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INDIVIDUAL TAX COMPLIANCE IN INDONESIA: EVIDENCE FROM TANAH ABANG MARKET AND BENFORD'S LAW

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ABSTRACT

This study intends to detect Unplanned Evasion (UPE) among individual taxpayers in the Micro, Small and Medium-Sized Enterprise (MSMEs) sector in Indonesia. UPE refers to manipulation by taxpayers at the time of filing their tax obligations. The focus of this study is the Tanah Abang market, which has vital role in the garment and textile trade in Indonesia, where most of the sellers are MSMEs. This research uses Benford's law and internal data from the Directorate General of Taxes (DGT). The results based on the first digit and first two-digit tests showed that reported income did not follow Benford's law. The second digit tests yielded more mixed and only suggestive evidence of non-conformity with the law. To measure the magnitude of UPE, this study uses a distortion factor model, suggesting a distortion of –11.28%. The study concludes that there is substantial UPE at the aggregate. The study further explores heterogeneity by gender and age, finding that UPE is concentrated among men and older taxpayers. With the results of this research, it has an impact on DGT policy making to focus on counseling and supervising among men and older taxpayers.

Keywords: *MSMEs Sector; Benford's law; Individual Tax Compliance; Tax Evasion; Indonesia*

INTRODUCTION

Tax compliance in Indonesia is an interesting issue to discuss. While the proportion of formal tax compliance of corporate and individual non-employee taxpayers in Indonesia from 2017 to 2019 have tended to increase, the achievement of tax revenue targets has fluctuated (DGT, 2020). MSMEs in Indonesia play a significant role in the formal compliance of corporate and individual non-employee taxpayers because the proportion is 99% from all business sectors in Indonesia (Ministry of Cooperatives, 2019). Tanah Abang market, the focus of this research paper, gives valuable insight into MSMEs and tax compliance in Indonesia. It features uniform types of businesses and differences in demographic factors such as gender and age.

Tanah Abang Market is one of the best examples of MSMEs in Indonesia for several reasons. First, Tanah Abang Market has a significant role in the garment and textile trade in Indonesia. Based on the report from the Ministry of Trade of the Republic of Indonesia (2015), in a year, the visitors in Tanah Abang Market are about 73 million people. The trade value reaches IDR 42,6 trillion or 40 percent of the total national textile trade. Second, Tanah Abang Market is a popular place for buying and selling clothes and textiles in Indonesia, where most sellers are MSMEs.

Although the trend of formal compliance of corporate and individual non-employee taxpayers is rising, however, it does not reflect high tax revenues. One assumption why the relationship between increased tax compliance does not in line with the tax revenues is due to tax evasion. According to Ozili (2020), tax evasion will reduce tax revenues. If tax evasion does not occur, the tax revenues could be higher. Tax evasion means that the income reported in the tax return is different from the actual situation.

This thesis applies Benford’s law to shed light on the issue of tax evasion. According to Nigrini (1996), there is a type of tax evasion that can be detected using Benford's law, Unplanned Evasion (UPE). UPE occurs at the time when reporting tax returns. He assumed that if a tax evasion occurs, a digital frequency of income will be different from Benford's law frequency. Therefore, to detect the UPE based on income data, we use Benford's Law. If the digit frequency of all reported income in Tanah Abang Market does not follow the expected frequency from Benford's law, there is an indication of tax evasion. We predict tax evasion in aggregate, not as in individual taxpayers.

Furthermore, several factors might affect taxpayer compliance. In this research, we study the role of gender and age in tax compliance. There are several reasons for this focus; first, traders in the Tanah Abang market are relatively homogeneous in business sectors, sources of income, perceptions about the tax system, and relations between traders, all of which can be considered fixed or cateris-paribus. Therefore, demographic factors such as age and gender provide a source of variation and may predict tax compliance. Second, previous studies about the relation of age and gender on tax compliance show mixed results. Third, this research is related to DGT's efforts to increase compliance with taxpayers through counseling, possibly leveraging gender and age.

To sum up, this research aims to analyze the individual tax compliance problem faced by the sellers in Tanah Abang Market in 2019. We use Benford’s law to detect tax evasion based on income. Besides, this study will also use internal factors such as gender and age, to determine individual tax compliance. This research is a meaningful contribution for the Directorate General of Taxes, helping to identify ways to increase tax compliance and minimize the evasion, as well as to the taxation literature in Indonesia as a whole.

The Overview of Benford’s Law

In 1881, Simon Newcomb discovered that the initial page of a logarithmic book is dirtier than the page in the later. He proposed that it is not just happened by an accidental but follow the distribution law. In 1938, based on this assumption, Frank Benford, who is a physicist, successfully rediscovered this phenomenon which called "Law of Anomalous Numbers". He tested the first digit number of the extensive data set, such as the length of the river, the US population, weight of molecular, the number of the street address and the number of death rates. The result shows that the distribution of the first digit number follows a particular pattern as called today Benford's law.

Usually, the first digit from the data set has an equal proportion of around 11%, with every number from 1 to 9. However, Benford sees that the proportion of the first, second, third and four digit will follow the logarithmic pattern that the small digit number will appear more than the higher digit number. Benford then found an expected frequency known as Benford's Law. (See table 1)

Table 1. Expected Digital Frequencies of Benford's Law

	Position in Number			
Digit	**1st**	**2nd**	**3rd**	**4th**
0	-	0.11968	0.10178	0.10018
1	0.30103	0.11389	0.10138	0.10014
2	0.17609	0.10882	0.10097	0.10010
3	0.12494	0.10433	0.10057	0.10006
4	0.09691	0.10031	0.10018	0.10002
5	0.07918	0.09668	0.09979	0.09998
6	0.06695	0.09337	0.09940	0.09994
7	0.05799	0.09035	0.09902	0.09990
8	0.05115	0.08757	0.09864	0.09986
9	0.04576	0.08500	0.09827	0.09982

Source: Nigrini (1996)

According to Mark (2011), the number that could have expected as Benford's law should have the following criteria: first, the figure measures facts or events, such as population and financial data. Second, there are no maximum and minimum limits such as income, sales, and account payable. Third, this number does not constitute an identity, for example, tax identity number, identity card.

From Theory to Empirical Study

The most important study was conducted by Nigrini (1996). He was the first person to use the Distortion Factor Method to determine whether data were manipulated downward or upward based on digit numbers. He assumes that with the more use of lower digits, it indicates understatement, while the more use of higher digits indicates overstatement. The results show that the interest received by taxpayers; lower digits are frequently used, so it indicates understatement. On the contrary, the interest paid by taxpayers, the use of higher digits is more common, which indicates there is an overstatement. Another study in taxation was done by Busta and Sundheim (1992). They conducted a study in The USA using tax return data from 1982 to 1983. They use the first digit, second digit and third digit test. The results show that with the first digit test, tax return data almost follow Benford law. Nevertheless, on the second and third digit tests, the result is reasonably close to Benford's Law.

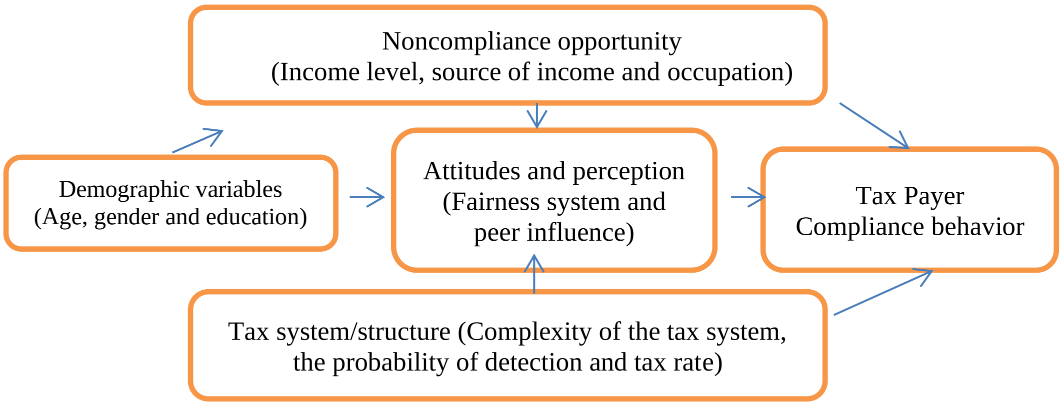
In Indonesia, studies that use Benford law specifically for taxation are limited. Hidayat and Budiman (2016) explained that Benford's law could be used in computer-based auditing. The study results show that Benford law can be used to detect data manipulation through computer-based accounts. Furthermore, Prasetyo and Djufri (2020) tried to detect inaccuracies of tax invoices using the first digit test, the second digit test, and the first two-digit test. Using Benford's law, the tax auditor can determine which tax invoice is a priority in the tax audit.

Based on the results of the empirical study above, we can take some essential points. First, Benford's law can be applied in various fields such as accounting, tax and forensics. Second, the use of the first digit test, the second digit test and the first two digits are the most widely performed in studies. Third, in taxation, measuring the magnitude of non-compliance with Benford's law can be calculated with Distortion factor models. Fourth, to measure the goodness of fit, several ways can be used, such as the Z test, Mean Absolute Deviation and Chi-Square.

Taking everything into consideration, this study will: first, use the first digit test, the second digit test and the first two-digit test. Second, use the distortion factor model to measure magnitude. Third, to measure the goodness of fit, we use the Z statistic test, mean absolute deviation (MAD) and Chi-square test. Unlike the previous studies, this research will use the internal data from DGT and become the first research to explore the tax evasion in the MSMEs sector, particularly in Tanah Abang Market, using Benford's law.

The Effect of Gender and Age on the Tax Compliance

After determining the tax evasion using Benford's law that is crossed with age and gender, then we will further look at the micro data of tax compliance that is affected by age and gender. The first complete study of tax compliance is conducted by Jackson and Milliron (1986). They found 14 factors that affected the taxpayers to comply with the tax law. Fischer et al. (1992) then categorized those 14 factors into four groups called Fischer Model. (See Figure 1)



Source: Fischer et al. (1992)

Figure 1. Fischer Model of Tax Compliance

We use Fischer's Model as a conceptual framework since; first, it is argued that the model is very comprehensive to describe tax compliance. The tax compliance model combines three essential parts, i.e. economic, sociological and psychological factors, becoming one comprehensive model. Second, as seen in the model, the demographic factor is indirectly related to taxpayer compliance, and it has a direct relationship to the noncompliance opportunity, attitude and perception. In this study, noncompliance opportunity, attitude and perception factors are considered constant because the data samples from Tanah Abang Market have the same characteristics in terms of sources of income, employment and peer relationships. So, being a non-compliant opportunity, attitude and perception stated as constant, age and gender will ultimately affect tax compliance.

The results of the studies about the effect of age level on tax compliance mixed. The positive relation is found by Chung and Trivedi (2003) and Kurniati (2011). The positive relation means the older age, the higher tax compliance and the younger age, the lower tax compliance. On the other hand, the negative relation is found by Al-Mamun et al. (2014). Negative relation implies that younger people are more likely to comply with the tax obligation than older people. Based on those previous research, we assume that that age has a significant positive effect on tax compliance.

The study of gender concerning tax compliance also has a contradictory result. As a study from McGee dan Smith (2007) stated that women are more obedient to the law. It is argued that women are more likely to seek conformity, more conservative with the rules and more obedient. On the contrary, men are also mentioned as more comply with the law based on the study from Houston and Tran (2001). Based on the results of the empirical research above, it is known that the gender of the taxpayer is significantly related to tax compliance.

Several studies on the effects of socioeconomic demography on tax compliance—most of the studies conducted used external data; survey data, and questionnaires such Cahyonowati (2011). Different from previous research, in this study, we use internal data from DGT, not only to look at the age and gender effects of tax compliance but also to detect tax evasion on the reported income by taxpayers.

METHODS

Data Preparation

The internal data were obtained with legal permission from the Directorate General of Taxes. This data consists of gender, age, and final income tax 2019 under Government Regulation (PP) Number 23 of 2018 in Tanah Abang Market. Internal data were taxpayers' data whose identities had been deleted to protect the confidentiality of taxpayers. In Tanah Abang Market, by 31 December 2019, there were 7662 registered taxpayers as a population. From those numbers, only 1402 stated as "normal" taxpayers as sample. Meanwhile, 6260 taxpayers are categorized as "non-effective". Therefore, to measure compliance, we only use normal taxpayer, which amounts to 1402 data. From this number, only 955 paid taxes are counted as compliance. In contrast, 448 data stated as non-compliance, which are not paying taxes. The amount of income is predicted from the final tax paid in 2019 under PP Number 23 of 2018. With a tax rate of 0.5%, we could predict the income for a year. We use Microsoft Excel to determine the first digit, the second digit and the first two digits. Finally, we compare the percentage of each digit sample with the frequency of Benford's Laws as in Table 1.

Conformity Tests

In this study, we follow Nigrini (1996) and Drake and Nigrini (2000) that use three conformity tests; the absolute mean deviation (MAD), the Z-statistic test and the Chi-square test. The mean absolute deviation (MAD) test is used to measure overall conformity of the actual data with expected from Benford's law. The MAD test ignores the number of observations. The formula for calculating the mean absolute deviation is $\sum_{i=1}^{K} \frac{|AP-EP|}{K}$, where K is the number of digits in each test digit. Expected Proportion (EP) is a proportion of Benford's law, while Actual Proportion (AP) is the actual data proportion. The numerator is the difference from the actual proportion minus the expected proportion of Benford's law. The difference is in absolute value, which means that though the value is negative, it will always be positive.The MAD is then compared to the table of critical values and conclusions from Drake and Nigrini (2000). (See Table 2). The higher MAD means more significant the difference between the actual proportion of data and expected data from Benford's law.

Table 2. The Critical Values and Conclusions for MAD values

Digits	Range	Conformity
First Digit	0.000 to 0.006	Close
	0.006 to 0.012	Acceptable
	0.012 to 0.015	Marginally Acceptable
	Above 0.015	Nonconformity
Second Digit	0.000 to 0.008	Close
	0.008 to 0.010	Acceptable
	0.010 to 0.012	Marginally Acceptable
	Above 0.012	Nonconformity
First-Two Digits	0.0000 to 0.0012	Close
	0.0012 to 0.0018	Acceptable
	0.0018 to 0.0022	Marginally Acceptable
	Above 0.0022	Nonconformity

Source: Drake and Nigrini (2000)

The Z-statistic test is useful for determining whether the difference in digit frequency from actual data and expected data of Benford's law statistically significant or not. Unlike the previous MAD test, which ignored the number of observations, the number of observation data is essential in the Z-statistic test. This study uses a 5% significant level, so the Z-statistic value cutoff is 1.96. If the Z-statistic result is higher than 1.96, the difference between actual data and Benford's law is significant. The significant difference in the particular digit is an indication of evasion. Thus, DGT could conduct a further examination of the taxpayers' income.

The Chi-square test compares the actual count of numbers with the expected count of numbers. The assumption is that the actual data will follow Benford's law. So, the null hypothesis is the actual data following Benford's law. Then we compare the results to the cut off value. The cut off value could be found in the statistics table or calculated using Microsoft Excel with the formula =CHIINV.

The overuse of lower digits in the actual data indicates underreported income. However, the magnitude is unknown. Nigrini (1996) introduced the distortion factor model (DF) to estimate the level of manipulation of the data. To calculate the DF, we need the mean value of the Benford's set. Then, we compared the mean value of the actual data. Because Benford's set can be large or small, the exact mean value of Benford set is unknown. So, to calculate the mean, we follow Nigrini (1996) by shifting decimal numbers into the range numbers of (10,100) or 10 ≥ x < 100. The mean value of the Benford's set is called the expected mean (EM). The mathematical calculation of EM was not discussed in this study. Based on Nigrini, (1996), the EM value was 39.08. If the number has the same probability of appearing in the range of (10,100), then the average value is 55, [(10 + 100)/2]. However, as in the Benford's set, the number of lower digits is more proportional, then the expected mean is smaller, equal to 39.08. Furthermore, to calculate the distortion factor (DF), we use the following stages: first, we move the digit numbers into the range (10,100). Second, we erase numbers that having values below 10, including numbers that have a value of 0. The aim is to ensure that all numbers have the first and second digits. Next, we move digit numbers that are greater than 100 into the range (10,100) and calculate the Actual Mean (AM) of the data sample. Finally, we calculate the Expected Mean (EM) of the Benford's set and calculate the distortion factor with the formula = $\frac{(\text{Actual Mean}-\text{Expected Mean})}{\text{Expected Mean}}$. After that, the DF is multiplied by 100 to determine the percentage of distortion factor from AM to EM. If the distortion factor's value is negative, then lower digits are used more in the actual data. Meanwhile, if the distortion factor value is positive, the higher digits are used more in the data.

The Effect of Age and Gender on Tax Compliance

To confirm the result of Benford's law in the detection of tax evasion that crossed to age and gender, we use a regression model. The dependent variable is compliance 2019, while the independent variables are age and gender. The Model is as follows:

$$\text{Compl}_\text{i} = \propto_0 + \propto_1 Age_\text{i} + \propto_2 \ Gender_\text{i} \ + \varepsilon_\text{i}\,) \qquad \ldots\ldots..1$$

where; i denotes individual taxpayers, t refers to the fiscal year of 2019.

$Compl_i$: Tax compliance, represented by paying the final tax on the fiscal year 2019.

$\propto_1 Age_\text{i}$: Age level, ∝_1 is expected to be positive since, in Indonesia, the older people are more as a role model to younger people.

$\propto_2 Gender_\text{i}$: Gender, ∝_2 is expected to be negative as women in Indonesia are usually more comply with the law.

Table 3. Summary Variable

No	Variable	Description Dummy Variable	Frequency	Percentage
1	Compliance 2019	Comply (1)	955	68.11%
		Not Comply(0)	447	31.89%

2	Gender	Male (1)	1086	77.46%
		Female(0)	316	22.54%

Source: Author calculation using Microsoft Excel (2020)

In general, the internal data from the Directorate General of Taxes is a cross-section data in 2019. Those data consist of age, gender, tax payments in 2019. The summary of the data can be seen in the table 3. The dependent variable is tax compliance in 2019, which is divided into two parts: compliant and non-compliant. Based on the PP Number 23 of 2018, taxpayers are stated as complying if they paid the final income tax. Thus, compliance is defined as taxpayers who paid final income tax in 2019, while non-compliant taxpayers are taxpayers who did not pay taxes at all. Since the dependent variable's outcome is compliant and non-compliant, this study uses a binomial variable of 1 if a taxpayer complies and 0 if a taxpayer is not compliant. Overall, the sample data in this study were 1402 taxpayers.

Independent variables can be divided into two variables: age and gender. The age variable is numeric. This study shows that the youngest sample is 18 years old, while the oldest is 85 years old. The average age in the sample is 49 years old. (See table 4) Next, the gender variable is binomial. Men were categorized as 1, while women were categorized as 0. The sample data found 1086 men or 77.46%, while women were 316 (22.54%).

Table 4. Age Summary

Variable	Max	Min	Mean	Standard Deviation	Median
Age	85	18	49	11.6872	48

Source: Author calculation using Microsoft Excel (2020)

This research paper uses quantitative methods. The dependent variable is tax compliance, whether the taxpayer was compliant or not. So there are only two values of the dependent variable, 1 if the taxpayer is compliant and 0 if the taxpayer is not compliant. In other words, the dependent variable is the dichotomy or binary variable. Gujarati and Porter (2003) said that if the dependent variable is a binary variable such as tax compliance, then the model aims to determine the probability of an event. One method is used in this study for variable binary responses, Logit model.

RESULTS AND DISCUSSION

First Digit Analysis

The first digit analysis aims to determine the general picture of the data because it detects visible irregularities. From the table first digit frequencies, it can be seen that the MAD is 0.0258. (See Table 5) When we compare it to the conformity table (see table 2), the MAD value is categorized in the non-conformity category. The first digit analysis suggests that the reported income indicates irregularity with Benford's Law. In general, the data shows non-conformity with Benford's Law. However, we do not know precisely which digits are experiencing the discrepancy.

The bias column shows the difference between the actual data and the expected frequency of Benford's law. Positive values indicate that the actual value exceeds the expected value of Benford's law. Conversely, negative values indicate that the actual value is less than Benford's law. Based on the first digit frequency table, the digits of 1, 2 and 3 show positive values while digits 4, 5, 6, 7, 8 and 9 show negative values. We can interpret that the use of numbers 1, 2 and 3 in the first digit is higher than the expected frequency of Benford's laws while the use of numbers 4 to 9 is smaller than the expected frequency of Benford's law. Next, based on the Z-statistic test, five-digit numbers significantly indicate irregularities, numbers 2, 3, 5, 6 and 7, whereas numbers 1, 4, 8 and 9 are statistically insignificant.

When the taxpayers were reporting their income, they might report smaller income than the actual income to reduce the tax. Under PP Number 23 of 2018, the income limit using a 0.5% tax rate is 4.8 billion rupiahs. Consequently, there is a possibility that taxpayers will report their income below the threshold value by using many numbers of 1, 2, 3, or 4 in the first digit. The first digit test results indicate the use of numbers 1, 2, 3 is more than the expected frequency of Benford's Law. The statistical Z test value also reinforces this indication, marked by the positive bias that is statistically significant in numbers 2 and 3. These results follow studies from Nigrini (1996) stating that individual taxpayers in the USA tended to reduce their income and increase the tax expense. The results showed that tax evasion occurred by reporting lower-income, marked by the overuse of lower digits than Benford's laws expected frequency.

Table 5. First Digit Frequencies

First Digit	Benford	Overall Sample		
		Actual	Bias	Z stat
1	30.10%	32.15%	+	1.34
2	17.61%	21.26%	+	2.92*
3	12.49%	18.43%	+	5.50*
4	9.69%	9.11%	-	0.55
5	7.92%	3.87%	-	4.57*
6	6.69%	3.35%	-	4.07*
7	5.80%	4.08%	-	2.20*
8	5.12%	3.98%	-	1.52
9	4.58%	3.77%	-	1.11
Observation		955		
Chi-Square		80.09		
MAD		0.0258		

* Significance at 5%

Source: Author calculation using Microsoft Excel (2020)

Next, we compare the chi-square with the cut-off value of the first digit of 15.50. The null hypothesis is that the actual data will follow Benford's law. We can reject the null hypothesis if the chi-square of actual data exceeds the cut-off value. The chi-square of actual data is 80.09; it exceeds the cut-off value, meaning that we can reject the null hypothesis. We can say that the actual data do not follow Benford's law.

Second Digit Analysis

Similar to the first digit test, the second digit test is also used to find out the conformity of the sample data with Benford's law. The MAD value of the second digit test is 0.008. (See Table 6) By looking at the conformity table results, the sample data is categorized as acceptable conformity with Benford's law.

Table 6 Second Digit Frequencies

Observation	955
Chi-Square	8.91
MAD	0.008

* Significance at 5%

Source: Author calculation using Microsoft Excel (2020)

Furthermore, the chi-square value is 8.91. (See Table 6) This value is still below the cut-off for the second digit test of 16,919. We do not have enough evidence to reject the null hypothesis, so the sample data follow Benford's Law. The Z-statistic results also show that the difference in each digit is not significant. It can be concluded that although there is a difference in the proportion between data sample data and Benford's law, the difference is not statistically significant.

The First Two Digit Analysis

The last test is the first two-digit test. This test is relatively more accurate than the previous two tests. For overall data, the MAD is 0.0036 (see table 7). Compared to the table of MAD conformity, it is categorized as non-conformity with Benford's Law. Based on the Z statistic test, 7 out of 90 groups of digits have a statistically significant difference. Those digits are 18, 20, 29, 36, 38, 39, 44 and 61. Most of the digits are lower digits except digit 61. Digit 61 is significantly different because no taxpayers report income with the first two digits of 61. Except digit 61, the sign of the differences is positive, meaning that the use of the lower digits is more than the expected frequency from Benford's law. It indicates that the income reported is smaller than it should be (Nigrini, 1996).

The chi-square value is 156.61, which exceeds the cut-off value for the first two-digit test of 112.02. So, we can reject the null hypothesis, which means the actual data does not follow Benford's law.

Table 7. First Two Digit Frequencies

First-Two Digit	Number of Observation	Chi-Square	MAD
Overall Sample	955	156.61	0.0036
Male	753	145.64	0.0039
Female	202	88.24	0.0058

Young	396	145.65	0.0055
Old	559	97.97	0.0034

Source: Author calculation using Microsoft Excel (2020)

Next, we conduct the first two-digit test based on gender differences. The number of observational data for males and females is 753 and 202, respectively. Accordingly, the MAD is 0.0039 and 0.0058 for males and females (see table 7). It shows that income data from both males and females are categorized as nonconformity with Benford's Law. Slightly different results are shown from the chi-square test. The chi-square value for female's income is 88.24. The cut-off value of the first two digits is 112.02. Then, the chi-square value does not exceed the cut-off, meaning that we do not have enough evidence to reject the null hypothesis. Women's income data are following Benford's law. On the contrary, the chi-square value of the male is 145.64, which exceeds the cut-off. We can reject the null hypothesis, which means that male income data does not follow Benford's law. Based on the Z statistic test, there are four digits from 90 digit groups that are statistically significant on male's income. The numbers are 18, 30, 34 and 38. All the bias sign is positive, meaning that those numbers are overused compared to Benford's law's expected frequencies.

The MAD values for young and old are 0.0055 and 0.0034, respectively (see table 7). Based on Drake and Nigrini (2000) cut-off table, both young and old data are categorized as non-conformity with Benford's law. Based on the chi-square test, the results differ between older and younger people. Young people have a chi-square of 145.65, which exceeds the cut off value. We can reject the null hypothesis that younger people’s data do not follow Benford law. Simultaneously, the chi-square value of older people is 97.97, which is still below the cut off of 112,02. It can be concluded that we do not have enough evidence to reject the null hypothesis; the data follow Benford’s law. With Z-statistic tests, we can find out the details of groups of digits that have significant differences. The significant difference in the young group is in digit 18, 20, 29, 38 and 39. All digits have a positive bias sign. All digit groups are included in the lower digits, so there is an indication of underreported income from the younger group. On the contrary, in the older group, the significant bias was found only in digit 14 and 17.

To measure the magnitude of the deviation that occurs between the actual data and Benford's law, we use the Distortion Factor (DF) model developed by Nigrini (1996). The results of the DF model can be seen in Table 8. For all 955 income data, the actual mean value is 34,676, while the expected mean value is 39,086. Thus, the distortion factor value is -11.28%. The DF value is statistically significant at the 5% level based on the statistical Z test results of 2.79. The negative sign means that the lower digits are more frequently used than the expected frequencies. Further data will then be categorized based on gender differences. The income data from males is 753 samples, while the income data from females is 202. Next, the actual mean values of the male and female income are 34.72 and 34.08, respectively. The values the distortion factor model are -11.15% and -11.76% for males and females, accordingly. Although the DF value is almost similar but based on the Z-statistics test, the DF value is not significant on the female income. However, the results that DF value on income from male differ significantly.

Then, the data is separated based on age differences. We will discuss income differences reported by older and younger people. We categorized young and old taxpayers using the age limit from the Ministry of Health of The Republic of Indonesia (Ministry of Health, 2009). The maximum age of young people is 45 years old. In contrast, the old group is those who are more than 45 years old. The actual mean value of the income of younger people and older people is 34.59 and 34.73. The DF of younger and older people is -11.50 and -11.13, respectively. Again, the DF values are almost similar, but it has different significance. In younger people, the DF value is not statistically significant, but the DF value is significant in older people.

Negative values in DF indicate that the number reported is less than what should exist in Benford's Set. That is because what is reported is income; there is an indication that the reported income is below the actual value.

Table 8. The Distortion Factor

	Overall Sample	**Male**	**Female**	**Young**	**Old**
Number Of Observation	955	753	202	396	559
Actual Mean	34.676	34.726	34.489	34.591	34.736
Expected Mean	39.086	39.086	39.086	39.086	39.086
Distortion Factor (%)	-11.28	-11.15	-11.76	-11.50	-11.13
Z Statistics	2.79 *	2.45 *	1.34	1.83	2.11 *

* Significance at 5%

Source: Author calculation using Microsoft Excel (2020)

The Effect of Age and Gender on the Tax Compliance

Based on the regression results of Logit method, all the variables; gender and age, statistically significantly affected the 2019 tax compliance. First of all, according to Gujarati and Porter (2003), one way to measure the goodness of fit is to look at the pseudo R-square and classification model. The pseudo-R-square of logit method is 0.0091 (see Table 10). If we look at the logit method results, only 0.9% of the age variable can explain tax compliance; other variables outside the model explain the remaining 90.1%.

Next, we use the classification tests to determine whether the logit method is a good model. From Table 9, it can be seen that the model can predict at 68.12% of actual conditions. The model can predict the relationship between 2019 tax compliance with age and gender.

Table 9. Classification Model

Sensitivity	99.27%
Specificity	1.79%
Positive predictive value	68.28%
Negative predictive value	53.33%
False + rate for true ~D	98.21%
False - rate for true D	0.73%

False + rate for classified +	31.72%
False - rate for classified -	46.67%
Correctly classified	68.12%

Source: Author calculation using STATA 15 (2020)

Finally, we look at the P-value. The null hypothesis is independent variables that simultaneously do not influence the dependent variable. To reject the null hypothesis, the p-value must be less than 0.005. The result of the logit method shows that the p-value is 0.0012. So, we can reject the null hypothesis, which means that all independent variables can explain the dependent variable.

Regression results show that the coefficients in all independent variables have positive value. (See table 10) Gender significantly influences tax compliance. The marginal effect coefficient is 0.0504, meaning that men are more likely to comply with tax obligations by five percentage points than women. This study's results are in line with studies from Houston and Tran (2001) that women tended to do tax evasion more often than men.

The relationship between age levels and tax compliance is also positive, meaning that older people are more likely to comply with tax obligations. The age coefficient based on the logit method is 0.0233, meaning that older people tend to have a higher probability of compliance by 2.33% compared to younger people. For every increase in age by one year, the probability of taxpayers to comply will increase by 2.33 percentage points. These results are consistent with our hypothesis that older people tend to be more obedient to tax obligations than younger people because older people are role models for younger people in Indonesia. According to Tittle (1980), the relationship between age and tax compliance is due to experience and generational differences. He argued that younger people tend to be less sensitive to punishment and more willing to take risks. Furthermore, they also have quite significant psychological differences compared to older people (generational differences). Moreover, Chung and Trivedi (2003) also argued that younger people are less compliant than older people.

Table 10. Regression Result

Variable	Marginal Effect Logit Model
Gender	0.0504 *
	(0.0289)
Age	0.0219 ***
	(0.0071)
Age_sq	-0.0002 ***
	(0.0000)
Number of Obs	1402
Prob>Chi2	0.0012

Pseudo R2	0.0091

Significant at 10%=*, 5%=**, 1%=***

Standard Error in parenthesis

Source: Author calculation using STATA 15 (2020)

Since 2015, in the Tanah Abang Market, there has been a tax outlet called "Gerai Pajak". It is provided in collaboration with the DGT, represented by Jakarta Tanah Abang Dua Small Tax Office, DKI Jakarta regional government, and the Tanah Abang Market management. The function of this tax outlet is to provide tax information to traders in the Tanah Abang Market. This tax outlet makes traders easy to fulfill their tax obligations without having to come to tax offices. The obstacle faced by traders is the limited time to come to tax offices to fulfill their tax obligations. Hence, this tax outlet is a solution given to taxpayers, especially traders in the Tanah Abang market. One indication of the success of this tax outlet is the high tax compliance from traders in the Abang Market.

Although the DGT has made many counseling activities for the younger generation, based on the analysis results, younger people are less likely to comply with tax than older people. Therefore, it is necessary to conduct massively targeted counseling activities.

Table 11. Odds Ratio Logistic Regression Model

Variable	Odds Ratio	Z	P>Z
Gender	1.264 (0.170)	1.74	0.083
Age	1.107 (0.037)	3.05	0.002
age_sq	0.999 (0.000)	-2.74	0.006
_cons	0.120 (0.099)	-2.57	0.010

Source: Author calculation using STATA 15 (2020)

All independent variables have statistically significant effect on the dependent variable. Based on gender variables, men's odds ratio to comply in 2019 is 1.26 times higher than women (see table 11). Furthermore, from the age variable, older people tend to have 1.1 times higher odds ratio to comply with taxes than younger people.

CONCLUSION

Based on the analysis, the first digit test results show that in general, the income data are not in conformity with Benford's Law. The use of lower digits, such as 2 and 3 is higher than the digital frequency of Benford's Law. The second digit test shows that in general, income data falls into the acceptable conformity category for Benford's law. Furthermore, more specific and accurate tests can be performed with the first two-digit test. Income data are categorized as non-conformity with expected digital frequencies. Digits 18, 20, 29, 36, 38, 39 and 44 are statistically significantly different from Benford's law. All bias is positive, meaning that the use of digits is more than the expected frequency.

To measure the magnitude of the difference with Benford's law, we use the Distortion Factor Model (DF) developed by Nigrini (1996). The results show that, in general, income data have a DF value of - 11.28%. The negative sign means the lower digits are overused compared to the frequency of Benford's law. Furthermore, based on age and gender differences, DF values are statistically significant for males and older people.

Henceforth, after exploring UPE using Benford’s law, we look at the effect of gender and age on the tax compliance in 2019 using Logit regressions at the individual level. The analysis of the regression results found that gender has a significant correlation on tax compliance in 2019. Men are more likely to comply than women. Furthermore, age also has a positive and significant effect. Older people have a higher probability of compliance than younger ones. We can conclude that in 2019’s tax compliance, males tended to be more obedient in reporting and paying taxes. However, there were indications that the amount of tax paid or reported income was lower than the real income (UPE). Then, in terms of age, older people tended to be more compliant than younger people, but their reported income also indicated underreported income.

In this study, in tax compliance variables, we did not distinguish whether taxpayers are late or not in reporting or paying taxes. So, the taxpayer’s status was the same between those who reported on time or late. The recommendation for the next research is to be able to distinguish between taxpayers who are on time and late. Moreover, we only used two independent variables: age and gender. In the next research, other independent variables, such as the level of income or education, would be fruitful. Benford's law in the field of taxation in Indonesia is still rare, so there is still potential for further studies. Due to time and data limitations, we only reviewed income based on predictions of the amount of taxes paid. Future studies could use income data reported by taxpayers in the annual tax return.

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