Appendix 8.7

This case study forms part of the overarching
2017–19 ACIAR Mango Agribusiness Research Program

Project:	**Challenges and opportunities for meeting requirements of Chinese mango markets**
Study:	**The Chinese Mango Market: E-commerce study**
Project number:	**AGB/2016/007**
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Contents

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1 Acknowledgements

This study report for the Mango Markets project was prepared by Alec Zuo and Wenzhu Tang from the University of Adelaide, and Robin Roberts from Griffith University.

2 Case summary

Online platforms are fast becoming major channels for consumers looking to purchase fresh produce. Given the rapid increase in the volume of mangoes consumed across China, gaining a better understanding of how online prices of mango crops are affected can provide valuable economic insights in this sector. In this study, a hedonic model was used to analyse price information collected from Tmall.com (Tmall), one of the largest Chinese online retail platforms. The results show that mangoes sourced in Australia, Taiwan and Thailand have a relatively high price premium over domestic mangoes from Hainan, whereas mangoes from Yunnan and Vietnam are discounted in price compared to mangoes from Hainan. Regarding the time of sale, mango prices in February and October were found to be much higher than those in January, while June and July experienced the lowest mango prices. Lastly, customer feedback is particularly important in enabling online retailers to achieve a premium price. Retailers with higher customer satisfaction ratings tend to sell mangoes at higher prices. A similar positive correlation exists when a same-city, 24-hour delivery service is offered.

3 Introduction

3.1 Project background

According to the Food and Agriculture Organization records (FAOSTAT) (2019), the total value of mango production worldwide increased considerably between 2000 and 2011, from USD12.8 billion to USD34.6 billion. However, after 2011, production slowly declined to USD30.0 billion in 2016. At the same time, the trend in China was somewhat different. Between 2000 and 2010, the annual value of Chinese mango production fluctuated around USD6 billion, and then rose rapidly to USD11.1 billion in 2013, before dropping back to USD6.1 billion three years later. However, despite this fluctuation, both the area of Chinese mango plantations and the production volumes increased steadily between 2000 and 2016 (RCRE, 2017). Records also found that Guangxi, Hainan, Yunnan, Sichuan and Guangdong were the primary mango producing regions in China. The volume of mango consumption rose considerably from 896 metric tonnes in 2010 to 1,869 metric tonnes in 2016 (RCRE, 2017).

3.2 Study objectives

The internet is becoming a major purchasing channel for consumers as online shopping continues to grow at a rapid pace. The total transaction volume of online sales in 2020 is estimated to reach RMB10 trillion, accounting for more than 16% of total social consumer goods sales (Deloitte, 2016). While Chinese people continue to buy fresh produce from wet markets and physical retail stores such as supermarkets, an increasing number of consumers order their food online. Products range from vegetables to meats, from grains to dairy products and from domestic products to imported food and beverages. According to iiMedia Research (2015), imported fruit was the most popular category within online markets in China. The report revealed, among the respondents, 35.4% purchased imported fruits via online platforms, with mangoes being sold in relatively large amounts. As a result, studying the online price dynamics of mangoes is likely to enable a better understanding about the Chinese mango market. The number of mango sellers on the largest fresh produce online platform, Tmall, exceeds 1,000 during the peak season, and they are involved in selling mangoes of different sizes, varieties and places of origin (Meng and Zuo, 2018). Due to intense competition among online vendors, there is a need to diversify their approach to selling mangoes in order to gain a competitive edge in the market. Therefore, this study aims to answer the following research questions:

1. What is the market share of mangoes across different places of origin in the Chinese e-commerce retail space?
2. Is there a price premium for imported mangoes in comparison to domestic mangoes?
3. What non-mango related characteristics of the seller are associated with the online price charged?

3.3 Study methodology

This study utilises a unique dataset that captures daily information from more than 1,000 mango sellers on two major online shopping platforms in mainland China – JD.com (JD) and Tmall – between 1 September 2017 and 31 August 2018, and investigates trade characteristics associated with listed prices. An example of on online listing can be seen in Figure 1, where Vietnamese mangoes sold by a store on Tmall are listed with a price of RMB68 for 4kg.

The theoretical foundation of the empirical analysis used in this study is the hedonic approach, which is useful for estimating the value of a variety of characteristics that contribute to or detract from the value of a product. The characteristics that have been hypothesised to affect the value of mangoes include: brand, variety, size, place of origin and information provided by online sellers. Furthermore, the availability of data over an entire year makes it possible to capture the online retail price dynamics over a complete mango trading season. From the analysis, consumer preferences in terms of different mango varieties and places of origin are presented, with the outcomes providing useful information for stakeholders engaged in the direct supply and trade of mangoes to consumers through online channels. The characteristics that have been hypothesised to affect the value of mangoes are: season, variety, order size, place of origin, and product descriptions (attributes, images, consumer feedback and fast delivery options).

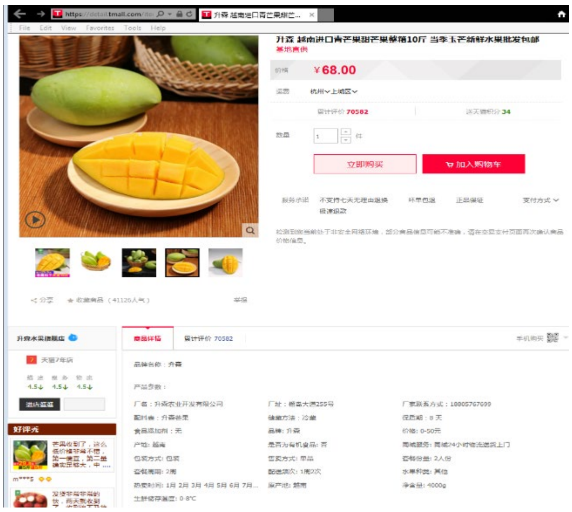

Figure 1. An example of Vietnamese mango listed on Tmall

Source: Tmall

A web crawler software application was used to systematically collect product (mangoes, in this instance) data from the aforementioned websites. Depending on what was available on the source websites, product data included name, price, description, images, place of origin and other metadata. The crawler used website-specific plugins to extract product data and store it in a relational database, which could then be exported to other formats such as Excel, XML, JSON and many others. The web crawler was deployed on Amazon Cloud and ran continuously using a system schedule. Data exporting and reports were available in real time.

The hedonic approach uses a regression method to estimate the following model:

$$Y_{ij} = \alpha + X_{ij} \cdot \beta + \varepsilon_i$$

Where Y_{ij} is the listed price, in natural logarithm form, for mango i on day j. X_{ij} is a vector of characteristics of the listed product (mangoes) and the seller, and monthly dummies. α is the constant. β is a vector of parameters to be estimated and ε_i is a classical error term. To account for the same online store selling multiple mango products, the estimated standard errors were clustered at the store level. Linear regression (Ordinary Least Squares (OLS)) is the most commonly used estimator for a hedonic price model. However, in the presence of unequal variance in ε_i – namely heteroscedasticity – the parameters of log-linearised models estimated by OLS lead to biased estimates of the true elasticities (Silva and Tenreyro, 2006). As an alternative, the Poisson pseudo-maximum-likelihood (PPML) estimator with robust standard error option was employed which resulted in unbiased estimates and correct inference (Silva and Tenreyro, 2006; StataCorp, 2017).

4 Literature review

The foundations for the standard hedonic price model were developed by Rosen (1974) in his seminal paper, with early empirical applications of the theory focusing on property prices and cars (Maguire et al., 2004; Schamel and Anderson, 2003; Thrane, 2004). The pivotal idea behind hedonic pricing resides on the hypothesis that goods are valued for their utility-generating attributes (Schamel and Anderson, 2003). Therefore, the price of any product is a function of its immanent utility-bearing attributes as determined by the consumer (Thrane, 2004).

Tronstad et al. (1992) found that size, storage method, grade and seasonality were the most important influences on apple prices in their hedonic price estimations. In a study that employed a hedonic price function to estimate price discounts and premiums associated with quality and market characteristics for apples marketed in British Columbia, Carew (2000) found that grade is one of the principal characteristics influencing apple prices, with cultivar, storage, marketing season and fruit size accounting for a relatively significant proportion of prices. More recently, Troncoso and Aguirre (2007) undertook a hedonic approach to determine the influence of size, variety, destination port and month of sale on the export price of apples in Chile. The results in this study showed that the most influential variable on the final price of apples was destination port, which was then followed by variety, month of sale and size. In terms of sale month, March and April showed negative and null marginal prices respectively, which suggests that the best choice was May. Significantly in this case, the cost of cold storage can offset the advantage of a late sale (Troncoso and Aguirre, 2007).

Hedonic studies of mango pricing are much rarer; however, Basker (1992) found that the differences in hedonic taste ratings and scores between fruit and vegetables (including grapes, grapefruit, tomatoes, carrots, sweet corn and spinach) were not significant. For mangoes and orange juice, however, the conventional rather than organic type was preferred since, in both instances, the result could be attributed to fruit being tasted closer to its optimum maturity. Furthermore, in the case of mangoes, no significant mean taste differences were found between the ‘blush’ and yellow halves of any sample, indicating that this unique characteristic of mangoes did not affect taste results and therefore was not likely to be a factor that influenced price (Basker, 1992). Within a detailed survey study of mango consumer preferences in Pakistan, Badar et al. (2015) found that nearly 80% of respondents preferred roadside sellers to others due to the combination of good-quality fresh mangoes and reasonable prices. A similar purchase pattern was observed in India by Ali et al. (2010).

The hedonic approach has been successfully applied to the pricing of other consumer products. Maguire et al. (2004) were able to combine a unique dataset with the hedonic framework to estimate consumers' (in this instance, parents of babies) value reductions in pesticide exposure as evidenced from the organic baby food market. Results indicated individuals were willing to pay between 16–27% more for organic baby food compared to conventional varieties. Schollenberg (2012) determined that hedonic pricing allowed for an investigation of what Swedish consumers pay for various coffee attributes and, based on the estimations within this study, it was possible to identify the relative impact of the different attributes of coffee on its market price. However, hedonic pricing did not reveal information on consumers' market behaviour or about their attitudes (Schollenberg, 2012).

E-commerce has now emerged as a new mode of consumption and is increasingly favoured by more and more people. In recent years, online sales of fruit and vegetables have expanded at a dramatic rate and the development of e-commerce has meant that this marketing format is increasingly being used within agribusiness (Zhou et al., 2018). Furthermore, it is predicted that online sales of fresh products will continue to maintain rapid momentum in the near future (Kong et al., 2016; Zhang et al., 2016; Zhou et al., 2016, 2017; Tian and Chen, 2017). Research suggests that fruit is the most prevalent fresh product sold via e-commerce (Zhou et al., 2018).

In China, the trading volume of agricultural produce through online channels increased from USD0.60 billion in 2010 to USD11.22 billion in 2015 (Jin et al., 2017). Despite this, the circulation of fresh fruit and vegetables via e-commerce is lagging in comparison with mainstream retail outlets. This phenomenon is mainly due to two reasons: (1) the cold chain infrastructure and logistics distribution system for fresh fruit and vegetables are both underdeveloped, which results in high unit delivery costs; and (2) the perishable nature of fresh produce poses a challenge for long-distance transportation, particularly given the fact that Chinese consumers are highly sensitive to freshness (Bai et al., 2008). Furthermore, although online channels for fruit sales have certain advantages, there are still several obvious issues that need to be resolved. The perishable nature of fresh fruit also leads to difficulties with pricing, and the way in which products are priced is often a tactical choice for e-commerce retailers (Zhou et al. 2018).

More broadly, many studies have demonstrated that quality is generally of greater importance to consumers than price, particularly when prices are varied within the expected commercial range (Harker et al., 2003). Given that the quality of fruit cannot generally be assessed first-hand, these findings represent another potential obstacle to online sales. More recently, He et al. (2016) found that consumption and transportation, along with the online software platform and payment method, were all important factors influencing the development of e-commerce solutions for agricultural products in China.

Pearson et al. (2014) conducted an analysis of prices and potential competition between fruit and vegetable outlet types in New Zealand and found that, based on an a balanced weekly 'food basket' for two adults and two children, a move from non-online supermarkets to an online supermarket would result in a NZD13.00 saving (for example, carrots, onions, potatoes, pumpkin and tomatoes were significantly cheaper). As part of a study of citrus retailers in Florida, US, Moss et al. (2003) reported that specialty fruit producers have utilised online platforms to directly market their fruit to consumers, thus bypassing the brokers. This innovation has reduced the cost of specialty fruit to consumers by replacing several steps within the marketing channel.

Although there have been no studies to date specifically focusing on the online price of mangoes in comparison to physical retail outlets, given the strong consumer emphasis placed on the quality of mangoes (Badar et al., 2015; Yaseen et al., 2016), e-commerce marketers will need to recognise that customers strongly favour the characteristics of fruit colour, blemish-free, firmness, fruit size and homogenous texture when selecting mangoes (Yaseen et al., 2016). Therefore, conveying these desired qualities to consumers, as well as overcoming the challenges discussed above, will be paramount for harnessing the many opportunities of e-commerce, both in terms of business growth and achieving price savings for customers.

Carew (2000) discovered that ‘quality’ attributes (such as cultivar, grade and fruit size) and marketing factors (such as cold storage, package size and seasonality of sale) were major determinants of apple prices in British Columbia. Furthermore, it was found that the way in which apples are packaged, along with their size and the season when they are marketed, had a significant impact on their price (Carew, 2000). Given the usual trend whereby the reward structure tends to favour larger size and redder apples, it is reasonable to expect larger apples to fetch higher price premiums over smaller or medium-sized fruit. However, wholesale fruit buyers are willing to pay higher prices for medium-sized apples over smaller or larger ones. (Carew, 2000). This was supported by a survey that showed 73% of Canadian households prefer medium-sized apples (Benchmark Research, 1998).

Finally, bearing in mind the range of influences described above, Yin et al. (2008) investigated why branding is so much less prevalent for fresh produce in comparison to other consumer goods. The authors suggested that consumers are able to predict quality of produce based on intrinsic external attributes and, thus, branding may be less effective in conveying quality signals for fresh produce. A bad experience, however, will cause consumers to stop buying a particular product for a period of time, change type of cultivar and/or change to other types of fruit (Harker et al., 2003).

5 Results and discussion

Following data validation, 198,003 observations from Tmall and 176,907 from JD still remained in the dataset. We then grouped mangoes according to their place of origin – namely, five groups from mainland China (Hainan, Guangdong, Guangxi, Yunnan and Sichuan), one from Taiwan and four from overseas (Australia, Myanmar, Thailand and Vietnam). Figure 2 and Figure 3 display the average price of mangoes by place of origin on Tmall and JD, respectively. Mangoes from Australia were priced highest on both websites. Mangoes from Thailand were available throughout the year and generally obtained higher prices during winter months in comparison to summer months, when the supply of mangoes on the Chinese market reaches its peak. Prices for both Australian and Thai mangoes fluctuated more than prices for other types of mangoes. Mangoes from Vietnam were available most of the year and had a relatively low and stable price. In the case of mangoes from mainland China, prices from different provinces were similar during the peak summer time. However, Hainan mangoes generally obtained a good price (above RMB20/kg) early in the domestic season, while the price of Sichuan mangoes fetched above RMB20/kg during the end of the domestic season.

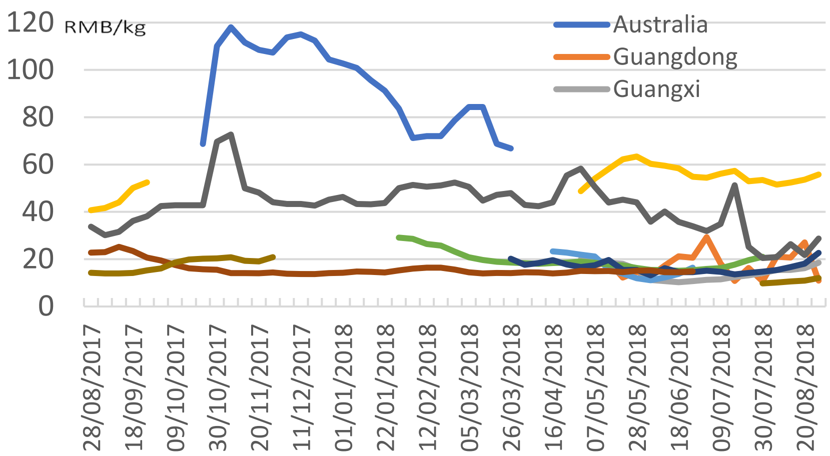

Figure 2. Tmall price of mangoes from different regions (Aug 2017–Aug 2018)

Source: Author’s analysis

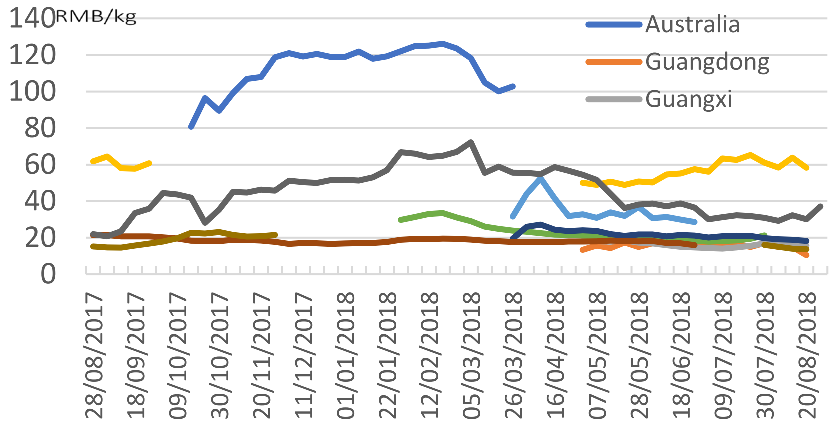

Figure 3. JD price of mangoes from different regions (Aug 2017–Aug 2018)

Source: Author's analysis

Mangoes from Hainan (34% of total SKUs) and Vietnam (29% of total SKUs) were the most popular varieties in terms of both number of stores and SKUs. This was followed by mangoes from Guangxi (17% of total SKUs) and Sichuan (11% of total SKUs) (see Table 1). Mangoes from other places of origin had a much smaller presence, either due to a short supply period (Yunnan and Guangdong) or a small number of sellers (Australia, Taiwan and Myanmar). In terms of seasonality, it is apparent that the peak season for domestic mango production is from May to July, when the number of SKUs totals more than 1,500 each month. If imported mangoes are considered, there is also an abundant supply in April (more than 1,500 SKUs) because mangoes from Vietnam have a large presence in this month. From September onwards, the total number of SKUs for sale decreased significantly to less than 700 and dropped further to 478 in December before increasing again to 522 in January. Therefore, the low season for mango supply on Tmall is December and January, when there are no domestic mangoes available for sale. Given e-commerce businesses usually list their products on both Tmall and JD, a separate table has not been provided for JD since it is expected to have similar mango sales patterns.

Both Tmall and JD present information on the number of attributes described on the website, number of images about the product on the website, rating scores by customers, number of text comments by customers, place of origin, variety, pack size and price. In addition, Tmall offers further information on transaction volume during the previous 30 days, whether the mangoes are loose or sold in a gift pack, and if 24-hour delivery is available. The correlation coefficients between price and other continuous variables for Tmall and JD respectively are statistically different from zero, except for those between price and number of product images for Tmall (see Table 2). The strength of most of the correlations is relatively weak. Only one variable is positively correlated with price – rating score by customers – while all the other variables have negative correlations with price. Since the correlations do not take into consideration other variables also associated with price, further analysis (such as regression) is necessary to provide controls for different price influences simultaneously.

Table 1. Number of stores and SKUs for mangoes from different origins by month, on Tmall

Content	Month	Origin									
		Hainan (6)*	Vietnam (10)*	Guangxi (4)*	Sichuan (4)*	Yunnan (5)*	Thailand (12)*	Guangdong (4)*	Australia (6)*	Taiwan (5)*	Myanmar (3)*
Stores	Jan		206				11		18		
	Feb	136	198				12		14		
	Mar	347	268				17		6		
	Apr	433	273			67	17				7
	May	425	229	163		86	17	47		11	24
	Jun	396	139	310		110	18	52		9	19
	Jul	308		329		88	17	37		12	
	Aug			231	356	53	10	20		12	
	Sep		57		206		20			6	
	Oct		154		116		7		8		
	Nov		179		61		7		12		
	Dec		192				4		16		
SKUs	Jan		484				13		25		
	Feb	338	451				14		21		
	Mar	821	627				28		7		
	Apr	1,071	606			99	26				11
	May	1,079	455	319		119	36	60		16	39
	Jun	1,009	225	813		169	38	67		16	26
	Jul	673		879		134	31	51		20	
	Aug			485	749	80	14	25		18	
	Sep		141		474		44			8	
	Oct		371		263		10		13		
	Nov		439		124		10		17		
	Dec		451				6		21		
	Total	4991 (34%)	4250 (29%)	2496 (17%)	1610 (11%)	601 (4%)	270 (1.9%)	203 (1.4%)	104 (0.7%)	78 (0.5%)	76 (0.5%)

Source: Author's analysis
Note: The number in brackets represents the number of months of the year when mangoes are available for sale in China.

Table 2. Correlation coefficients between price and other characteristics of sellers

	Price per kg (Tmall) n=191,076	Price per kg (JD) n=150,186
Number of orders in the previous 30 days	-0.15	N/A
Number of attributes described on the website	-0.08	-0.07
Number of images on the website	-0.003[a]	-0.02
Rating scores by customers	0.09	0.04
Number of text comments by customers	-0.08	-0.08
Order net weight	-0.46	-0.07

Source: Author's analysis
Note: Results are not significantly different from zero. All other correlation coefficients are significantly different from zero at the 0.01 significance level.

Given the data from Tmall contains more information than JD (of particular importance is the transaction volume during the previous 30 days to control for the scale of the online store), the hedonic regression model was estimated using Tmall data only. Overall, the data fits the model well and achieves a high value of adjusted R-squared (0.36). There is no serious multicollinearity problem among the independent variables, with individual variance inflation factor (VIF) being smaller than 5 and average VIF being 2.20. The standard errors are adjusted for clusters at the store level to account for the same store selling multiple SKUs and also for heteroscedasticity.

Table 3 displays the results from the PPML regression model. Controlling for a range of variables (including seasonality and variety) in comparison to mangoes from Hainan province (which is one of the major mango production provinces in China), mangoes from Guangxi, Taiwan, Thailand and Australia enjoy a statistically significant price premium, while mangoes from Yunnan and Vietnam have a statistically significant price discount. The average price for Hainan mango is RMB18.0/kg, whereas the average price for Australian mangoes is RMB63.2/kg – a 251% price premium when compared to Hainan mangoes. However, there is no significant difference between the price for Hainan mangoes and the price for Sichuan, Guangdong and Myanmar mangoes (see Figure 4).

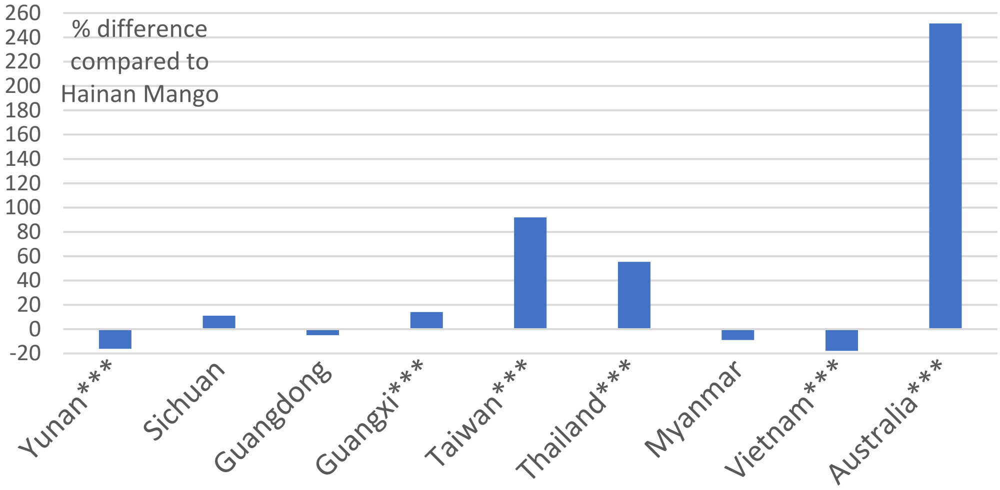

Figure 4. Estimated price difference (%), place of origin compared to mangoes from Hainan

Source: Author's analysis
Note: Price difference is statistically significant at the 0.01 significance level

In terms of seasonal effects, mango prices in February and October are significantly higher (12%) in comparison to prices in January, while prices are significantly lower (-16%) during summer months (June, July and August). As measured by a rating score, customer feedback is found to have a significant correlation to mango price. Overall, customer satisfaction ratings are generally high, with an average of 4.6 out of 5. However, if the average rating improves by 0.4 to the best possible rating (5.0), the price increases by 20.6% (with everything else being held constant). This suggests stores that receive a 100% satisfaction rating via customer feedback can charge a much higher price than those that have an average rating.

In addition to the customer satisfaction score, text feedback is optional for customers who wish to provide specific comments regarding their positive or negative experiences. Controlling for the transaction volume, the number of customer feedback instances available for the product is not significantly related to mango price. The reason might be that text feedback includes both positive and negative experiences, and our model is unable to separately capture the number of positive and negative feedback instances. Therefore, an overall number of text feedback instances did not detect any significant effect on price.

Both the number of attributes and number of images have a quadratic relationship with mango prices (see Figure 5 and Figure 6). Furthermore, net weight of each order has a negative and significant relationship with mango prices. For instance, same-city, 24-hour delivery results in a 11.7% price increase of advertised mangoes. Finally, whether mangoes are sold in packaged format or loose does not have a statistically significant relationship in terms of mango prices. Therefore, in addressing the third research question, our findings suggest that seasonality, consumer feedback, number of attributes, number of images and availability of same-city, 24-hour delivery are all statistically significant in terms of online mango prices.

Table 3. Regression model results

Content	Coef.	Robust Std. Err	P>|t|
Number of orders in the previous 30 days (in natural logarithm)	-0.069	0.007	0.000
Number of attributes described on the website	-0.044	0.023	0.057
Number of attributes described on the website squared	0.001	0.001	0.098
Number of images on the website	-0.018	0.007	0.006
Number of images on the website squared	0.001	0.000	0.000
Average rating scores by customers	0.468	0.136	0.001
Number of text comments by customers (in natural logarithm)	0.005	0.005	0.406
Package (1 if mangoes are packaged; 0 if mangoes are loose)	0.007	0.031	0.811
Same-city, 24-hour delivery (1 if available; 0 if not)	0.111	0.033	0.001
Order net weight	-0.131	0.008	0.000
Place of origin (reference: Hainan)			
Yunnan	-0.176	0.068	0.010
Sichuan	0.105	0.157	0.504
Guangdong	-0.049	0.044	0.270
Guangxi	0.132	0.046	0.004
Taiwan	0.652	0.097	0.000
Thailand	0.441	0.143	0.002
Myanmar	-0.094	0.102	0.360
Vietnam	-0.197	0.052	0.000
Australia	1.257	0.144	0.000
Variety (reference: Kent)			
Tainong	-0.251	0.070	0.000
Guiqi	0.004	0.067	0.951
Nam Dok Mai	0.018	0.151	0.903
Aiwen	0.352	0.100	0.000
Jinhuang	0.059	0.067	0.377
Jinyaodai	0.080	0.199	0.687
Others	-0.029	0.062	0.636
Monthly dummies (reference: Jan)			
Feb	0.117	0.040	0.004
Mar	-0.035	0.035	0.313
Apr	-0.024	0.036	0.506
May	-0.047	0.038	0.224
Jun	-0.163	0.040	0.000
Jul	-0.153	0.042	0.000
Aug	-0.093	0.052	0.072
Sept	-0.011	0.061	0.858
Oct	0.110	0.062	0.074
Nov	0.048	0.043	0.265
Dec	-0.023	0.039	0.552
Constant	2.136	0.665	0.001
Number of observations	190,964		
Number of products	3,567		
Number of stores	909		
McFadden(adjusted) R^2	0.36		
Wald Chi2-stat	3986.4 (p-value=0.00)		

Source: Author's analysis
Note: Standard errors are adjusted at the store level

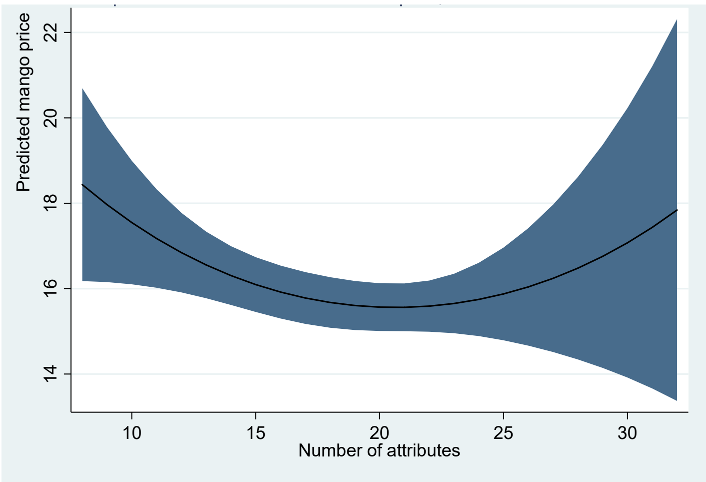

Figure 5. Relationship between number of attributes and price, with 95% confidence interval

Source: Author's analysis

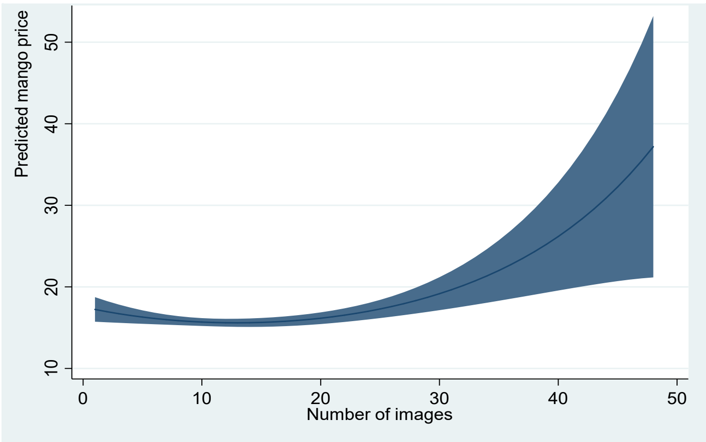

Figure 6. Relationship between number of image and price, with 95% confidence interval

Source: Author's analysis

6 Conclusion

Mango consumption in China is increasing every year and represents a market with huge potential, which makes this country attractive to mango producers worldwide. Focusing on Chinese online mango sales, this research analysed 374,910 online listings of mangoes from Tmall and JD, and modelled the listing price from Tmall using a hedonic approach. The results show that the place of origin, variety and seasonality of mangoes, along with customer satisfaction rating of the retailer, description of mangoes (including attributes and images) and the availability of a same-city, 24-hour delivery service are all important factors associated with online mango prices in China.

Using mangoes from Hainan as the reference point, mangoes produced in Australia, Taiwan, and Thailand have a relatively high price premium, while mangoes from Yunnan and Vietnam have a discounted price. In terms of month of sale, we observed that mango prices during February and October are much higher than those in January (as the reference point), while June and July experience the lowest mango prices.

In conclusion, this is the first study of fresh fruit price determinants within an e-commerce platform in China, using mango as an example. By employing a hedonic pricing model, our analysis has revealed a number of important factors associated with prices charged by individual online stores.

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