Our data exhibit a strong positive correlation between online spending and regional income. This observation holds for urban and rural areas. Equally interestingly, as the urban–rural income divide is still

1. http://www.stats.gov.cn/tjsj/zxfb/201801/t20180118_1574935.html.

evident in China today, we see that prefectural cities with a large urban–rural income gap seem to have less e-commerce spending. Our empirical regressions confirm all our previous findings. Moreover, with higher average wage income, more people in a particular region enjoy Internet shopping. They also purchase more products online.

This chapter joins a growing literature on the nexus of consumption, income, and age cohorts. Recent studies, such as Fernandez-Villaverde and Krueger (2007), estimate the life cycle of American consumption, using American consumption survey data and controlling for other related factors, such as age cohort, time-specific fixed effects, and demographic information. The studies find that consumption increases significantly over the life cycle for durable and nondurable goods.

Similar to China, many rich economies, such as the United States, have experienced a sharp increase in income inequality (Heathcote et al., 2010). By contrast, consumption inequality in such countries has not increased much. This divergence is due, in large part, to different trends in within-group rather than between-group inequality, as recognized by Krueger and Perri (2006). The within-group inequality is a residual measure that captures the idiosyncratic income shocks not captured by the traditional between-group inequality attributable to the characteristics revealed by consumers, such as gender and education level. If consumers can trade contingent consumption claims, Krueger and Perri (2006) show that the within-group consumption inequality can be interpreted as the within-group income inequality.

Developing countries usually rely on seasonal agriculture for their main incomes. Paxson (1993) thus examines whether rural consumers track income across seasons over the course of a year. She does not find much evidence to support this hypothesis. However, to the best of our knowledge, thus far, there has not been a systematic study on Chinese people's consumption behavior, especially from the online transaction e-commerce perspective, although China has already become one of the economic giants in the world. This chapter thus aims to fill this gap.

The rest of the chapter is organized as follows. Section 2 broadly describes the development of e-commerce in China, particularly the JD company. Section 3 explores the essential facts and features of China's e-commerce consumer spending via JD's platform, through the perspectives of festival time spans, product categories, age cohorts of consumers, and regional income heterogeneity. Section 4 takes a step forward to examine empirically the nexus between online consumer spending and regional income. Finally, Section 5 concludes.

2. Overall development of China's e-commerce

E-commerce is a new solution to mitigate the asymmetric information problem between producers and consumers. The online platform is helpful for tremendously reducing the costs of trade by removing the brokers or middle persons in transactions. Moreover, e-commerce enhances the quality of the goods purchased online, by offering a unified platform for market competition.

2.1 China's main online retailers

In the past two decades, the online store has become a necessary part of the manufacturer's selling system. Traditional retail giants such as Walmart, Carrefour, and Costco have developed online departments, while upstarts such as Amazon, eBay, and Alibaba have established new e-dynasties. Starting from selling books online, Amazon.com has become the most significant global online store in the world. In 1994, when Jeff Bezos founded the giant, no one indeed believed such a new way of selling would become so prevalent.

In 2004, Amazon entered China by acquiring Zhuoyue.com, which was one of the largest online book stores in China at that time. It was traditional wisdom that this international e-commerce giant would conquer China's market with its rich experience and sufficient capital endowment. Again, no one would have believed that Amazon.cn would still be struggling to exceed 1% market share 24 years later. This is a very interesting puzzle to explore. What are the characteristics of China's e-commerce market that made it the Waterloo for the global successor?

In May 1999, a company called 8848 was founded in Beijing. As the first consumer-to-consumer entity in China, it competed vigorously with Yiqu, which was established 4 months later at the beginning of the e-commerce era in China. Alibaba, the current e-commerce empire, was not founded until 4 years later. Then, Yiqu brought another big name, eBay, one of the largest online stores in the United States, into the battle, and the fight became white-hot between Yiqu and Alibaba. The war ended with eBay's withdrawal from China. Alibaba built its foundation for the future by winning the war and started its business-to-consumer (B2C) online store in 2008.

Even earlier than T-mall, Alibaba's B2C brand, another pioneer of e-commerce was already running the B2C business 4 years ago. JD initiated its online store in 2004, selling computer, communication, and consumer electronics commodities. JD has continued to expand its market share over the past decade.

E-commerce has grown faster in China than in any other country over the past decade. According to JD's financial reports, its gross merchandise volume reached RMB 0.93 trillion (US$0.014 trillion) in 2016 and increased to RMB 1.30 trillion (US$0.19 trillion) in 2017. Meanwhile, total retail sales in China reached RMB 33.23 trillion (US$4.74 trillion) in 2016 and RMB 36.63 trillion (US$5.39 trillion) in 2017, according to the *China Statistical Yearbooks*. JD itself contributed around 3% of the sales of consumer goods in China, and this proportion has grown larger since then.

2.2 JD's E-Commerce data

We extracted data from JD, which has its headquarters in Beijing. It is one of the two massive B2C online retailers in China by transaction volume and revenue (301.8 million active users in 2018), a member of the Fortune Global 500, and a significant competitor of the Alibaba-run T-mall. Fig. 9.1 shows the market shares of the dominant Chinese online retailers. In 2017, JD was the second largest online retailer, with a market share of 32.5%, following T-Mall, which is operated by Alibaba, an e-commerce giant in China that occupies 52.73% of China's online retail market.

Our data set covers the daily top 20 product categories sold on specific holidays and the week before them on JD. The data set includes the 10 most popular festivals that people celebrate in China today. The traditional Chinese festivals are celebrated in the lunar calendar as follows. The Spring Festival is the first day of the lunar year, which usually is at the end of January or beginning of February. The following Chinese festivals include the Lantern Festival (i.e., lunar January 15), Tomb-Sweeping Day (i.e., April 5), Dragon Boat Festival (i.e., lunar May 5), Chinese Valentine's Day (i.e., lunar July 7), Mid-Autumn Day (i.e., lunar August 15), and the Double Ninth Festival (i.e., lunar September 9). The data set also covers the online shopping information for three popular Western holidays: Valentine's Day, Halloween, and Christmas.

Our data set covers festival shopping information for two years—2016 and 2017. Ideally, we would have 80 days of coverage for each year, given that the data set includes 10 festivals. However, because of the changing overlap of the Gregorian and lunar calendars, by which the Chinese festivals are defined, the coverage period may vary across years. We have 78 of 365 days of coverage in 2016 (21% of the year). There are 2 days of overlap between the Spring Festival and Chinese Valentine's Day. Similarly, our data

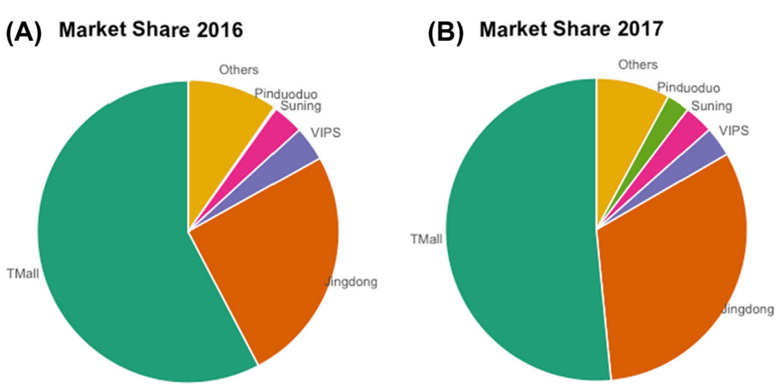


FIGURE 9.1 Market share of JD.com in the year (A) 2016 and (B) 2017.

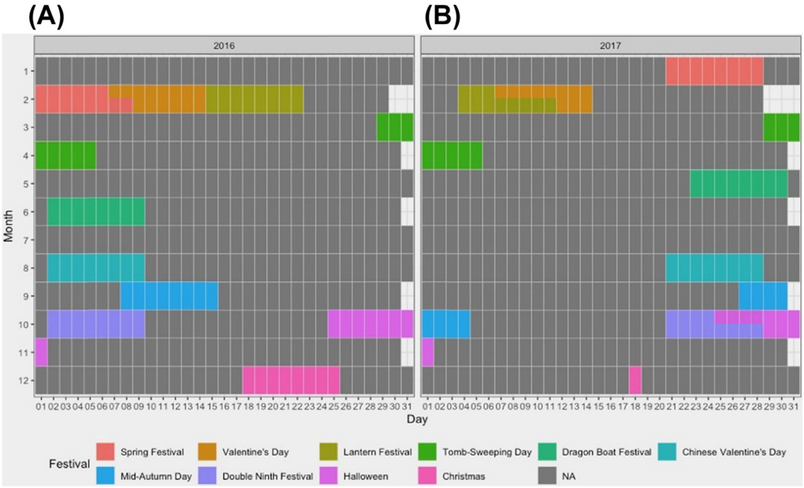


FIGURE 9.2 Distribution of festivals and holidays. (A) 2016 and (B) 2017.

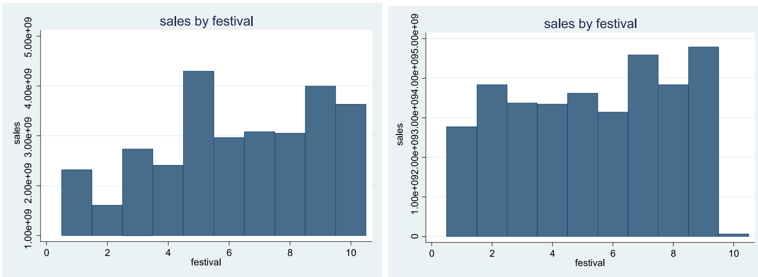
set covers 64 of 365 days in 2017 (18% of the year). In 2017, 5 days overlap between the Lantern Festival and Chinese Valentine's Day, and 4 days overlap between the Double Ninth Festival and Halloween. The shopping information for Christmas in 2017 is incomplete, as the data were extracted by December 18. Accordingly, we only have 1 day of shopping information for Christmas 2017. To have a better understanding of the exact days covered by our data set, Fig. 9.2 offers a calendar with nonmissing festival information.

Our data set also includes information on consumer age cohorts, together with product industrial category, sales volume, quantity sold, number of buyers, and number of orders for each online transaction.

3. Patterns and key features of China's e-commerce

3.1 Online consumer spending, by festival

We use data from the 10 most important festivals and holidays in China: Chinese Valentine's Day, Halloween, Mid-Autumn Day, Christmas, Double Ninth Festival, Spring Festival, Tomb-Sweeping Day, Dragon Boat Festival, Lantern Festival, and Valentine's Day. As shown in Fig. 9.3, in 2016, China's highest level of online consumer spending was during the Dragon Boat Festival, followed by the Halloween, Christmas, Mid-Autumn Festival, and Double Ninth Festival. By comparison, the most popular festival for large



Note: The 10 holidays are 1. Spring Festival, 2. Valentine's Day, 3. Lantern Festival, 4. Tomb-Sweeping Day, 5. Dragon Boat Festival, 6. China's Valentine's Day, 7.Mid-Autumn Festival, 8 Double-Ninth Festival, 9. Halloween, and 10. Christmas. The chart on the left shows online consumer spending in 2016; the chart on the right shows that in 2017.

FIGURE 9.3 Online consumer spending, by festival.

online consumer spending during 2017 was Halloween, followed by the Mid-Autumn Festival, Valentine's Day, Double Ninth Festival, and Dragon Boat Festival.[2]

Two interesting observations stand out. First, Chinese consumers exhibit strong propensity to spend during Western festivals. In particular, consumer spending during Halloween was large and stable in these 2 years and even registered the greatest online consumer spending in these 2 years. By sharp contrast, there is a lot of fluctuation in online consumer spending during other popular Western festivals, such as Valentine's Day and Christmas. Online consumer spending for Valentine's Day was negligible in 2016, but it increased to a huge amount in 2017. Online consumer spending for Christmas decreased substantially from 2016 to 2017 because of the incomplete information on sales of Christmas in 2017. It is interesting that online consumer spending for Christmas is not that much. This finding is different from online consumer spending in Western countries such as the United States.

Second, although the Spring Festival is the most important festival in Chinese culture, it is surprising that there is not much online consumer spending during this festival, at least compared with other festivals. There are two possible reasons for this puzzle. First, Chinese people are more likely to stay with their family at home and hence spend less during the Spring Festival. Second, and perhaps more importantly, Chinese people are more used to purchasing consumer goods onsite and in person rather than through online shopping, given that they have a 2-week national vacation during the Spring Festival.

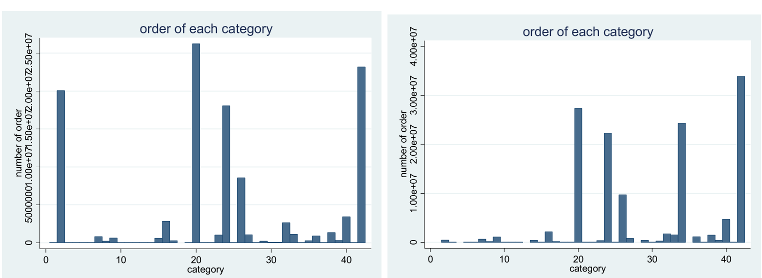
2. Note that sales data of Christmas in 2017 is incomplete.

3.2 Online consumer spending, by product

JD.com lists a variety of product categories on its Internet surface, covering 42 categories. The categories are different from other standard industrial classifications, such as the Chinese Industry Classification System adopted by China's National Bureau of Statistics and the Harmonized System adopted by China's Customs. These categories include not only manufacturing products but also agricultural products.

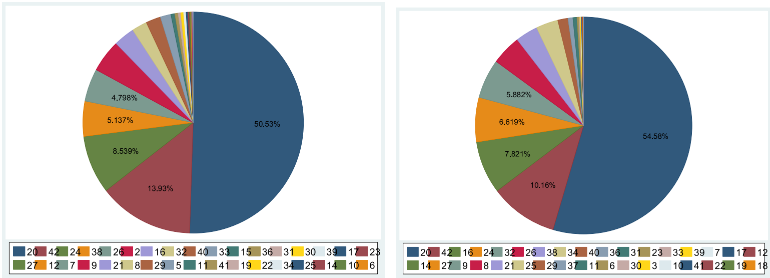
Fig. 9.4 shows online consumer spending by product category in 2016 and 2017. The top five largest product categories in 2016 were cell phones (code: 20), food and beverages (code: 43), makeup and cosmetics (code: 02), digital products (code: 23), and lifestyle and travel goods (code: 25). In 2017, food and beverages, cell phones, beauty and cosmetics (code: 34), digital products (code: 23), and lifestyle and travel goods (code: 25) remained the top five online consumer goods categories, although their relative rankings switched a bit. For instance, the largest consumption sector was cell phones in 2016, but it switched to food and beverages in 2017. By way of comparison, the composition of online consumer spending in China is much different from that in other high-income countries, such as the United States, where art is one of the important consumer products, as American people treat art as a profitable way to invest (Mandel, 2009). However, today Chinese people still spend a lot on some necessities.

It is also worthwhile to explore the products on which Chinese people spend the most for each key festival, particularly the festivals with the largest consumer spending. The top five festivals for consumer spending in 2017 were the Halloween, Mid-Autumn Festival, Valentine's Day, Double Ninth Festival, and Dragon Boat Festival. We now check the most popular products purchased during those festivals.



Note: The names of the product categories refer to Appendix Table A.1. The chart on the left shows the number of online orders, by category, in 2016; the chart on the right shows that in 2017.

FIGURE 9.4 China's e-commerce orders, by product category.



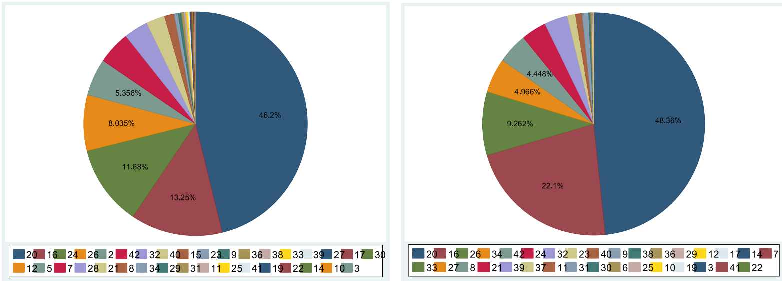
Note: The names of the product categories refer to Appendix Table A.1. The chart on the left shows online consumer spending in 2016; the chart on the right shows that in 2017.

FIGURE 9.5 Products sold online during the Mid-Autumn Festival.

As shown by the pie on the left in Fig. 9.5, during the Mid-Autumn Festival in 2016, the most popular products sold online were cell phones (code: 20), followed by food and beverages (code: 42), apparel and underwear (code: 24), and alcohol (code: 38). The cell phone category itself accounted for more than a half of total online sales. These top five categories accounted for around 80% of all products sold online during the Lunar Double Ninth Festival. The other 37 product categories accounted for 20% of spending.

Three important observations appeared in 2017 for the dynamic behavior of Chinese people's e-commerce, as exhibited by the pie on the right in Fig. 9.5. First, the most important products were still cell phone, followed by food and beverages (code: 42), household appliances (code:16), apparel and underwear (code: 24), and stationary (code: 32). The top three products were almost identical to those in 2016. Second, the five top products accounted for around 84% of all online sales during the festival. The other 37 industries accounted for 15%. Finally, and most importantly, we also observe that the distribution of online consumer spending by industry is even more skewed toward to the cell phone industry, for which the share increased from around 50% in 2016 to around 55% in 2017.

The most popular Western holiday for online consumer spending in China is Halloween. So, it is interesting to ask whether Chinese people's spending behavior during the Western holiday is consistent with that during the popular Chinese festivals. Fig. 9.6 picks up this task. As shown in the pie on the left in Fig. 9.6, the most popular products sold online for Halloween are cell phones (code: 20), household appliance (code: 16), apparel and underwear (code: 24), mother and baby products (code: 26), and makeup and cosmetics (code: 02). The top three categories are very close to those for the Mid-Autumn Festival. The big sales of makeup and cosmetics are also very intuitive, given the essence of Halloween. Thus, this finding hints that Chinese people are



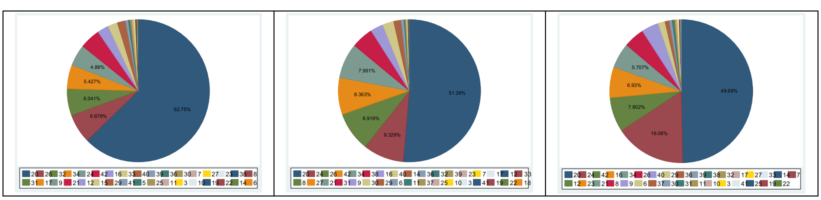
Note: The names of the product categories refer to Appendix Table A.1. The chart on the left shows online consumer spending in 2016; the chart on the right shows that in 2017.

FIGURE 9.6 Products sold online during Halloween.

consistent in their spending behavior. They do not show much heterogeneity by the cultural origin of the festivals.

Do Chinese people have significant consumption preferences during different important festivals? To explore this question, we compare Chinese people's online spending during the Mid-Autumn Festival to other popular festivals, the Dragon Boat Festival, Chinese Valentine's Day, and Mid-Autumn Festival.

As seen in Fig. 9.7, e-commerce spending for the Mid-Autumn Festival was similar to that during the Valentine's Day (left pie), Double Ninth Festival (middle pie), and Dragon Boat Festival (right pie) in 2017. The top products sold online were also very similar to those sold during the Mid-Autumn Festival. The top five products purchased online were cell phones (code: 20), mother and baby cares (code: 26), makeup and beauty (code: 02 and 34), apparel and underwear (code: 24), and food and beverages (code: 42). Although the rankings of the products vary by year and by festival, these five



Note: The names of the product categories refer to Appendix Table A.1. The pie on the left shows online spending during the Valentine's Day; the middle pie shows that for Double Ninth Festival, and the pie on the right shows that for the Dragon Boat Festival. All the data are for 2017.

FIGURE 9.7 E-commerce spending, by product category and festival.

product categories still maintain the plateau of Chinese people's e-commerce spending.

Figs. 9.6 and 9.7 also deliver the interesting and important message that Chinese people's spending behavior is mainly focused on basic consumption demand, such as food and clothing and communication instruments such as cell phones. Higher-level consumer products, such as art and auction items (code: 21), music (code: 41), and outdoor and sports goods (code: 36), only account for a small proportion of people's spending. We suspect that this is positively correlated with consumers' income, which will be carefully explored in the next section.

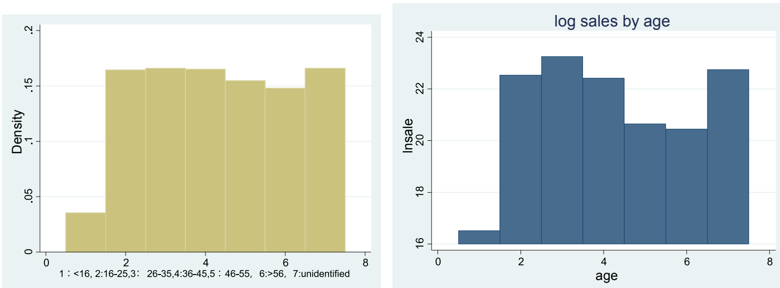
3.3 Online consumer spending, by age cohort

This section explores China's online consumer spending by age cohort. Our data set has information on consumer age, as JD.com asks its online consumers to provide such information. JD.com offers seven age categories on its web page. We hence separate all consumers into seven cohorts by age: younger than 16 years (code: 1); 16−25 years (code: 2); 26−35 years (code: 3); 36−45 years (code: 4); 46−55 years (code: 5); older than 56 years (code: 6); and unidentified (code: 7). Around 1,078,000 transactions are recorded as "unidentified" of the entire 6,496,000 transactions. That is, for around 16% of online transactions, consumers' ages are not specified because of missing information when such consumers registered online.

However, 84% of the people report their age cohort. Although it is nearly impossible to examine consumers' exact year born, there are two substantial reasons to believe that the information for age cohort is accurate and truthful. First, as JD offers shopping recommendations to different cohorts, it is in consumers' self-interest to reveal their age. Second, it is possible that consumers scan their other Internet communication surfaces, such as WeChat, to register quickly on JD.com. In this case, all personal data can be shared across Internet communication surfaces, which require real personal data, as they are combined with consumers' banking information.[3]

Fig. 9.8 shows number of transactions for each age cohort (left chart) and the corresponding online sales for each age cohort (right chart). In addition to the 16% of transactions for which the consumer's age is not specified, around 3.5% of the transactions were purchased by children. This is possible, given that high school students are familiar with Internet shopping and equipped with smartphones with a high coverage ratio—almost "one person−one phone." However, online consumer spending by the nonadult cohort is only a small proportion. This makes good sense as well: students or kids do not have

3. One possible exception is that consumers use other people's credit cards to pay. In this case, we cannot precisely know consumers' personal data. This may explain the large proportion of consumers in the unidentified age cohort.

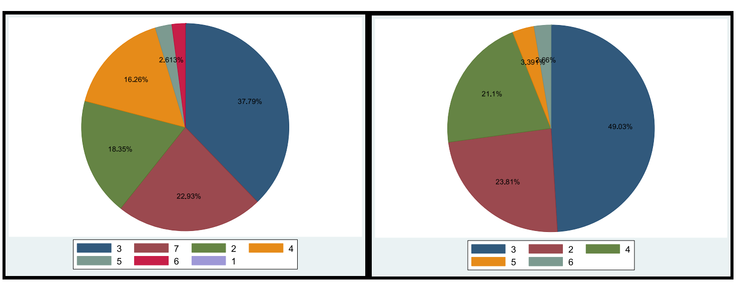


Note: The chart on the left shows the number of transactions for each age cohort; the chart on the right shows the online sales for each age cohort. All the data are for 2017.

FIGURE 9.8 China's e-commerce consumer spending by age cohort.

income and cannot spend much. However, the unidentified age cohort had the second largest online consumer spending in 2017.

The pie on the left in Fig. 9.9 shows the online consumer spending distribution for the entire seven age cohorts. The unidentified age cohort accounts for 16.3% of total online purchases. To guarantee that our statistical analysis is not contaminated by the missing information associated with the unidentified and nonadult age cohorts, we drop these two age cohorts from our analysis. The pie on the right in Fig. 9.9 shows the online consumer spending distribution for the other five age cohorts. Consumers ages 26–35 years have the largest share of online purchasing, registering 49% of all online consumer spending by the five age cohorts, followed by the 16–25 years cohort, at 24%, and the 36–45 years cohort, at around 21%. These three age cohorts account



Note: The numbers represent the following age cohorts: younger than 16 years (code: 1); 16-25 years (code: 2); 26-35 years (code: 3); 36-45 years (code: 4); 46-55 years (code: 5); older than 56 years (code: 6); and unidentified age (code: 7). All the data are for 2017.

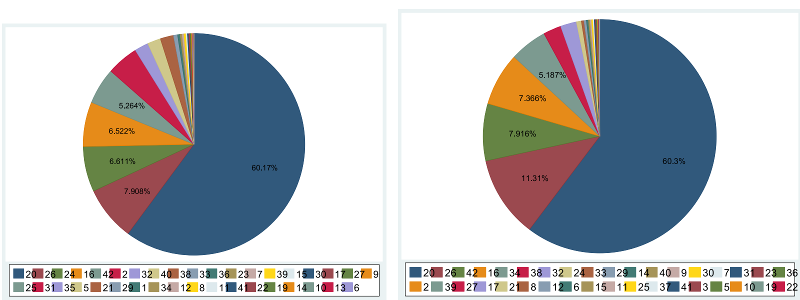
FIGURE 9.9 Composition of e-commerce consumer spending, by age cohort.

for more than 80% of all online consumer spending. This is also true when we include the other two age cohorts (i.e., unidentified age and nonadult), as shown in the pie on the left in Fig. 9.9.

Such statistical findings are intuitive. On the one hand, compared with younger people (i.e., younger than age 26 years), consumers in the 26–35 years cohort have more accumulated income, and hence they have higher marginal propensity to consume. On the other hand, compared with older age cohorts, consumers in the 26–35 years cohort are more familiar with online shopping. Older Chinese people still prefer onsite shopping, although they may use Internet surface payment kits, such as WeChat.

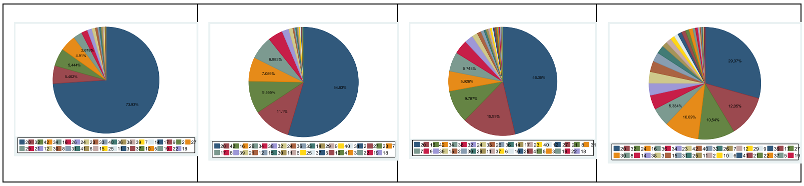
The next interesting question is as follows: what are the most important products consumed by each age cohort, particularly by the cohort with the largest online spending? Fig. 9.10 picks up this task. The pie on the left represents the industrial categories for goods purchased by consumers' ages 26–35 years. Two observations are apparent. First, the top five product categories consumed by people in this age cohort are cell phones (code: 20), mother and baby cares (code: 26), apparel and underwear (code: 24), household appliances (code: 16), and food and beverages (code: 42). This list is similar to the product categories exhibited in Fig. 9.4. Second, by comparing the data for 2016 in the pie chart on the left and those for 2017 in the pie chart on the right, we see that consumers in this age cohort increased their share of purchases of mother and baby cares. The proportion of food and beverages in their consumption package increased significantly, from 7.9% to 11.3%.

Fig. 9.11 shows that consumers with large online spending in other age cohorts (i.e., 16–25, 36–45, and 46–55) have an industrial product distribution that is similar to the consumers in the 26–35 years cohort. The most interesting exception is the nonadult cohort exhibited in the pie on the right. The top goods consumed by children are cell phones (code: 20), stationary



Note: The names of the product categories refer to Appendix Table A.1. The chart on the left shows online consumer spending in 2016; the chart on the right shows that in 2017.

FIGURE 9.10 Categories of products purchased by consumers in the 26–35 years age cohort.



Note: The names of the product categories refer to Appendix Table A.1. The pie on the left shows online consumer spending for those in the 16-25 years cohort; the second pie from the left, for those in the 36-45 years cohort; the third pie from the left, for those in the 46-55 years cohort; and the pie on the right, those younger than 16 years. All the data are for 2017.

FIGURE 9.11 Categories of products purchased, by consumers' age cohort.

(code: 32), apparel and underwear (code: 24), household appliance (code: 16), and outdoor and sports (code: 36). The finding that cell phones are the most popular products for the nonadult cohort is very consistent with the reality in China today. The other findings also make good senses. The teenagers are usually in schools and have more spending on stationary and sports instrument.

3.4 Online consumer spending, by region

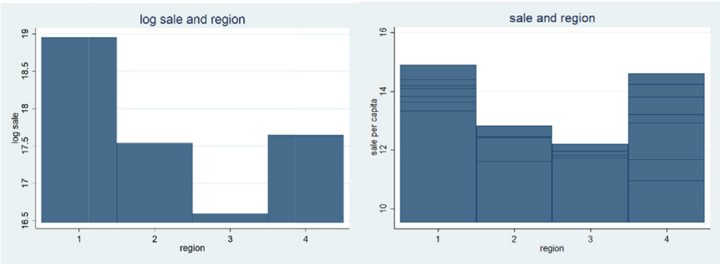
It is well known that China has 31 provinces (or centrally governed municipality or autonomous region). The economic scale of each province differs. For instance, Guangdong province, the largest province in GDP, has a similar economic size as Australia. The GDP of Tibet, which is the smallest autonomous region in economic scale, is similar to that of Bosnia. Usually the east coastal provinces are economically larger, as they have easier access to the Pacific Ocean and better local roads and highways (Liu et al., 2017). For instance, the top three largest provinces (i.e., Guangdong, Jiangdu, and Shandong) are all located in the east coastal region. By contrast, the middle and the west regions have relatively poor infrastructure and are landlocked. They have smaller economic size. Similarly, in terms of standard of living, or more precisely, GDP per capita, we see a descending order of the geographic regions: east, middle, and west. The province-like centrally governed municipalities, including Tianjin, Shanghai, and Beijing, have the highest GDP per capita.

If a region has greater GDP or GDP per capita, it would be expected that the region would have greater online consumer spending, given that people there have higher purchasing power. To see whether this is supported by the data, we separate the entire country into four regions: east, middle, west, and northeast. We have added a region, the northeast, to the standard classification. This is because the northeast region is capital-intensive and hence has relatively greater GDP; however, its GDP per capita is not necessarily high. As exhibited in Appendix Table A.2, the east region includes the following 10 provinces: Beijing, Tianjin, Hebei, Shandong, Jiangsu, Shanghai, Zhejiang, Fujian, Guangdong, and Hainan. The middle region includes Shanxi, Henan, Hubei, Anhui, Jiangxi, and Hunan. The northeast region includes three provinces: Heilongjiang, Jilin, and Liaoning. Finally, the remaining 12 provinces are classified in the west region.

Fig. 9.12 shows that the east region has the largest online consumer spending in terms of GDP and GDP per capita. This is consistent with our expectation. However, an interesting finding is that the west region has the second largest e-commerce, which is higher than its counterparts in the middle and northeast regions. One possible reason is that the west region includes many provinces. Some of the inland provinces, such as Sichuan and Chongqing, indeed have high GDP and GDP per capita.

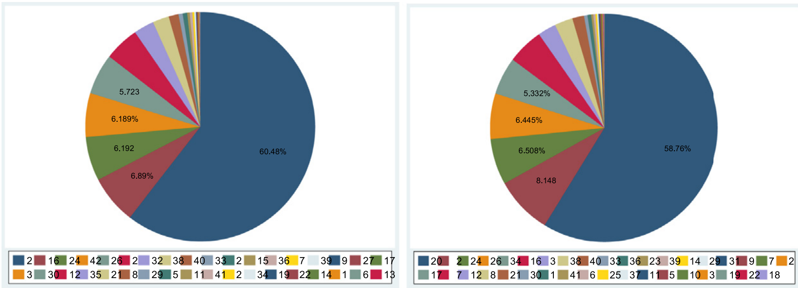
Over the past four decades, Chinese people's annual income has increased from less than US$100 in 1978 to US$8643 in 2017. It is interesting to ask whether people, especially those in the rich regions, have upgraded their consumption basket or changed the composition of their spending. Fig. 9.13 aims to answer this question. Although we only have data for 2 years, we use these data to explore the dynamic changes in people's online consumer spending behavior. The data are good enough to understand the short-run movement of people's spending activity. As shown in Fig. 9.13, the most popular industry for online consumer spending is cell phone (code: 20), followed by food and beverage and apparel and underwear. Interestingly, the proportion of spending in another category with large consumption—food and beverage (code: 42)—increased from 6% in 2016 to more than 8% in 2017.

Do people in different regions exhibit consumption heterogeneity? To check this out, we compare the sectoral online consumer spending in 2017 in three regions: middle, northeast, and west, as shown in Fig. 9.14. The most



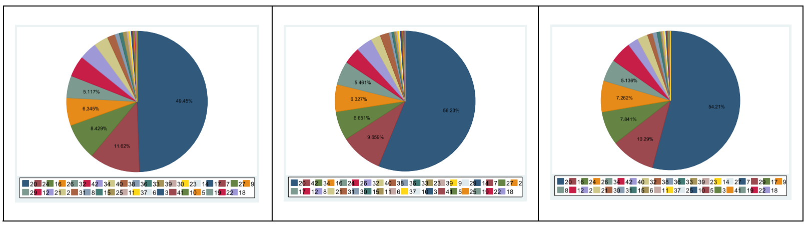
Note: Region 1 (2, 3, 4) denotes the east (middle, northeast, west) region, respectively. The chart on the left shows log sales by region; the chart on the right shows log sales per capita by region. All the data are for 2017.

FIGURE 9.12 E-commerce sales, by region.



Note: The names of the product categories refer to Appendix Table A.1. The chart on the left shows online consumer spending in 2016; the chart on the right shows that in 2017.

FIGURE 9.13 Categories of products purchased by consumers in the east eegion.



Note: The names of the product categories refer to Appendix Table A.1. The pie on the left (middle, right) shows online consumer spending in the middle (northeast, west) region. All the data are for 2017.

FIGURE 9.14 E-commerce spending, by product category and region.

popular sector is still cell phones, which accounts for around a half in all these three regions. Overall, people in different regions have no significant online spending heterogeneity.

4. E-commerce spending and regional income

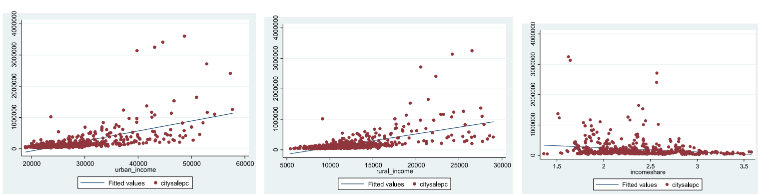
4.1 Trends and patterns against regional income

It is well known that China faces a severe urban–rural divide (Naughton, 2017). Chinese people in urban areas have higher incomes than those in the rural areas, as the manufacturing factories are concentrated in urban areas, so it is easier for the people living in those areas to find a job or a better job with higher wages. In this sense, urbanization and industrialization indeed are a nexus in China's economic development (Lin, 2012). China has a large urban–rural income ratio, but the gap has grown smaller over time. The ratio decreased from 3.5 in 2007 to 2.33 in 2016 and 2.30 in 2017, as shown in our data. The urban–rural income ratio can be used as a proxy for the skilled–unskilled labor income ratio because skilled workers usually reside in urban areas. With this proxy measure, China's skilled−unskilled income ratio is higher than its counterparts in the United States (where the ratio is 1.8) and the European countries (where it is about 2), as introduced by Feenstra (2010).

China has 294 prefectural cities. Dropping population less than 1000 people and missing information on cities' incomes, we have 285 prefectural cities in our data set. Similar to other countries, such as the United States and Japan, China's prefectural cities include urban residents and rural farmers. Taking the data for 2016 and 2017 together, the top five prefectural cities with highest urban income per capita are Shanghai, Beijing, Hangzhou (Zhejiang), Ningbo (Zhejiang), and Guangzhou; the next five cities are Shaoxing (Zhejiang), Nanjing(Jiangsu), Jiaxing (Zhejiang), Wuxi (Jiangsu), and Shenzhen (Guangdong).

For rural incomes, the top five prefectural cities are the following: Jiaxing (Zhejiang), Ningbo (Zhejiang), Zhoushan (Zhejiang), Hangzhou (Zhejiang), and Huzhou (Zhejiang). By contrast, for the urban−rural income ratio, the top five prefectural cities are Xinzhou (Shanxi), Longnan (Gansu), Tianshui (Guizhou), Yan'an (Shanxi), and Qingyang (Guangdong). Different from high-income cities, which are mostly concentrated in Zhejiang and Guangdong, the cities with the largest income gap are mostly located in the west region. Although the average income gap between urban and rural areas is 2.32, the largest income gap is 3.56 (Xinzhou) and the smallest is 1.38 (Zhongshan).

How does a city's income affect its online consumer spending? We plot prefectural cities' online sales against their urban income and rural income, respectively, in Fig. 9.15. Clearly, as shown in the left and middle plots in Fig. 9.15, cities' online consumer spending is positively associated with income, regardless of whether the plot is for rural (the plot on the left) or urban areas (the plot on the right). Although the plots have some outliers, the cities' online consumer spending is much higher than their income, and the fitted lines are not affected by the outlier observations.



Note: The plot on the left shows cities' online sales per capita against their urban income. The middle plot shows cities' online sales per capita against their rural income. The plot on the right shows cities' online sales per capita against their urban-rural income gap.

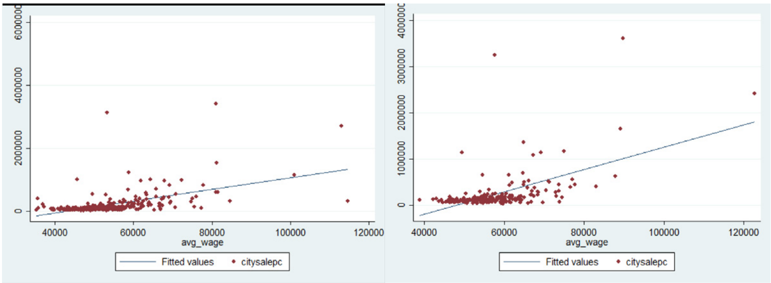
FIGURE 9.15 E-commerce and prefectural city income.

An even more interesting question is the relationship between a city's e-commerce and its urban—rural income ratio. As shown in the plot on the right in Fig. 9.15, cities with a larger urban—rural income divide have smaller online consumer spending. This observation makes good sense. Within a particular prefectural city, a city with large urban income has a lot of online consumer spending. Simultaneously, the same city with small rural income is associated with less e-commerce. Taking these two factors into account, a city with a large urban—rural income gap tends to have small online sales, as suggested by the plot on the right in Fig. 9.15.

Finally, it is interesting to ask whether Chinese people use their permanent income or current income to support their online consumer spending. This question matters because people may finance their spending from other sources, such as banks and other financial institutions. This is particularly true in the United States. In this case, it is possible that people with lower wage income still have high consumer spending (including online purchases). To see whether this is also the case in China, Fig. 9.16 plots city per capita online consumer spending against city-level average income. Evidently, cities with higher wage income are associated with higher e-commerce. This is true for 2016 (the plot on the left) and 2017 (the plot on the right).

4.2 Estimation results

We now move to the econometric analysis. As discussed, our data set includes the following information for each online transaction: sales, quantity sold, number of orders, number of buyers, and the festival and prefectural city in which the sales take place. Table 9.1 reports the main summary statistics for the key variables.



Note: The plot on the left shows cities' online sales per capita against their wage income in 2016; the plot on the right shows that in 2017.

FIGURE 9.16 E-commerce and prefectural city wage income.

TABLE 9.1 Summary statistics for key variables.

Variable	Observations	Mean	Standard deviation
Number of orders	6,496,912	38.430	170.414
Quantity sold	6,496,912	78.361	473.675
Sales	6,496,912	9761.602	136,093
Number of buyers	6,496,912	37.001	162.400
City population	5,341,376	455.904	328.010
City total wages	3,918,323	39.220	84.168
City average wage	4,608,363	55557.86	10725.27
City rural income	5,246,117	12967.85	4220.587
City urban income	5,284,619	29068.11	7049.806

Table 9.2 reports the regression results. There are more than 4,553,000 observations in each regression. In column (1), we regress online sales on city-level average wage income, city population, urban–rural income ratio, and a variety of age cohort variables. We also control a rich set of 42 industry-fixed effects and 31 province-fixed effects. Three findings appear. First, cities with a large population have more online sales, indicating that the greater is the number of consumers, the larger is e-commerce in the city. Second, if a city has higher average wage income, it has more online sales. Third, the larger is the urban–rural income gap, the smaller is the city's amount of online sales. These three empirical findings are consistent with the data analysis in the previous section.

The regression in column (1) in Table 9.2 also includes the age cohort variables. Taking the nonadult group as the default group, all other online consumers are classified by age into six groups: 16–25 years, 26–35 years, 36–45 years, 46–55 years, older than 55 years, and age unidentified. Compared with nonadult online spending, all six groups exhibit more online consumer spending. The ranking of online spending for these six age cohorts is the following: 26–35 years, age unidentified, 36–45 years, 16–25 years, 46–55 years, and older than 55 years. This ranking is identical to the analysis conducted in the previous section, suggesting that the ranking is preserved even if we control for other important factors.

Our data are for 2 years. To rule out possible time trends, column (2) in Table 9.2 runs a similar regression, controlling for year-specific fixed effects. We also control for province-specific fixed effects in column (2). It turns out that the estimation results in column (2) are very close to those in column (1) statistically and economically. The rest of Table 9.2 replaces online sales with the number of orders, quantity sold, and number of buyers as the regressand. After controlling

TABLE 9.2 Estimation results.

	(1)	(2)	(3)	(4)	(5)
Dependent variable	**Sales**	**Sales**	**Number of orders**	**Quantity sold**	**Number of buyers**
Population	26.41***	19.25***	0.07***	0.15***	0.07***
	(131.10)	(61.90)	(224.05)	(148.02)	(229.01)
Average wage	1.55***	1.18***	0.00***	0.01***	0.00***
	(239.42)	(111.49)	(377.35)	(250.19)	(389.47)
Urban–rural income gap	−6009***	−3880***	−10.29***	−17.48***	−10.15***
	(−38.10)	(−16.58)	(−42.54)	(−23.44)	(−44.27)
Age cohort					
16–25	23,750***	24,791***	85.02***	155.99***	83.30***
	(63.35)	(66.45)	(220.57)	(131.24)	(227.83)
26–35	41,314***	42,310***	141.52***	292.49***	137.30***
	(109.80)	(113.00)	(365.80)	(245.18)	(374.19)
36–45	27,271***	28,346***	100.69***	204.95***	97.75***
	(72.53)	(75.75)	(260.42)	(171.90)	(266.56)
46–55	14,951***	15,971***	54.56***	100.82***	53.37***
	(39.99)	(42.95)	(141.97)	(85.09)	(146.43)

Older than 55	14,806***	15,822***	52.08***	96.14***	50.99***
	(39.44)	(42.38)	(135.01)	(80.82)	(139.36)
Unidentified	23,403***	23,933***	106.18***	196.35***	102.71***
	(63.04)	(64.81)	(278.26)	(166.87)	(283.79)
Festival-fixed effects	Yes	Yes	Yes	Yes	Yes
Year-fixed effects	No	Yes	Yes	Yes	Yes
Province-fixed effects	No	Yes	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	4,553,281	4,553,281	4,553,281	4,553,281	4,553,281
R-squared	0.03	0.05	0.36	0.23	0.36

Note: Numbers in parentheses are t-values. *** (**,*) denotes significance level 1% (5%, 10%), respectively. The default group for the age cohort variables is the nonadult group.

for several fixed effects (including year, province, industry, and festival-specific fixed effects), all our previous findings are still apparent. For each prefectural city, with higher average wage income, more people enjoy Internet shopping. They also purchase more products online. Compared with the nonadult group, this observation also holds for all other age cohorts. The effect is most pronounced for the 26–35 years age cohort.

5. Concluding remarks

We have systematically explored the patterns, trends, and main characteristics of China's e-commerce by relying on data on JD's online sales. One of the most interesting findings is that China's online consumer spending is positively correlated with regional income. In addition, people's online consumer spending behavior exhibits regional heterogeneity and age cohort heterogeneity. People in the east region exhibit the strongest online consumer spending capacity. Finally, the most popular products sold online at JD are cell phones, followed by food and beverages, makeup and cosmetics, digital products, and lifestyle and travel goods.

Several caveats merit consideration here. First, although JD's online data are rich enough for us to understand the big picture of China's overall e-commerce development, we also see some limitations of this particular data set. For instance, the data only provide the top 20 products sold online by JD. Other small products are not covered in this data set. Second, the data set is silent on Chinese online transactions on nonfestival days. Thus, the stylized facts and estimation results presented in this chapter should be treated as the lower bound of China's e-commerce. Nevertheless, the richness of this data set provides helpful information for understanding China's recent booming e-commerce.

Appendices

TABLE A.1 Product industrial classifications.

01	Computers and accessories
02	Personal care
03	Secondary goods
04	Health care
05	Agricultural material
06	Agricultural green plants
07	Medical goods
08	Kitchenware

TABLE A.1 Product industrial classifications.—cont'd

09	Books
10	Prescribed drugs
11	Pet products
12	Furniture
13	Fitment and decoration
14	Home textiles
15	Soft decoration
16	Household appliances
17	House building material
18	Industrial products
19	Film and television products
20	Cell phones
21	Auction
22	Education videos
23	Digital products
24	Apparel and underwear
25	Travel
26	Mother and baby cares
27	Automobile accessories
28	Overseas purchases
29	Toys and instruments
30	Jewelry
31	Fresh food
32	Stationary
33	Gifts, bags, and suitcases
34	Beauty and makeup
35	Nutriments
36	Outdoor and sports products
37	Stamps and coins
38	Alcohol

Continued

TABLE A.1 Product industrial classifications.—cont'd

39	Watches and clocks
40	Shoes and boots
41	Audio products
42	Food and beverages

TABLE A.2 Regional classification.

East	Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan
Middle	Shanxi, Anhui, Jiangxi, Henan, Hunan, Hubei
Northeast	Heilongjiang, Jilin, Liaoning
West	Chongqing, Yunnan, Xinjiang, Guangxi, Gansu, Inner Mongolia, Shaanxi, Guizhou, Qinghai, Tibet, Sichuan, Ningxia

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