Riwayat: Educational Journal of History and Humanities, 6 (3), 2023, pp. 2145-2153
P-ISSN: 2614-3917, E-ISSN: 2775-5037
DOI: https://doi.org/10.24815/jr.v6i3.34379

Transaction Intensity on Electronic Marketplace in Indonesia: Study of Clothing Product Purchases Based on Transactional Data

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Article history
Received : 2023-04-13
Accepted : 2023-07-22
Published : 2023-08-31

Keywords:
Consumer Behavior; Transaction Intensity; Electronic Marketplace

Abstract: This research studies the impact of time trends on transaction intensity through electronic marketplaces, especially in purchasing high-risk products such as clothing. We monitored the intensity of clothing product transactions since the first purchase of 60,341 sample accounts from January 2018 to December 2019. We estimate log-linear model parameters with random effects from unbalanced panel data involving several control variables. The results show that the transaction intensity has decreased over time since the first purchase. This indicates consumers accept risks that exceed benefits, or in other words, the courage to transact through the electronic marketplace is decreasing for the purchase of clothing products.

Abstrak: Penelitian mempelajari dampak time trend terhadap intensitas transaksi melalui electronic marketplace untuk produk dengan risiko pembelian tinggi seperti sandang. Peneliti memantau intensitas transaksi produk sandang sejak pembelian pertama dari 60.341 sampel akun selama Januari 2018 sampai Desember 2019. Peneliti mengestimasi parameter model log linier dengan efek acak dari data panel tidak seimbang yang melibatkan beberapa variabel kontrol. Hasil menunjukkan intensitas transaksi mengalami trend penurunan dari waktu ke waktu sejak pembelian pertama. Hal tersebut mengindikasikan konsumen menerima risiko yang melampaui benefit, atau dengan kata lain keberanian dalam bertransaksi melalui electronic marketplace semakin menurun untuk pembelian produk sandang.

INTRODUCTION

Online *trade transactions* are growing rapidly both globally and domestically. The total value of sales through *e-commerce* in the world in 2019 was recorded at 3.6 trillion US dollars, or an increase of 48.4% compared to 2017. The increase in sales value was also followed by an increase in users by 15.7% to 1.9 billion in 2019 (Statista, 2020b). In the same period, the value of *e-commerce* transactions in Indonesia grew by 210.3%, although the value only reached 19 billion US dollars in 2019. Meanwhile, the number of users in Indonesia reached around 119 million in 2019 which grew 69.5% compared to 2017 (Statista, 2020a).

An increase in the value and number of users indicates a shift in shopping behavior that can have both positive and negative implications. Sellers can take advantage of low marketing costs (Peterson et al., 1997) and utilize them for other productive activities. In particular, Micro, Small, and Medium Enterprises (MSMEs) in Indonesia benefit from

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online transactions in the form of market expansion and increased sales (Rahayu &; Day, 2017). In addition, the use of *online* transactions is also useful as an alternative economic driver in the conditions *of the Corona Virus Disease 2019* (COVID-19) pandemic as well as being one way to fight the spread of Covid-19 due to the lack of direct interaction between buyers and sellers.

However, shifting shopping behavior can be a challenge for state revenues because on the one hand, the tax base on *offline* transactions is declining, while on the other hand, only a small percentage of *online* transactions are taxed. In 2018, potential taxes on *electronic marketplaces* ranged from Rp11.75 trillion to Rp16.64 trillion, with 90% being Value Added Tax (VAT) (Setiawan, 2018). Data on the realization of tax revenue from *online* transactions that began to be implemented in August 2020 shows that during August - November 2020 it was only IDR 566.16 billion.

Consumers transacting *online* can receive benefits in the form of low search costs. Decreasing search costs will improve the quality of information (Goldfarb &; Tucker, 2019) so that consumers can get products with the best offers (Bakos, 2001). Consumers also benefit from reduced search costs in the form of relatively lower product prices (Brown & Goolsbee, 2002; Goolsbee & Klenow, 2018; Morton et al., 2001; Orlov, 2011), ease in searching for rare and special products (Yang, 2013), and improved matching quality between buyers and sellers (Kuhn & Mansour, 2013; Kuhn & Skuterud, 2004).

At the same time, consumers also face the risk of uncertainty as the products traded online vary (Lester et al., 2005; Quan & Williams, 2018). Product quality is one of the reasons consumers are reluctant to transact through *electronic marketplaces* (Statista, 2020a). In addition, the Indonesian Consumer Foundation (YLKI) in 2019 recorded 15.3% of total customer complaints against transaction services through *electronic marketplaces* related to product non-compliance with specifications. This uncertainty risk will increase for highly differentiated products such as clothing.

For products with high purchase risk, consumers need a direct product evaluation by feeling, touching, or trying the product first. This process cannot be done in *online* transactions. Therefore, the need to feel and touch products is a dominant deficiency in all online transactions (Kangis &; Rankin, 1996) including clothing products (Rathee &; Rajain, 2018). The need to touch products is directly negatively related to order rates, particularly for clothing products (Citrin et al., 2003).

Despite the high level of uncertainty risk, clothing products in general are commodities with the largest transaction intensity in several *electronic marketplaces* in Indonesia. During 2018-2019, the frequency of transactions on *the electronic marketplace* was mainly related to the purchase of clothing products, followed by health, education, recreation, and sports products, transportation, communication, and financial services products, housing products, water, electricity, gas & fuel, other products, and food products, finished food, beverages, cigarettes, and tobacco. However, this information cannot explain consumer behavior in it.

Several previous studies have shown that consumers tend to shop *online* for products that have a low risk of uncertainty (Lee & Tan, 2003; Peterson et al., 1997; Vijayasarathy, 2002). Similar results are also shown from the research of Soopramanien et al., (2007). Nevertheless, the study provides additional important information related to the heterogeneity of consumer behavior. Groups of consumers who had previously shopped *online* showed a stronger preference for purchasing products over the Internet despite the increased level of risk for the purchase of certain products such as clothing. This indicates that the decision to transact through one channel since the first purchase can reflect consumer behavior.

This study wants to see the influence of *time trends* since the first purchase on consumer transaction intensity, especially for products that have a high purchase risk such as clothing. The benefits, among others, from a decrease in product search costs may exceed the risk of obtaining products that are not suitable so the intensity of purchasing clothing products increases. To be able to answer this, the study will examine individual consumer behavior based on panel data from a sample of around 60 thousand accounts that transact through several *electronic marketplaces* in Indonesia. The transaction intensity of each consumer was observed from January 2018 to December 2019. The period between times (*time trend*) begins to be calculated when the first transaction is made. Several control variables derived from consumers and environmental factors were used in this study.

METHODS

This study uses sample data from consumer shopping transactions in several *electronic marketplaces* in Indonesia with an observation period from January 2018 to December 2019. Transaction intensity is an accumulation of clothing product transactions carried out by each consumer for one month from January 2018 to December 2019. The transaction intensity is 0.1, 2, 3,... and so on which are a discrete type of data (Greene, 2008) and transaction frequency following the *Poisson distribution* (Wooldridge, 2013).

The unit of analysis is the individual consumers identified from accounts on each *electronic marketplace*. Data acquisition in collaboration with *the E-Commerce Big Data* Management Team, Bank Indonesia. A total of 130 thousand accounts were selected for the sample with a total of about 4 million transactions. Data quality control is carried out by paying attention to the fairness of transactions and the consistency of information between transactions. In addition, the criteria for eligible transactions to be further analyzed are clothing product purchase transactions, with a maximum individual transaction intensity of 30 times a month, and the first transaction was carried out before December 2019. Because the first transaction during the study period can vary among consumers, the data structure in this study is an unbalanced panel. Based on this process, the number of samples that can be used further is 60,341 accounts with a total number of observations of 867,738.

RESULTS AND DISCUSSION

Descriptive Analysis

The identity of consumer transactions through *the electronic marketplace* for the purchase of clothing products is not high and the spreader is in a wide range. Based on descriptive statistics, the average value of consumer transaction intensity was recorded at 0.88 or less than 1 transaction each month. Percentile information supports low transaction intensity as up to 50% of observations still have no transactions.

Table 1 Descriptive Statistics of Transaction Frequency on *Electronic Marketplace* in Indonesia

Jumlah observasi	:	867,738
Rata-rata	:	0.88
Standar deviasi	:	2.36
Skewness	:	4.93
Kurtosis	:	36.33
Nilai minimum	:	0.00
Nilai maksimum	:	30.00

Percentil	1%	25%	50%	75%	90%	95%	99%
Nilai	0	0	0	1	3	5	12

Source: Bank Indonesia, processed

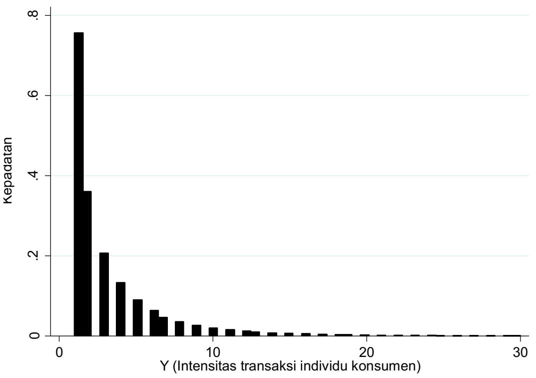

Figure 1 Histogram of Transaction Frequency Distribution on *Electronic Marketplace* in Indonesia
Source: Bank Indonesia, processed

The intensity of transactions between disperser consumers over a wide range is reflected by the variance value which is almost seven times the average value. The symmetrical size of data distribution is also not fulfilled which can be seen from *the skewness* of 4.93, above the symmetrical data distribution size of 0. A positive *skewness value* indicates that the data distribution has a tail to the right of the most value. In addition, the kurtosis value is also high reaching 36.33 which shows the value of data concentration is far above the average. Completing the description, the results of *skewness & kurtosis normality tests show that the data does not follow the normal distribution. The frequency distribution tends to follow the Poisson distribution*. Graphically, the distribution of these data can be seen in Figure 4.1.

Based on average data, the number of individual consumer transactions from January 2018 to December 2019 experienced an increasing trend accompanied by seasonal patterns (Figure 4.2). When viewed based on demographic factors, gender, and age group, it tends to show differences in the intensity of clothing product transactions on the *electronic marketplace*. In the gender group, women are 2.3 times higher than men group.

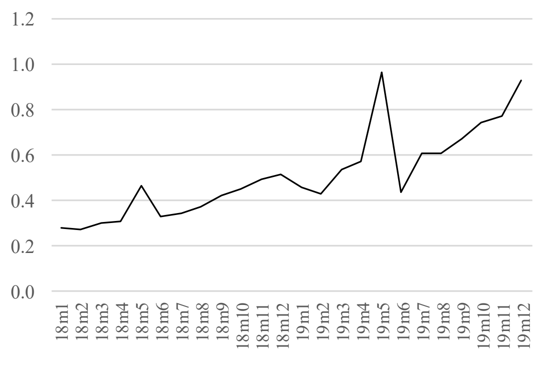

Figure 4.2 Average Intensity of Individual Consumer Transactions over time
Source: Bank Indonesia, processed

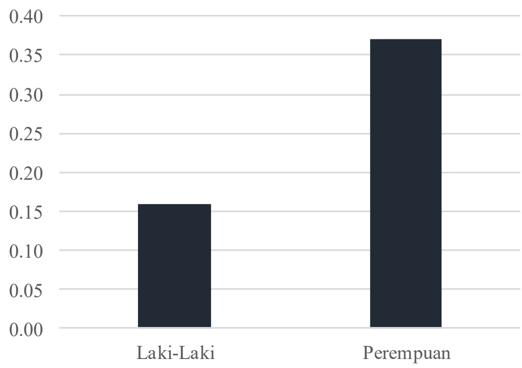

Figure 4.3. Average Transaction Intensity by Gender
Source: Bank Indonesia, processed

When viewed based on age, consumers in the age group of 22-44 years are more active in transacting clothing products than other groups. Meanwhile, judging from the seasonal pattern, the average individual transactions in the Eid, Christmas, and New Year periods show higher transaction intensity than non-seasonal periods. The average transaction intensity by gender, age group, and seasonal period can be seen in Figures 4.3, 4.4, and 4.5.

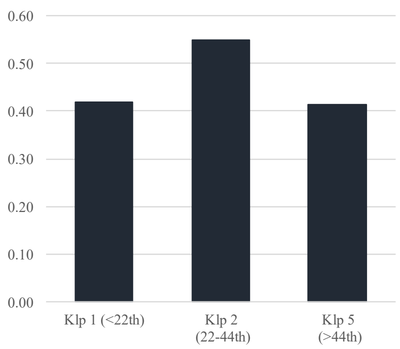

Figure 4.4. Average Transaction Intensity by Age Group
Source: Bank Indonesia, processed

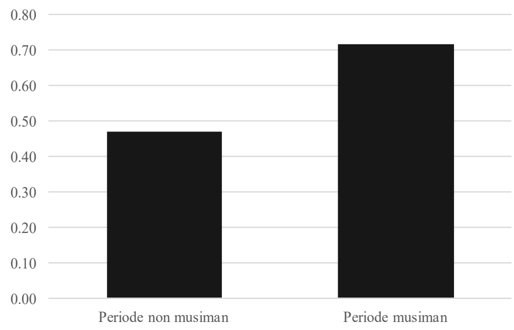

Figure 4.5 Average Transaction Intensity by Seasonal Pattern
Source: Bank Indonesia, processed

Parameter Estimation

To obtain robust parameter estimation results, researchers use several model specifications and testing based on subsamples. Based on the specifications, Model 0 was built to include only the *time trend* factor which was the main hypothesis in this study. Model 1 is built by incorporating *time trends* and controlling internal consumer factors, namely gender and age. Model 2 is Model 1 by adding control factors beyond the consumer (environmental) industry such as seasonal patterns and market characteristics. Meanwhile, based on subsamples, models are grouped based on the location of buyers, namely Java and outside Java.

Based on the results of parameter estimation, the model shows that the model can explain the variation of the independent variable to the dependent variable. This is shown from the value of the chi$^{test\ 2}$ which shows a significant level (Pchi2 = 0.000). Based on the testing of each parameter, the model also shows the level of significance as reflected by the value of Pvalue = 0.000. This means that the independent variable significantly affects the dependent variable. The results of the estimated model parameters can be seen in Table 4.2.

Further interpretation of the model is carried out. By considering the use of *linear log models*, the relationship between the dependent variable and the independent variable cannot be explained linearly. The explanation of the impact of the dependent variable on the independent variable is in the form of *expected changes* from the *event log*. For example, in model 2, the significance of *a time trend* can be interpreted as every increase one month since the first transaction will decrease the *expected changes* in the logarithm of shopping intensity by 0.082. In other words, the relationship can be interpreted as an increase every month since the first transaction will cause the transaction intensity to grow negatively by 8.2.

Table 4.2 Model Parameter Estimation Results

	Spesifikasi					Subsampel	
	Model 0	Model 1 (Model 0 + Karakteristik Konsumen)		Model 2 (Model 1 + Faktor Lingkungan)		Jawa	Luar Jawa
		Model 1a	Model 1b	Model 2a	Model 2b		
Time Trend	-0.03954***	-0.08066***	-0.08072***	-0.08238***	-0.08167***	-0.07532***	-0.10504***
Jenis Kelamin, base (Laki-Laki)							
(Perempuan)		0.47412***	0.48229***	0.48402***	0.16711***	0.12035***	0.26277***
Interaksi Jenis Kelamin & Time Trend		0.05310***	0.05310***	0.05278***	0.05213***	0.05378***	0.05365***
Usia, base (22-44 tahun)							
(<22 tahun)			-0.13733***	-0.14482***	-0.22892***	-0.24800***	-0.16550***
(>44 tahun)			-0.14264***	-0.14363***	-0.01151	0.01202	-0.13934**
Musiman, base (Non-Lebaran/Natal)							
(Lebaran/Natal)				0.28158***	0.28064***	0.28558***	0.26333***
Marketplace, base (A)							
(B)					-0.14423***	-0.14984***	-0.10677*
(C)					-0.39049***	-0.41139***	-0.23847*
(D)					0.81445***	0.83411***	0.83586***
Constant	0.22682***	-0.04023***	-0.00574	-0.05475***	-0.38608***	-0.40037***	-0.37973***
P_{chi2}	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Observasi	867,738	867,738	867,738	867,738	867,738	663,131	204,607
Group	60,341	60,341	60,341	60,341	60,341	46,589	13,752
AIC	2,306,867	2,289,029	2,288,849	2,278,945	2,272,045		
BIC	2,306,902	2,289,087	2,288,931	2,279,038	2,272,173		

keterangan: * $p<0.05$; ** $p<0.01$; *** $p<0.001$

Source: Regression results with Bank Indonesia transactional sample data for purchases through several *electronic marketplaces* in Indonesia specifically for clothing products.

With the addition of variables, the impact of *time trends* on transaction intensity is consistent and the influence is getting stronger. When viewed in comparison between Model 0, Model 1, and Model 2, *the time trend* coefficient still shows significance with a negative sign. This shows the results of consistent estimation of *time trend* parameters. Meanwhile, the value of the *time trend* parameter coefficient increased from 0.040 in Model 0 to 0.081 in Model 1a and was relatively stable around 0.081 to 0.082 in later model specifications. When incorporating consumer characteristics, especially gender, the influence of *time trends* more than doubled. This condition shows that the gender variable is a moderating factor for the impact of the *time trend* on transaction intensity after the first transaction. Meanwhile, other factors such as age, seasonal influences, and market characteristics are controls in this study as reflected in the impact of *time trends* that tend to be stable on transaction intensity.

The negative significance of the *time trend* variable on shopping intensity since the first transaction can indicate two things related to consumer behavior. First, is the value consumers receive between benefits and risks. In this study, the test results indicate the benefits of transacting through the *electronic marketplace,* among others, because the decrease in information retrieval costs is not able to exceed the risks faced by consumers, one of which is receiving inappropriate products. Consumers receive net risk since the first transaction so over time the intensity of transactions experiences a downward trend. Second, *time trends* indicate a decreasing level of courage in making transaction decisions through *electronic marketplaces* for products with high purchase risk such as clothing.

When viewed based on subsamples, the influence of *time trends* also shows results that are in line with estimates in the whole sample model. Both for subsamples in Java and outside Java, *the time trend* has a significant impact on decreasing transaction intensity. However, the impact of decreasing transaction intensity is stronger for consumers outside Java. Inequality in ICT development, both infrastructure and human resources, maybe the cause of the difference in impact.

The female consumer group shows a higher intensity of transactions through *the electronic marketplace* than the male consumer group for purchasing clothing products. The significance of gender variables that distinguish the intensity of consumer transactions occurs in models 1 and 2 as well as in tests based on subsamples. The difference in transaction intensity that occurs between genders is greater in the subsample of consumers outside Java. Female consumers outside Java tend to have a higher transaction intensity than women in Java. This result is generally in line with most previous studies showing that for the purchase of clothing products, the transaction intensity of the female consumer group is higher than that of the male group.

The variable of interaction *between time-trend* and gender describes the difference (delta) in transaction intensity between groups of men and women between time since the first transaction. The women's group showed significantly higher differences in transaction intensity compared to the men's group over time. Discrepancies occur both in the overall sample model and in subsample-based analysis. This shows that the difference in transaction intensity between the women's group and the men's group will be wider over time.

The age factor can distinguish the intensity of transactions between groups. The highest transaction intensity was carried out by the age group of 22-44 years. Meanwhile, the age group less than 22 years showed significantly lower transaction intensity either in Model 1, Model 2, or in subsample analysis. Meanwhile, the age group above 44 years is significant showing lower transaction intensity in Model 1 and also consumer groups outside Java. Meanwhile, for Model 2 and also a subsample of consumers in Java, there is not enough evidence to show that the intensity of transactions in the age group over 44 years is different from the age group of 22-24 years.

Environmental factors such as seasonal patterns and market characteristics as controls of consumer transaction behavior. Seasonal variations in Indonesia, namely before Eid al-Fitr and related to Christmas / New Year, significantly increase transaction intensity growth by around 26% to 28% compared to other periods. The increase in transaction intensity during seasonal periods is in line with the seasonal pattern of offline sales of clothing products.

In addition, market characteristics are also a source of variation in the intensity of transactions in clothing products. This can be seen from the sign of significance of parameters that vary from *one electronic marketplace* to another. This condition indicates that *marketplaces* have features including merchant information, different products, and services. Therefore, for products that have a high purchase risk such as clothing, consumers will use one of the marketplaces will also consider the various features provided.

The intensity of transactions that show a decline over time since consumers make their first purchase is an important result of this study and has far-reaching implications for policymakers. This research may be the initial study that directly evaluates consumer behavior transacting on *electronic marketplaces* for purchasing products that have a relatively higher risk than other products. The results of this study have implications for industry and policy-making authorities. The shift in online transaction behavior for products that have a high purchase risk at this time may not occur because individually the trend of purchasing clothing products shows a decline. For industries, including MSMEs, the decrease in transaction intensity can be taken into consideration in marketing strategies for online clothing products. Segmented product marketing strategies, including clothing products specifically for women, maybe a space that can be utilized by players in the clothing industry. In addition, because there is no evidence of shifting, the tax base derived from the sale of clothing products offline may not decrease so tax policies on *online* transactions may be selective by considering product characteristics and consumer behavior that transacts. Meanwhile, the provision of better payment system infrastructure to support online transaction activities must continue. The availability of a conducive payment system infrastructure can provide additional benefits while reducing risk for consumers who make online transactions, including the purchase of clothing products.

CONCLUSION

Based on the results of data processing and analysis, several conclusions obtained from this study include. First, Time trends significantly negatively impact transaction intensity over time from the first purchase. This relationship may indicate consumer behavior that accepts risks greater than benefits. In other words, amid increased risks, especially for the purchase of clothing products, consumers tend not to dare to take the risk of transacting through electronic marketplaces. The downward trend in transaction intensity is stronger among consumer groups outside Java. Second, the gender factor moderates the influence of time trends on consumer transaction intensity. In addition, the female consumer group shows a higher transaction intensity compared to men, and over time the gap widens. Third, age factors and environmental factors become controls that support the consistency of the impact of time trends on transaction intensity. In particular, the consumer group aged 22-44 has the highest relative transaction intensity compared to the group under 22 years old. Meanwhile, the age group above 44 years showed significantly lower transaction intensity only in the subsample of consumers outside Java. Fourth, Environmental factors such as seasonal periods, namely Eid, Christmas, and New Year significantly increase transaction growth compared to non-seasonal periods. In addition, the characteristics of the electronic marketplace can also be a source of variation in the intensity of clothing product purchase transactions.

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