Individual Tax Compliance in Indonesia: Evidence from Tanah Abang Market and Benford's Law

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Dedication Page

For my beloved wife Amy,
To my dear son Damas,
And for my parents,
You are my best supporters.

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List of Acronyms

AM	Actual Mean
AP	Actual Proportion
AURI	Indonesia Air Force
COGS	Cost of Goods Sold
DGT	Directorate General of Taxes
DKI	Special Capital Region (of Jakarta)
EM	Expected Mean
EP	Expected Proportion
IDR	Indonesia Rupiah
IMF	International Monetary Fund
IRS	Internal Revenue Services
KSWP	Taxpayer Status Confirmation Service
LAKIN	The Performance Report of the Directorate General of Taxes
MAD	Mean Absolute Deviation
MSMEs	Micro, Small and Medium-Sized Enterprises
NPWP	Taxpayer Identification Number
OECD	Organisation for Economic Co-operation and Development
PE	Planned Evasion
PGMTA	Tanah Abang Metro Wholesale Center
PP	Government Regulation
UPE	Unplanned Evasion
USA	United States of America
VOC	Vereenigde Oost-Indische Compagnie

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 main focus of this study is the Tanah Abang market, which has a vital role in the garment and textile trade in Indonesia, where most of the sellers are MSMEs. This research uses internal data from the Directorate General of Taxes to contribute to novel evidence. The study uses Benford's law to detect UPE under the assumption that if taxpayers report their taxation correctly, digit numbers will follow the Benford's law distribution. If the digit frequency of reported income in Tanah Abang Market does not follow Benford's law's expected frequency, there is an indication of tax evasion in the aggregate. 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 in this marketplace. The study further explores heterogeneity by gender and age, finding that UPE is concentrated among men and older taxpayers. The Benford’s law analysis is complemented with an individual level investigation of the effect of age and gender on tax compliance. Regression results indicate that men were more likely to comply than women, while older people tended to comply with taxes more than younger people. The study concludes by discussing tax policy implications in the context of Indonesia.

Relevance to Development Studies

In Indonesia, formal tax compliance tended to increase in recent years, while the achievement of tax revenue targets has fluctuated. If tax revenue is low, it will affect the government’s financing space to induce social and economic development. This study is related to development studies because taxes are important fiscal instruments. In Indonesia, taxes are the primary source of the government’s development financing. This study aims to help improve tax performance in increasing tax compliance and reducing tax evasion in Tanah Abang Market and Indonesia as a whole.

Keywords

MSMEs Sector, Benford’s law, Individual Tax Compliance, Tax Evasion, Indonesia, Tanah Abang Market

Chapter I
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 has tended to increase, the achievement of tax revenue targets has fluctuated. 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 (Kemenkop, 2019). MSMEs are productive businesses carried out by individuals or business entities that meet specific criteria in net worth and annual sales as regulated in law. 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. This research aims to detect the existence of unplanned tax evasion (UPE) using Benford's law and explore the effects of gender and age on taxpayer compliance in Tanah Abang market. UPE is a striking manipulation of filling tax obligations right at the time of tax reporting.

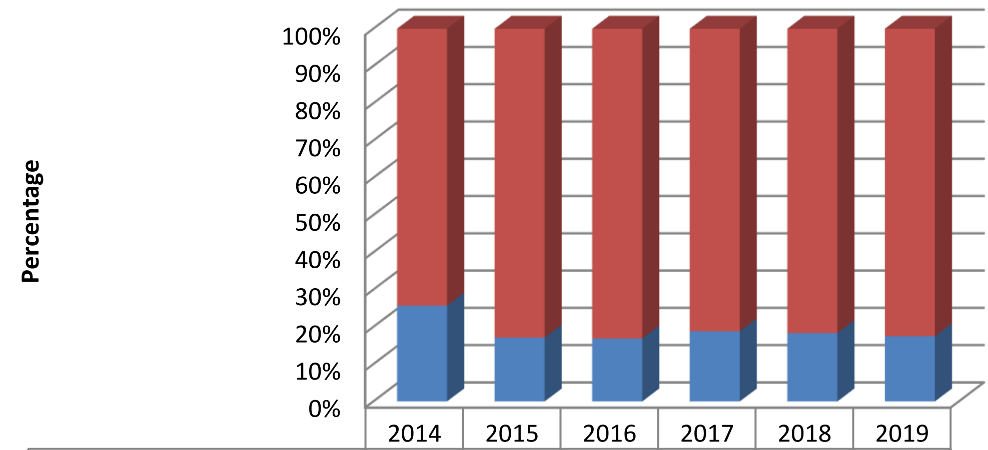
1.1. Background

As stated in the opening of the 1945 Constitution, the vision of Indonesia is to create a sovereign, fair, and prosperous state. Development is one of the paths taken to realize this vision—the notion of development links to infrastructure and human resource development. Equitable infrastructure is allocating economic resources effectively and efficiently. On the other hand, human resource development is also needed as the primary driver of development. Improving the quality of human resources links to education, health and social security. To finance all these activities, any country like Indonesia needs a significant amount of funding from taxes.

As stated in Law Number 6 of 1983 concerning the general provisions on taxation, taxation is a compulsory contribution of every citizen who is compelled by law, which does not receive direct compensation and is used to finance development. There are several factors of concern between the government and the representative council in determining the tax revenue target in the state budget in 2019. Some of these factors can be divided into internal and external factors (Financial Note of the Government of Indonesia, 2019). Internal factors are related to the condition of the Indonesian economy and fiscal policy in the form of the tax amnesty in 2016 and 2017, tax reform and information technology in taxation services. External factors are related to the global economy's condition, especially the economic policies of developed countries such as the United States, China and the Middle East. Those policies could affect domestic economic growth and international trade.

Taxes are a significant source of revenue for Indonesia. Based on the Ministry of Finance (2019) data, from 2014 to 2019, the proportion of tax revenues to the state revenue fluctuated (see Figure 1). In 2014, the percentage of taxes on state revenue was 74.3%. In 2015, the proportion of tax revenues to state revenue rose to 82.3%. The highest proportion of tax was in 2016, with 82.6%. Then, in 2017, the proportion of tax revenues slightly decreased to 80.6%. In 2018, there was an increase in the proportion of tax revenues to 81.4%. In 2019, the tax percentage on the state revenue was slightly below the highest level to 82.5%.

Figure 1 Proportion of Tax Revenues to State Revenue



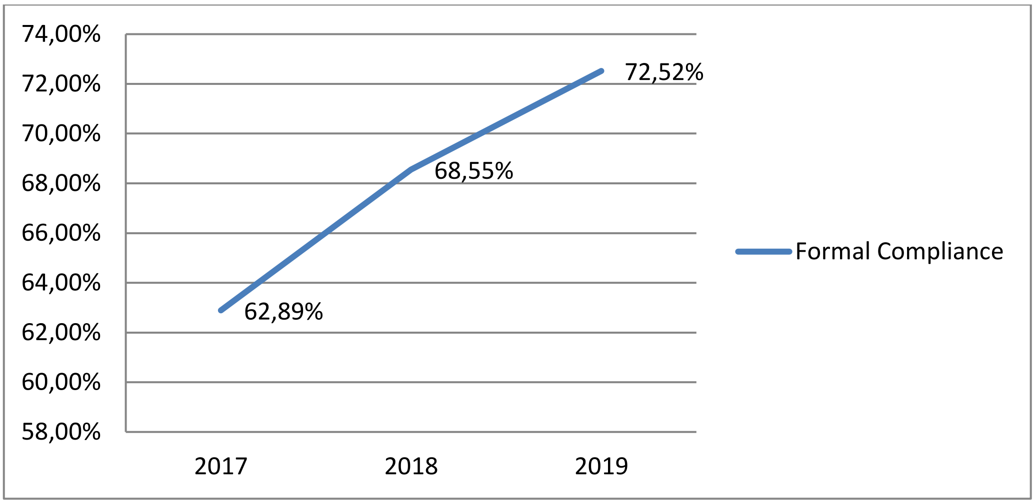
	2014	2015	2016	2017	2018	2019
Tax revenue	74,3%	82,3%	82,6%	80,6%	81,4%	82,5%
Non-Tax State Revenue and grant	25,7%	17,0%	16,8%	18,7%	18,3%	17,5%

Source: Ministry of Finance, 2020

Since 2017, there has been an increase in the trend of formal compliance of corporate and individual non-employee taxpayers. Formal tax compliance means the taxpayers submit annual tax returns, regardless of whether they paid taxes or not. The percentage of formal compliance is calculated based on the number of annual tax returns divided by the number of corporate taxpayers and individuals non-employee taxpayers who are required to submit annual tax returns. Taxpayers who are required to report their annual tax return must have a "normal" status with the last three-digit number in their tax identity being 000. Not all taxpayers who have a taxpayer identification number (NPWP) are required to conduct annual tax returns. Several taxpayers are not required to report their annual tax returns such as: treasurers, joint operations/branches/locations, taxpayers with representative office status, taxpayers who have tax obligations in other countries in the tax treaty, non-effective taxpayers and other taxpayers who are exempted from the obligation to report the annual tax return.

According to the data from DGT (2020), in 2017, formal compliance of corporate and individual non-employee taxpayers was 62.89% (see Figure 2). In the following year, there was an increase in formal compliance to 68.55%. In 2019, formal compliance was 72.52%. The formal compliance rate is relatively low, but the trend is positive (LAKIN, 2019). There are several reasons why the formal compliance rate of corporate and individual non-employee taxpayers is not optimal. First, DGT has not carried out optimal monitoring and confirmation of data to taxpayers who are required to report the Annual Tax Return. Second, some taxpayers pay taxes at a minimum level, below a particular value. Third, tax counseling has not been able to reach all taxpayers. Fourth, the taxpayer status confirmation service (KSWP) has not been equally distributed. This service is useful to record the number of active taxpayers.

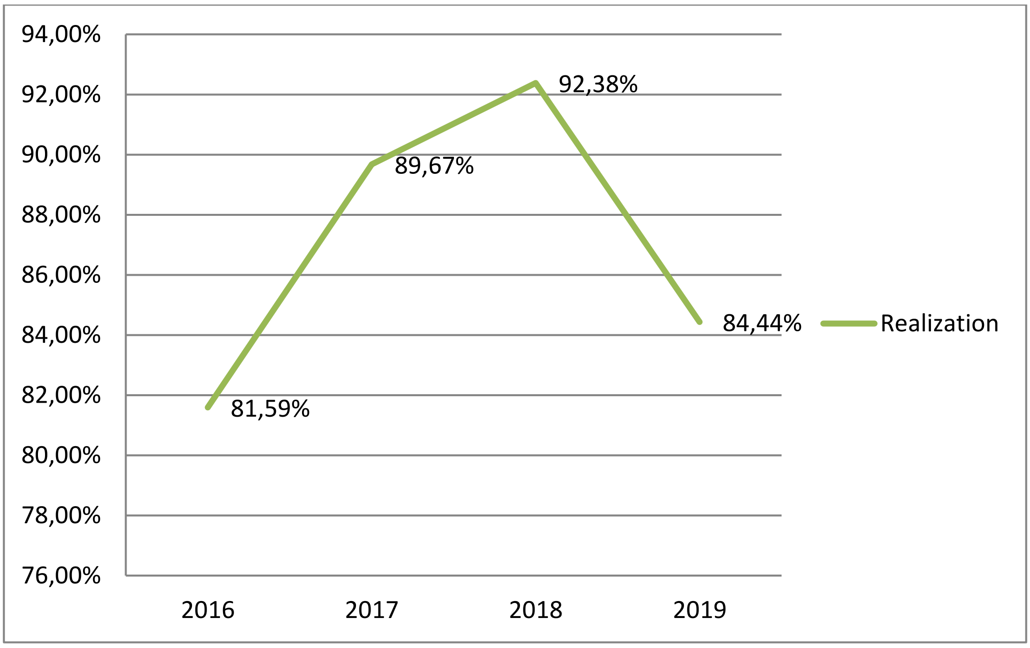
Figure 2 Formal Compliance of Corporate and Individual Non-Employee Taxpayers



Source: Directorate General of Taxes (DGT), 2020

Most of the formal compliance of corporate taxpayers and individual non-employee taxpayers are the MSMEs sector. According to the data from Kemenkop (2019), most business operators in Indonesia are the MSMEs sector. From 2015 to 2018, the proportion of MSMEs business actors compared to all business operators in Indonesia was 99%. MSMEs, according to Law Number 20 of 2008, are productive businesses carried out by individuals or business entities that meet the criteria. First, micro-enterprises have a maximum net worth of IDR Fifty million and a maximum annual sales of IDR 300 million. Second, small businesses have a net worth of 50-500 million rupiahs and yearly sales of 300 million - 2.5 billion rupiahs. Finally, medium-sized businesses have a net worth of 500 million to 10 billion rupiahs and annual sales of 2.5 to 50 billion rupiahs.

Figure 3 Realization of Tax Revenue from Target



Source: Directorate General of Taxes (DGT), 2019

However, the upward trend in formal tax compliance is not in line with the realization of tax revenues. It is hard to achieve a 100% tax realization. Only in 2008, the tax revenues reached more than 100% of the target. One reason for achieving this target was due to the sunset policy. Sunset policy is a program to eliminate tax penalties for taxpayers who voluntarily report and pay the tax owed. Since 2016, the realization of tax revenue has never reached 100% (see Figure 3). Based on the Directorate General of Taxes (DGT) data, in 2016, the realization of tax revenue was 81.59%. This figure was the lowest achievement in the last four years. In 2017, the achievement of the tax revenue target increased to 89.67%. In the following year, in 2018, the realization of tax revenue reached 92.38%, which was the highest achievement in the last four years. In 2019, the realization of tax revenue decreased to 84.4%.

Based on the performance report of the Directorate General of Taxes year 2019 (LAKIN, 2019), several reasons are underlying the 2019 tax revenue target is not achieved 100%. First, the global economic conditions are weakening, marked by the fall in international commodity prices such as coal, oil and palm oil, which affect the import income tax. Second, the factor related to the problem of non-compliance with taxpayers. Finally, there are many tax incentives in tax holidays, tax reductions and tax allowance. The reduction in tax rates is given to businesses in the MSMEs sector from 1% to 0.5%, starting in mid-2018.

Tanah Abang Market Condition

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 (Salim and Ernawati, 2015). Second, Tanah Abang Market is a popular place for buying and selling clothes and textiles in Indonesia, where most sellers are MSMEs. For example, in 2018, Mr. Joko Widodo (Jokowi), The President of The Republic of Indonesia, invited Christine Lagarde, the managing director and chairman of the International Monetary Fund (IMF), to visit Tanah Abang Market. Mr. Jokowi wanted to show the condition of micro-small and medium enterprises (MSMEs) in Indonesia. Third, there are around 28.000 traders who are categorized as MSMEs business unit. These data are roughly in line with the report from Gerintya (2018). She mentioned that there are at least 21,000 sellers and 1,300 street stalls in Tanah Abang Market. Most of the sellers are individual sellers in a similar retail sector.

However, the significance of economic turnover in the Tanah Abang Market over national figures cannot be seen from the tax revenues. Based on data from Jakarta Tanah Abang Dua Tax Office, the final tax revenues from the Tanah Abang market in 2019 were IDR 8.82 billion. In contrast, individual taxpayers who pay the final tax are 68.12%. The percentage of taxpayers who pay the final tax is slightly below the national formal tax compliance of 72.5% but the total amount of tax paid is relatively small compared to the trading volume on the Tanah Abang Market.

1.2. Overview

1.2.1. Taxation System in Indonesia

In 1983, the taxation system in Indonesia changed from an official assessment to a self-assessment system. This tax reform is stated in Law Number 6 of 1983 concerning general provisions and procedures for taxation and Law Number 8 of 1983 concerning income tax. In the self-assessment system, taxpayers are allowed to carry out their tax obligations. The obligation starts with calculating the tax owed, paying taxes and reporting tax returns.

Individual taxpayers must report their annual tax returns every year no later than March 31 the following year. For example, the annual tax return for the fiscal year of 2019 must be reported no later than March 31, 2020. If they failed to submit their tax return, they would get a fine of IDR 100,000 (7 euros). Furthermore, the government regulation (PP), number 23 of 2018 concerning Income Taxes on Income from Businesses Received or Obtained by Taxpayers with Certain Gross Circulations, regulates taxes for MSMEs. Under this PP, the taxpayers included in the MSMEs category with a business circulation of less than IDR 4.8 billion a year can use a tariff of 0.5 % of turnover. That is, there is no minimum turnover limit for paying taxes; as long as the taxpayer conducts business and gets a turnover, they are obliged to pay taxes. This tax payment must be paid every month with a due date no later than the 15^{th} of the following month. The PP Number 23 of 2018 replaces the previous regulation, PP Number 46 of 2013. The new PP regulates tariff reduction from 1% to 0.5% of business circulation. The type of tax under PP 23 of 2018 is a final tax, meaning the tax paid cannot be credited in the annual tax return. This policy took effect on July 1, 2018.

In this study, we use the compliance of individual taxpayers under PP Number 23 of 2018. All of the taxpayers are traders. It can be categorized into retail traders and wholesale traders. The specific sectors are retail traders of clothes, textiles, suitcase and bags, footwear, slippers and shoes, carpets and tapestry, large traders of second-hand clothing, wholesale traders of clothes, textiles and others.

Based on the Jakarta Tanah Abang Dua Small Tax Office data, as the administrative office of tax management in the Tanah Abang Market, by 31 December 2019, there were 7662 registered taxpayers. From those numbers, only 1402 stated as "normal" taxpayers. Meanwhile, 6260 taxpayers are categorized as "non-effective". Non-effective taxpayer means that the taxpayers are still administratively registered as taxpayers in Jakarta Tanah Abang Dua Small Tax Office. However, they have no obligation to report or pay taxes. Taxpayers are categorized as "non-effective" due to some causes; first, taxpayers did not report and or pay taxes for three consecutive years. Second, the taxpayers were not at the address, as stated in the taxpayer's identification number. Third, the taxpayers applied to become a non-effective due to some circumstances, such as they did not carry out a business activity. 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.

1.2.2. The History of Tanah Abang Market

Quoted from a book entitled "Tenabang Tempo Doeloe" by Chaer (2017), long before turning into a market as it is today, Tanah Abang was a lush, hilly and swampy area. In 1628, the Mataram royal army invaded the VOC in Batavia, known as Jakarta now. The

Mataram army used this area as a base camp in the raid. Because the soil color in this area is red, which in Javanese is called "Abang", this area is known as Tanah Abang.

In 1648, a Chinese captain named Phoa Beng Gam, asked for permission from the VOC to use this area as farming land. It should be noted that the VOC was a Dutch trade union that controlled the archipelago for centuries having a central office in Batavia. Furthermore, in 1735, a member of the Dutch East Indies council named Justinus Vink obtained permission from the Governor-General of the VOC, Abraham Patramini. He got permission to build two markets; Senen Market and Tanah Abang Market. Tanah Abang market was initially open only on Saturdays and specialized in selling clothing, textiles and grocery items. While the Senen Market mostly sold fruits and vegetables.

In 1740, there was a tragic event called the *Chineezenmoord*, a massacre of ethnic Chinese that burned the entire market and paralyzed trade activities for a while. In 1881, the Tanah Abang market was rebuilt and reopened on Wednesdays and Saturdays. Subsequently, in 1926, the government in Batavia carried out a total demolition of the Tanah Abang market, replaced by permanent buildings.

The governor of DKI Jakarta, Ali Sadikin, has made very significant development progress. He built the Tanah Abang market into a modern market in 1972. Unfortunately, in 1990 there was a massive fire that burned most of the market buildings. In 2002, the Tanah Abang market was rebuilt into a more magnificent and modern building, making Tanah Abang market one of the largest markets in Southeast Asia.

Tanah Abang Market is located on Jalan Mas Mansyur, Jakarta, Indonesia. This market is divided into three main parts; Old Tanah Abang, Tanah Abang Metro and AURI. Old Tanah Abang consists of Tanah Abang market blocks A, B and F. Metro Tanah Abang consists of PGMTA (Tanah Abang Metro Wholesale Center) and Tanah Abang Metro Bridge. Next, AURI consists of several blocks; Blocks A, B, C, D, E, F, AA, BB, and CC. The Tanah Abang market is famous for being cheaper with a wide selection of goods. This market sells many clothes, Muslim clothes, batik, shoes, bags and many more.

1.3. Research Problem Statement

This research is concerned with the problem of MSMEs' tax compliance in Indonesia. 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.

Several factors might affect taxpayer compliance. Tittle (1980) examined the influence of demographic factors, age and gender on moral awareness. According to Fischer et al.

(1992), four categories affect tax compliance; demographic factors, non-compliance opportunities, attitude and tax structure.

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 show mixed results about the relation of age and gender on tax compliance. As an example, men are more obedient than women ((Friedland et al., 1978) and (Mason and Calvin, 1984)) while studies from Torgler and Schneider (2007) show that women are more compliant than men. Third, this research is related to DGT's efforts to increase compliance with taxpayers through counseling, possibly leveraging gender and age. Finally, because of data limitation on data and time, we focus on 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.

1.4. Research Question

The main research questions in this paper are:

1. What is the estimated extent of tax evasion for the market as a whole?
2. How do age and gender correlate with tax compliance?

Sub question: To what extent do the deviations from Benford's Law vary with gender and age?

1.5. Research Challenge and Limitation

1.5.1. Research Challenge

The challenge of this study is to get detailed data on income levels since those data are strictly confidential. It is related to Law 28 of 2007 in article 34, which said that the taxpayers' data are very confidential. However, with the formal procedure, the author obtained these data with legal permission from the DGT. For research purposes, all of the data are anonymous; no identity appears. The data consist of names and tax identification numbers disguised, gender, date of birth, address of taxpayers, the status of taxpayers, whether normal or non-effective, types of work which are all included in the retail category and the amount of tax paid in 2019. In the initial plan of this research, we will use two data, internal data from DGT and primary data in the form of a survey of traders in Tanah Abang market. Due to Covid-19, the survey to traders in Tanah Abang could not be carried out, so this study only utilizes internal data from the DGT.

1.5.2. Limitations

This study limits tax compliance to formal compliance. As long as taxpayers pay the final income tax per Government Regulation (PP) 23 of 2018, they are categorized as compliant taxpayers. The regulation stated that taxpayers who make payments are considered to report their tax returns. This definition is in line with the argument by Bird (1998) that tax compliance is seen as formal compliance.

Furthermore, taxpayers who have paid the final income tax under PP 23 of 2018, it is unknown whether they paid their tax based on their actual income or not. To detect evasion, we use Benford's law. In testing Benford's law, we only limited the detection of Unplanned Evasion (UPE). Unplanned evasion occurs precisely when the taxpayers report or pay their tax without any plans at the beginning of the year (Nigrini, 1996).

1.6. Contribution on the Literature

The application of Benford's law in Indonesia is rare, especially in taxation. One study from Murhaban and Jufrizal (2017) explored Benford's Law in audit planning at the Lhoksumawe Customs and Excise Office in Aceh. They concluded that Benford's law could be used to predict audit findings effectively. Furthermore, a study from Prasetyo and Djufri (2020) used tax invoice simulation data to detect fraud in tax invoices. They empirically illustrate that Benford's law could be used to detect possible fraud when taxpayers issued tax invoices. In contrast to previous studies, this research uses internal data from the DGT and detects aggregate tax evasion in the MSMEs sector, especially in Tanah Abang Market. Therefore, 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.

1.7. Chapter Scheme of Research

The thesis is organized into five chapters. The first chapter is the introduction that includes background, research problems and research question. Next, the second section is the theoretical framework and literature review. In the third section, there is a discussion about the data and methodology. The result and analysis will be described in the fourth section. Finally, the fifth section is the conclusion.

Chapter 2
Theoretical Framework and Literature Review

The second chapter will discuss the theoretical framework and literature review on the use of Benford's law in detecting tax evasion and the effects of gender and age on tax compliance. In this chapter, several sections will be discussed; first, we will explain the definition of taxes, tax compliance, and Benford's law. Next, we will explore the development of Benford's law theory and its application in the empirical study. Furthermore, we will also discuss some literature reviews on the use of Benford's law in various fields, especially taxation. The second part discusses the effect of age and gender in tax compliance and debates in previous research in tax compliance.

2.1. Tax Compliance and Benford's Law

2.1.1. The Definition of Tax

In the Tax Law No. 6 of 1983, taxes are "mandatory contributions to the state owed by individuals or entities that are coercive based on the Act, with no direct compensation and are used for the country's needs for the greatest prosperity of the people." By definition, three elements are fundamental as a tax (Sommerfeld, 1980; Brotodiharjo, 1984). First, there is an obligatory transfer from the private entity to the government. Second, from the payment to the government, taxpayers do not get any direct compensation. Lastly, all of those payments are used to run the governmental activities.

2.1.2. The Definition of Tax Compliance

There are some definitions of tax compliance. In general, tax compliance is the capability and willingness to obey the tax obligation to contribute to the government (Andreoni et al., 1998; Kirchler and Braithwaite, 2007). In specific terms, tax compliance is a situation where the taxpayers reported their actual income in the tax return in the self-assessment system (Allingham and Sandmo, 1972). Furthermore, the Organisation for Economic Co-operation and Development (OECD) divided the tax compliance into two. The first is administrative compliance, where taxpayers report the tax return as procedural/formal. Second, technical compliance refers to the material issues, including the validity in computing the tax obligation.

On the other hand, the definition of tax non-compliance has many perspectives; one thing that could be similar is when the taxpayers do not fulfill their tax obligation. Allingham and Sandmo (1972) argued that tax non-compliance included the underreported income in the tax return. Kirchler and Braithwaite (2007) also interpreted that even if the taxpayer submitted the tax return and they have not paid the tax, it is not accounted as tax compliance. However, in this study, we use the compliance of individual taxpayers, as stated in PP Number 23 of 2018. Compliance means the taxpayers pay the tax, while tax non-compliance means the taxpayers do not pay taxes. This study also does not take into account the lateness of the tax return. As long as the taxpayers pay the tax, they are categorized for tax compliance. Besides, some studies are also using formal compliance in measuring the tax compliance. Bird (1991) argued that formal compliance is more reliable than technical compliance as long as the taxpayers fulfill their tax return and pay tax.

2.1.3. The Overview of Benford's Law

Based on the self-assessment system, the taxpayers have an independency to report their tax return. Those reports could be underreported or underestimated. One way to detect the validity of the tax that has been reported is by using 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.

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, Mark J., 1996)

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 digit will follow the logarithmic pattern that the small digit number will appear more than the higher digit number. The first digit number 1 has a proportion whose value approaches the logarithm of 2 (2/1). Next, the first digit of number 2 is almost the same value as the logarithm 3/2. This pattern will repeat until number 9 has a proportion on the first digit of logarithm 10/9. So, Benford then found an expected frequency known as Benford's Law. The probability of a number appearing as the first digit was equal to:

$$P(D_1 = d_1) = \log(1 + \frac{1}{d1}), d_1 \ \mathcal{E}(1,2,\ldots,9) \quad (1)$$

where $P(D = d_1)$ = probability of the number d appearing as the first digit. As a result, the appearance of number 1 is 30.10%. Number 2 is around 17.61% and so on. (See table 1)

Then, the probability of a number appearing as the second digit using the equation:

$$P(D_2 = d_2) = \sum_{d_1=1}^{9} \cdot \log(1 + \frac{1}{d1d2}), d_2 \ \mathcal{E}(0,1,\ldots,9) \quad (2)$$

where $P(D_2 = d_2)$: the probability of the number d_2 appearing as the second digit of a number. Finally, the probability of the first two digits can be calculated with the equation:

$$P(D_1 D_2 = d_1 d_2) = \log(1 + \frac{1}{d_1 d_2}), d_1 d_2 \ \mathcal{E}(10,11,\ldots,99) \quad (3)$$

where P is the probability of the number of digits in parentheses, a log is a 10-based logarithm. 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.

2.1.4. The Development of Benford's theory

The first study after Benford (1938) was done by Goudsmit and Furry (1944). They argued that Benford's law is the usual result of writing numbers. In the following year, Furry and Hurwitz (1945) explained mathematically about Benford's law formula. The first use of Benford's law concerning human behavior was in 1948. Hsu (1948) asked his students to make 4-digit random numbers. The results showed that these figures did not follow Benford's Law distribution. Then he concluded that artificial numbers do not follow Benford's law and the incompatibility with Benford's Law does not always mean that there is a mistake or fraud.

One of the most significant studies of Benford's law was conducted by Pinkham (1961). He argued that if a frequency distribution is under a particular law, then it must be scale-invariant. Multiplication with a number other than zero will still produce an invariant digital distribution. For example, if digits of the data in the length of the river or the breadth of the lake follow a Benford's law, it does not matter if the measurement is in kilometers or miles. He later found out that Benford's laws are invariant on a multiplication scale. If a number distribution that matches Benford's laws is multiplied by a non-zero number, then the new number distribution will still follow Benford's law. The numbers that match with Benford's Law are called Benford sets.

Adhikari and Sarkar (1968) became the first Asians to contribute to Benford's law literature. They use mathematical operations to explain Benford's Law. Furthermore, Raimi (1969) made a non-mathematical study of Benford Law, which was then referred to the first digit event. After the study from Raimi, Benford's law is widely known among academics. Wlodarskl (1971) and Brady (1978) conducted a study by counting the first 300 and 2000 Fibonacci numbers (1, 1, 2, 3, 5, 8 ...). The results were consistent with Benford's Law. Next, Varian (1972) used Benford's law to measure the accuracy of demographic data prediction. He found that, either with real or prediction demographic data, it follows Benford's law.

Hill (1995) showed a significant digit of Benford's Law using mathematical derivation. He argues that Benford's law can be used in various applications such as computer design, mathematical models, and accounting fraud. Hill explained that if a data distribution is taken randomly (non-biased), then from the distribution of data, a random sample is taken, the results of the sample will converge to follow Benford's law.

2.1.5. From Theory to Empirical Study

Since the 1980s, Benford's law has been widely applied in accounting, taxation, forensic and auditing. The first application of Benford's Law in accounting was carried out by Carslaw (1988). He investigated company sales in New Zealand and found that managers tended to round up sales to a particular psychological level. For example, sales of 49,965 will be rounded to 50,000. This action is indicated by the higher number of 0s and a smaller number of 9s in the second digit. Furthermore, Thomas (1989) and Nigrini (2005) found that net sales in companies in the United States had many 0s in their second digit. More detailed research on accounting was carried out by Máté et al. (2017). They examined accounting data such as sales, Cost of Goods Sold and Account Receivables in Hungary from 2009 to 2015. The results show that some accounting data are not following Benford law, so there are indications of fraud committed by the company.

Some studies used Benford's law in taxation. First of all, Christian and Gupta (1993) tried to detect secondary tax evasion from reported taxable income. They assumed that in the table of taxable income boundaries with different tariffs within each boundary, they are likely to use lower rates by reducing their taxable income to lower boundaries. Benford's law is used to test this assumption. Moreover, Demir and Javorcik (2020) conducted a tax evasion study using international trade data in Turkey in 2011. They tried to detect tax evasion due to shock on tariffs. The results show that after a shock to the fare, there is an indication of tax evasion.

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 uses data from the Internal Revenue Services (IRS); the interest received and the interest paid by taxpayers in The USA in 1985 and 1988. 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. Next, Geyer and Williamson (2004) also tried to detect tax fraud using the Distortion Factor Method from Nigrini (1996) and the Bayesian method.

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 hypothesized that if the reported tax return were natural, according to actual conditions, they would follow the frequency of Benford's law. 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. The use of numbers 0 and 5 is more than Benford's law frequency.

In forensics and auditing, Nigrini (1994) asked whether Benford's law could be used to detect fraud or not in payroll data. He assumed that if the payroll data were correct, it would be following Benford's law frequency. Using the first two-digit test, he found that the distribution of numbers from the payroll data was non-conformity with Benford's law. In 10 years, he found at least $ 500,000 on payroll data fraud, and it was surprising that the value was significant in the last five years. Finally, he concluded that the perpetrators of cheating would repeat their fraud routinely if they were not caught.

The application of Benford's law was also conducted in accounting and auditing. Nigrini and Mittermaier (1997) made a test set of Benford law that can be used by both external and internal auditors to detect irregularities. They use account payable and electricity costs from oil companies. They found that generally, the data was reasonable conformity with Benford's law. Furthermore, Durtschi et al. (2004) concluded that Benford's law could be used as a useful tool for detecting fraud. Besides, they also reminded auditors to; first, be careful in interpreting the results of statistical tests. Second, Benford's Law is used only on specific data such as sales, COGS, Accounts Payable. Third, the auditor must be aware that not all types of fraud could be detected with Benford's law.

In Indonesia, studies that use Benford law specifically for taxation are limited. Some studies are more on accounting and auditing. However, it does not mean that Benford's law is not used in taxation because accounting and taxation are closely related. 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. The first digit test results show that the sample data is following Benford's Law. In contrast, the second digit and the first two digits test result do not follow Benford's law. Using Benford's law, the tax auditor can determine which tax invoice is a priority in the tax audit. To sum up, Table 2 shows the empirical study of Benford's Law. (See Table 2)

Table 2 Empirical Study of Benford's Law

Study	Variable	Dataset	Period	Estimation Technic	Outcome
Carslaw (1988)	Sales data	Corporate In New Zealand	1988	The first digit, second digit, using Z-statistic	Managers tend to round up sales to a particular psychological level.
Thomas (1989)	Net Sales	Compustat data Firm in The USA	1989	The first digit, second digit using Z-statistic	There was a deviation from expected frequency, many 0s in their second digit.
Christian and Gupta (1993)	taxable income	The US Tax Income	1979-1986	First two digits	Taxpayers were likely to use lower rates by reducing their taxable income to lower boundaries.
Nigrini (1994)	Payroll data	Companies in The USA	1994	First two digits	The distribution of numbers from the payroll data was incompatible with Benford's law.
Nigrini (1996)	interest received and the interest paid by taxpayers	IRS data	1985 and 1988	The first digit, second digit, using Z-statistic and Distortion Factor Model	The interest received by taxpayers indicates understatement. On the contrary, the interest paid by taxpayers indicates overstatement.
Nigrini	quarterly	companies in	2001	First and sec-	More 0s in the second

(2005)	income data	the United States	and 2002,	ond digit test	digit and fewer 8 and 9 in the second digit.
Geyer and Williamson (2004)	Tax data simulation	-	-	The Distortion Factor Model	The sample data is following Benford's law frequency.
Hidayat and Budiman (2016)	financial statements of companies	the Indonesia Stock Exchange	2006 to 2010.	First digit	Benford law can be used to detect data manipulation through computer-based accounts.
Máté et al. (2017)	accounting data such as sales, COGS and account receivables	Financial Statement of 562 companies in Hungary	2009-2015	The first and second digit, Z-statistic and Kolmogorov-Smirnov D-statistics, MAD	Some accounting data are not following Benford law, so there are indications of fraud committed by the company.
Demir and Javorcik (2020)	international trade data	Trade Transactions Database (TTD), in Turkey	2010-2013	First Digit	After a shock to the tariff, there is an indication of tax evasion.
Prasetyo and Djufri (2020)	Tax invoice	Data Simulation from DGT Indonesia	-	The first, second, first two-digit test using MAD and Z statistic	The first digit test corresponds to Benford law while the second and the first two digits test do not match Benford law.

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, Chi-Square, Kolmogorov-Smirnov D-statistics.

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.

2.2. The Effect of Gender and Age on the Tax Compliance

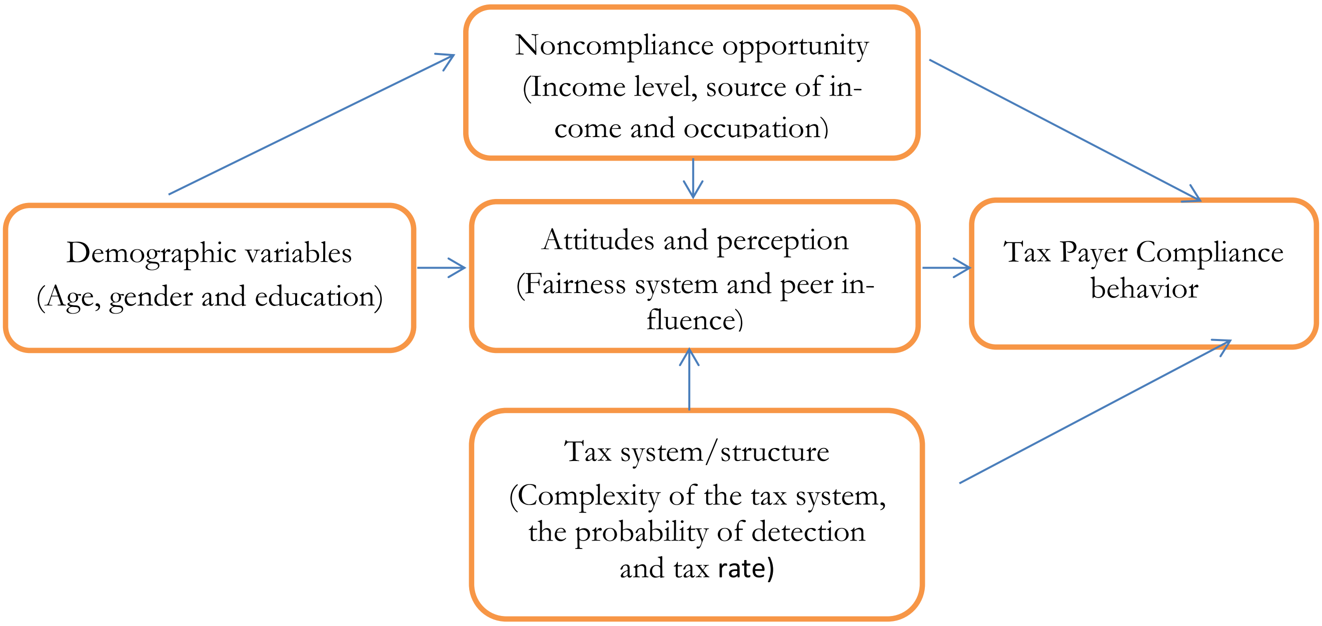
After determining the tax evasion using Benford's law that is crossed with age and gender, then we will further look at the micro data of tax compliance that is affected by age and gender.

2.2.1. Theoretical Framework

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 4). The first group is demographic variables such as age level, gender and education level. Next, the second group is noncompliance opportunity, e.g. income level, source of income and jobs/occupation. The third group is attitudes and perceptions, which included the fairness system and the influence of the peer. Finally, the tax system/structure is the fourth group, e.g., the complexity of the tax system, the probability of detection and the tax rate.

In this study, we use Fischer's Model as a conceptual framework since; first, it is argued that the model is very comprehensive to describe tax compliance by Jackson and Milliron (1986). 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.

Figure 4 Fischer Model of Tax Compliance



Source: Fischer et al. (1992)

2.2.2. The Current Debate in Academic Field

Fischer et al. (1992) mentioned two factors that might affect individual taxpayers to comply with the tax law. Those two factors are external and internal. External factors include tax system, while internal factors are related to the individual's tax morale and tax ethics. Tax morality refers to the awareness of taxpayers to comply with tax law. Torgler (2004) said that tax morale is close to intrinsic factors that taxpayers are full of awareness without coercion to fulfill their tax obligations. In comparison, tax ethics is defined as the action of awareness to pay and report tax responsibility (Siahaan, 2010). The internal factors that affect tax compliance could be seen by the demographic variables, i.e. age, gender and education (Saltzman and Tittle, 1981).

2.2.2.1 Age level

The results of the studies about age level and tax compliance mixed. The positive relation is found by Jackson and Milliron (1986) and Chung and Trivedi (2003). The positive relation means the older age, the higher tax compliance and the younger age, the lower tax compliance. Both studies used the survey method, but Jackson and Milliron (1986) also used the Internal Revenue Services (IRS) data in the US. On the other hand, the negative relation is found by Wärneryd and Walerud (1982). Negative relation implies that younger people are more likely to comply with the tax obligation than older people. Because of the different approach of the surveys, the results are very contrasting. As an example, Chung and Trivedi (2003) used more psychological questions than the study from Wärneryd and Walerud (1982) in which the questions are more on tax knowledge.

2.2.2.2 Gender

Gender also has a contradictory result concerning tax compliance. As a study from some scholars, Saltzman and Tittle (1981), Jackson and Milliron (1986) and Torgler and Benno (2004) 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 survey from Friedland et al. (1978). They set up a survey for undergraduate students related to tax knowledge. The result shows that women are less compliance than men. However, this study is less reliable as they use students that did not have an obligation to pay tax and did not earn income.

2.2.3. Empirical Study

Several studies on the effects of socioeconomic demography on tax compliance—most of the studies conducted used external data; survey data, and questionnaires. Only one study used internal data from DGT to find out the effect of demographic factors on tax compliance. 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. In summary, several studies conducted in Indonesia and outside Indonesia are as follows: (see Table 3)

Table 3 Empirical Studies of Demographic Factor

Study	Variable	Dataset	Period	Estimation Technic	Outcome
Tjaraka (2011)	age, gender, formal edu-	Surabaya, East Java	2011	Survey data with 165 respondents	Gender and informal education are statis-

	cation, and informal education				tically significant to tax compliance. However, other variables are not significant.
Cahyonowati (2011)	age, gender, economy, and education	Semarang, Central Java	2011	Questionnaire survey with 232 random taxpayers, then estimated using Partial Least Square (PLS)	All variables are not significant in tax compliance.
Alabede et al. (2014)	financial condition and risk preference	Nigeria	2011	Survey method on taxpayers, estimated using moderated multiple regression	Risk preference has a negative relation with tax compliance. Financial condition is not significant to affect tax compliance.
Engida and Baisa (2014)	Age, gender, sales income and education	Ethiopia	2014	Cross-section survey method on 102 taxpayers	Only age and gender are statistically significant. Others are not significant.
Widianto (2015)	Age, gender	Duren Sawit, DKI Jakarta	2013	Internal data from DGT using 2383 individual taxpayers. Estimated using Probit, Logit and Linear Probability Method	All variables are statistically significant.

Chapter 3
Data and Methodology

This chapter describes the data and methodology used. In the first part, Benford's law is used to detect tax evasion based on income. The second part explores the methodology to determine the effect of age and gender on tax compliance by using Logistic regression.

3.1 Benford Law

We use Benford's Law to detect early irregularities in income. Based on a study from Nigrini (1996), Benford's law can be used to detect unplanned evasion (UPE) in the individual income tax in the USA in 1985 and 1988. The advantage of using Benford's law is not only relatively inexpensive but can also be conducted as soon as the taxpayers reported their tax return. On the other hand, the disadvantage of Benford's law model is only to detect unplanned evasion (UPE). If the taxpayers conduct unplanned evasion (PE), it would not be detected with Benford's law.

The amount of income is obtained 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. To illustrate, in 2019, taxpayer B paid tax of IDR 6,018,500. By dividing the final tax paid to 0.5%, we predict the income of taxpayer A = IDR 1,203,700,000. Based on 1402 sample data, 955 taxpayers paid the final tax. So, the amount of income data is also the same, 955 taxpayers.

3.1.1 Data Preparation

We use Microsoft Excel to determine the first digit, the second digit and the first two digits. The first digit is obtained by using the LEFT () function. For example, in number 562.458.670, using the =LEFT () function in Microsoft Excel, the first digit and the second digits are 5 and 6, respectively. Next, to get the first two-digit, we use =MID () function. Then we get 56 as the first two-digit number. After knowing the first digit, the second digit and the first two digits, the next step is to calculate the number of relative frequencies of each digit using COUNTIF () function and find the percentage of each digit to the overall sample. Finally, we compare the percentage of each digit sample with the frequency of Benford's Laws as in Table 1.

3.1.2 Conformity Tests

After getting the first digit, the second digit and the first two digits are the conformity test. If the data are relatively small, we could test the compatibility of Benford's law visually by using a histogram. On the other hand, if the data are extensive, then there are several kinds of tests that we can use to do conformity tests. Those tests are mean absolute deviation (MAD), statistical Z tests, Chi-square tests, Kolmogorov-Smirnoff tests and the mantissa arc tests. However, in this study, we follow Nigrini (1996) and Drake and Nigrini (2000) that use three tests; the absolute mean deviation (MAD), the Z-statistic test and the Chi-square test.

3.1.2.1 Mean Absolute Deviation

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:

$$\text{Mean Absolute Deviation} = \sum_{i=1}^{K} \frac{|AP - EP|}{K} \qquad \ldots 1.1$$

where K is the number of digits in each test digit, for example, the value of K in the first digit test is 9 (1,2,3... 9), the second digit is 10 (0,1,2... 9), and the first-two digit is 90 (10, 11, 12.... 99). 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. In contrast, the denominator is the value of K.

Table 4 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 Dig-	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 Mean Absolute Deviation (MAD) is then compared to the table of critical values and conclusions from Drake and Nigrini (2000) (see Table 4). These tables and conclusions are based on their experiences and studies in conducting Benford's law test. The higher MAD means more significant the difference between the actual proportion of data and expected data from Benford's law. From the table above, we can see that in each digit of the test, the first digit test, the second digit test and the first two-digit tests have different critical points. However, in all tests, there are four types of conclusions: close conformity, acceptable conformity, marginally acceptable conformity and non-conformity.

3.1.2.2 Z-Statistics Test

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. Based on the study of Everitt and Fleiss (1981), the equation is as follows:

$$Z = \frac{|AP-EP| - \left(\frac{1}{2N}\right)}{\sqrt{\frac{EP(1-EP)}{N}}} \qquad \ldots 1.2$$

where AP is the actual proportion of data, EP is the expected proportion of Benford's law and N is the number of observations. 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.

3.1.2.3 Chi-Square test

Different from the previous Z-statistic test that compares the proportion of actual and expected values, 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. We use the Chi-square formula under Mark (2011):

$$\text{Chi Square} = \sum_{i=1}^{K} \frac{(AC-EC)^2}{EC} \qquad \ldots 1.3$$

where AC is the actual count, EC is the expected count, and K is the number of digits in the frequency test digit, 9 for the first digit test, 10 for the second digit test and 90 for the first two-digit test. 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. For instance, with a 5% significance, to calculate the cut off value of the first digit test, we use the formula =CHIINV (0.05.8). Then we get the cut off value of 15.50. If the results of the chi-square exceed 15.50, we can reject the null hypothesis. It means that our data are not per Benford's law. On the contrary, if the chi-square value is less than the cut off value of 15.50, then we do not have enough evidence to reject the null hypothesis. We could conclude that there is no significant difference between the actual data and Benford's law frequency.

3.1.3 The Distortion Factor Model

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 $10 \geq x < 100$. For example, 136,987 will be shifted into 13.6987. By changing the number on the scale (10,100), it will be able to find the mean and compare it with the Benford’s set value on the scale (10,100).

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:

1. Move the digit numbers into the range (10,100).
2. Erase numbers 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.
3. Move digit numbers that are greater than 100 into the range (10,100)
4. Calculate the Actual Mean (AM) of the data sample.
5. Calculate the Expected Mean (EM) of the Benford’s set.
6. Calculate the distortion factor with the formula.

$$\text{Distortion Factor (DF)} = \frac{(\text{Actual Mean} - \text{Expected Mean})}{\text{Expected Mean}}$$

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.

3.1.3.1 Limitations of the Distortion Factor Model

Pinkham (1961) argued that Benford's set is the only frequency distribution that does not change from expected distribution because of multiplication with a non-zero constant. This notion is then known as Pinkham's invariant theorem. If a data set has followed Benford's law, then we manipulate with a certain percentage either become smaller or larger, the new manipulation data set will still follow Benford's law. If the sample data follows this system, Benford's law cannot detect fraud.

In the case of taxation, according to the study of Nigrini (1996), we assume that if the taxpayers report their income without manipulation, the frequency of the data will approximately follow Benford's law. Manipulation in taxation is usually related to income and expenses. According to Cuccia (1994), when taxpayers report their tax returns, they consider many things, including the time of reporting, transaction events and the consequences. In contrast, other researchers said that taxpayers reported their tax returns based only on the time of reporting, not related to other things such as transaction and archiving basis. Therefore, we must determine what types of tax evasion can be applied with distortion factor models.

According to the study from Cowell (1985), Kidder and McEwen (1989), Klepper and Nagin (1989), tax evasion can be divided into two based on the truth of tax obligations and the time of reporting; planned evasion and unplanned evasion. Planned Evasion (PE) occurs when taxpayers intend to avoid tax payments from the beginning of the year by preparing all documents and supporting evidence. Meanwhile, Unplanned Evasion (UPE) is a tax evasion that occurs at the time of reporting as taxpayers prepare supporting evidence and cover it when they are reporting. The UPE is usually done by reducing income and inflating the expenses.

The real differences between those two types of evasion are a matter of time they are reporting, a person's ability to deal with tax and the taxpayers' intention. So, if there is a difference between real income and reported income, then there could be an element of planned evasion (PE), unplanned evasion (UPE) and purely human error. In this study, because we are discussing income, three possibilities occur. First, taxpayers intentionally do not report actual income from the beginning of the year by preparing the evidence. Second, taxpayers hide their income when reporting their tax returns. Finally, taxpayers report all of their income honestly.

In the planned evasion (PE), taxpayers intend to avoid taxes from the beginning. This action will usually be found at the time of the audit. So, Benford's law does not apply to planned evasion (PE). The unplanned evasion is when taxpayers compose numbers in reporting their income. In composing these figures, there is a particular limitation which in the study by Carslaw (1988) is called the main reference point. The main reference point is a limit that becomes a benchmark in doing something. For example, number 99 is considered cheaper for consumers than 100, even though the difference is only one point. So, there is the main reference point in tax compliance, usually a specific income limit with a different tax rate. Taxpayers are likely to reduce income at lower tax rates (Nigrini, 1996). Hence, Benford's law can be used to detect fraud or irregularities in the type of unplanned evasion (UPE).

In this study, the main reference point is 4.8 billion rupiahs. According to PP Number 23 of 2018, taxpayers whose turns over in a year are below 4.8 billion rupiah can use a 0.5% tariff. In comparison, taxpayers whose business sales are more than 4.8 billion rupiahs have to use normal tariffs. The normal tariff is stated in Article 17 of Law Number 36 of 2008 concerning income tax. So, in this study, we have the assumption that within the main reference point, taxpayers will try to reduce their income. The model distortion factor will fail if the main reference point cannot be determined. A significant result of the distortion factor indicates an unplanned evasion (UPE).

3.2 The Effect of Age and Gender on Tax Compliance

3.2.1 General description

According to the source, the data could be divided into two. First, the published data were downloaded from the Directorate General of Taxes, the Ministry of Finance and the Ministry for Cooperatives, Small and Medium Enterprises, the Republic of Indonesia. Those data were the reports on the proportion of tax revenues to the state revenue, the development of formal tax compliance, the realization of tax revenues and the Development of MSMEs in 2015-2018. Second, the internal data were obtained from the Directorate General of Taxes. This data consists of gender, age, and final income tax under PP Number 23 of 2018. Internal data were taxpayers' data whose identities had been deleted to protect the confidentiality of taxpayers.

3.2.2 Data Summary

Table 5 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%

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 below:

Table 6 Age Summary

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

3.2.2.1 Dependent Variable

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 concerning Income Taxes on Income from Businesses Received or Obtained by Taxpayers with Certain Gross Circulations, 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 under PP Number 23 of 2018, 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. Nine hundred fifty-five taxpayers, or 68.11%, were classified as compliant, while 447 taxpayers, or 31.89%, were categorized as non-compliant.

3.2.2.2 Independent Variable

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. 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%).

3.2.3 Methodology

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. We use Stata 15 software for analysis.

Chapter 4
Result and Discussion

Chapter Four explores the results and discussion to see; first, the aggregate tax evasion using Benford's law. Second, we discuss the effects of gender and age on tax compliance on individual taxpayers using the Logit method. Finally, we set the summary of this study. Using Benford's law analysis, the results show that the reported income is smaller than it should be (Unplanned Evasion). It could be seen from the overuse of lower digits in the actual data than the Benford's set.

Next, we explore the effect of age and gender on tax compliance. In the regression model, gender is statistically significant. Age is also statistically significant in affecting tax compliance. The relation is positive, meaning that older people have higher tax compliance than younger people. This analysis results in line with the current policy of DGT; counseling activities have been carried out to many young people, such as establishing tax centers in various universities, tax classes, and tax debate contests. The purpose is that the younger generation will understand and comply with taxes.

4.1 Application of Benford's Law

We will discuss the tax evasion using Benford's Law. The income of taxpayers is obtained by calculating the gross-up of tax paid under PP Number 23 of 2018. We use the first, second, and first two digits test of the income then compare it to the Benford's law.

4.1.1 First Digit Analysis

The first digit analysis aims to determine the general picture of the data because it detects visible irregularities. Drake and Nigrini (2000) used the Mean Absolute Deviation (MAD) in determining the goodness of fit test in Benford's law. The absolute mean deviation is obtained by adding up each digit's absolute deviation and dividing by 9 (the number of digits in the first digit test). The MAD results are then compared with the conformity table of Drake and Nigrini (2000). (See Table 4)

From the table first digit frequencies, it can be seen that the MAD is 0.0258. (see Table 7) When we compare it to the conformity table, 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.

Table 7 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
Number of Observation		955		
Chi-Square		80.09		
Mean Absolute Deviation (MAD)		0.0258		

* Significance at 5%

Source: Author calculation using Microsoft Excel (2020)

These results follow studies from Nigrini (1996) stating that individual taxpayers in the USA tended to reduce their income and increase the tax expense. He used internal data from the IRS in 1985 and 1988 on the interest received and the interest paid by taxpayers. The results showed that tax evasion occurred by reporting lower-income, marked by the overuse of lower digits than Benford's laws expected frequency.

On the other hand, Carslaw (1988) hypothesized that managers would tend to round up sales figures to get bonuses from companies. For the first time in accounting, he used Benford's law to detect upward rounding of companies' sales in New Zealand. The managers rounded up the sales numbers into a number that is psychologically higher than the actual sales. For example, if a company has sales of EUR 698,876, managers will tend to round them to Euro 700,000. His study results show that the use of number 0 in the second digit is more than the frequency of Benford's law, while the use of number 9 is less than the expected frequencies of Benford's law.

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.

4.1.1.1 Gender Differences

As one objective of this study is to determine the extent of the influence of gender and age on tax compliance, then the application of Benford's law will also divide the test according to gender and age. The total data of men is 753. The income data of men shows that the MAD value is 0.0259. Based on the MAD table, we can see that men's income data are non-conformity with Benford's law. This result is similar to the conclusion obtained from the MAD test with all income data. Furthermore, based on Table 8, the sign of bias in digits 1, 2 and 3 are positive. It shows that the digits 1, 2 and 3 in the sample data exceed the Benford's set frequency, while digits 4 through 9 are negative, meaning that the use of these digits is less than Benford's law frequency. The bias results indicate that the income reported by male taxpayers is underreported, as evidenced by the use of digits 1, 2 and 3, which are more than Benford's law. In the preceding, it is known that the cut-off value of using the tax rate of 0.5% is a maximum of 4.8 billion rupiahs. Therefore, taxpayers might report income below the cut-off value.

Table 8 First Digit Frequencies Based on Gender Differences

First Digit	Benford	Male			Female		
		Actual	Bias	Z stat	Actual	Bias	Z stat
1	30.10%	31.34%	+	0.70	35.15%	+	1.49
2	17.61%	20.98%	+	2.38 *	22.28%	+	1.65
3	12.49%	19.52%	+	5.78 *	14.36%	+	0.69
4	9.69%	9.30%	-	0.30	8.42%	-	0.49
5	7.92%	3.85%	-	4.07 *	3.96%	-	1.95
6	6.69%	3.45%	-	3.49 *	2.97%	-	1.98*
7	5.80%	4.25%	-	1.74	3.47%	-	1.27
8	5.12%	3.85%	-	1.49	4.46%	-	0.27
9	4.58%	3.45%	-	1.39	4.95%	+	0.09
Number of Observation		753			202		
Chi-Square		70.23			15.42		
Mean Absolute Deviation		0.0259			0.0266		

* Significance at 5%

Source: Author calculation using Microsoft Excel (2020)

Based on the Z-statistic test, the bias in digits 2, 3, 5 and 6 are statistically significant. Even digit 3 has the highest Z statistic, meaning that the use of digit 3 is more than other digits. Furthermore, the chi-square of male income data is 70.23. We compare the chi-square with the cut-off value of the first digit of 15.50. The null hypothesis is the actual data that will follow Benford's law. The actual chi-square value of the data exceeds the cut-off value, meaning we can reject the null hypothesis. We can say that the actual data do not follow Benford's law.

On the other hand, the total data of female income is 202. The mean absolute deviation (MAD) value is 0.0266. By looking at the MAD table, we can also conclude that in general, female's income data are not following Benford's law. Furthermore, based on the bias column in Table 8, numbers 1, 2 and 3 and 9 display positive signs while numbers 4 through 8 show negative signs. This result is similar to male's income. The positive sign shows that numbers 1, 2, 3 and 9 in the sample data exceed the Benford's law, while the numbers 4 to 8 are still below Benford's law. However, based on the Z statistic test, the results show that each digit's difference is not significant. Although the percentage of numbers in the digit frequency indicates the difference in Benford's law, the difference is not statistically significant. The results of the chi-square test support this claim. Chi-square results from women's income data is 15.42. Furthermore, if we compare the chi-square value with the cut-off value, the chi-square value is still below the cut-off value of 15.50. So, we do not have enough evidence to reject the null hypothesis that the actual data follow Benford's law.

4.1.1.2 Age Differences

Next, 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 (Departemen Kesehatan, 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 number of observational data for older people is 559, while the number of observational data for the younger ones is 396. The chi-square results for the younger and older people are 43.92 and 47.36, respectively. Then, we compare it with the cut-off value of 15.50. Those chi-squares exceed the cut-off value, so we reject the null hypothesis. It means that both observational data do not follow Benford's law.

Table 9 First Digit Frequencies Based on Age Factor

First Digit	Benford	Young			Old		
		Actual	Bias	Z stat	Actual	Bias	Z stat
1	30.10%	32.07%	+	0.80	32.20%	+	1.33
2	17.61%	22.22%	+	2.34*	20.57%	+	2.32*
3	12.49%	17.93%	+	3.20*	18.78%	+	5.67*
4	9.69%	10.35%	+	0.36	8.23%	-	1.36
5	7.92%	2.78%	-	3.70*	4.65%	-	3.62*
6	6.69%	3.03%	-	2.82*	3.58%	-	3.65*
7	5.80%	4.55%	-	0.96	3.76%	-	2.07*
8	5.12%	5.30%	-	0.06	3.04%	-	2.05*
9	4.58%	1.77%	-	2.55*	5.19%	-	0.40
Number of Observation		396			559		
Chi-Square		43.92			47.36		
Mean Absolute Deviation		0.0286			0.0266		

* Significance at 5%

Source: Author calculation using Microsoft Excel (2020)

Based on calculations, the value of MAD for older and younger people is 0.0266 and 0.0286, respectively. When we compare the result with the conclusion table of MAD from Drake and Nigrini (2000), both results are categorized as non-conformity with Benford's law. We will see more detail per number using Z-statistic. In both older and younger groups, the sign of bias in digit 1, 2, and 3 is positive, meaning that the use of those numbers exceeds the expectations of Benford's law. In comparison, the sign of bias in digit 5, 6, 7, 8 and 9 in the younger and older people is negative. It means that the usage is below the expected number. For older people, the sign of bias is statistically significant in digit 2, 3, 5, 6, 7 and 8. On the other hand, the bias of digit 2, 3, 5, 6, and 9 are statistically significant for younger people. From the two groups above, we can conclude that the use of the lower digit exceeds Benford law's expectations, and the use of a higher digit is less than the expected frequencies of Benford's law.

4.1.2 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 0.0080. By looking at the conformity table results, the sample data is categorized as acceptable conformity with Benford's law. (see Table 10)

Furthermore, the chi-square value is 8.91. 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.

Table 10 Second Digit Frequencies

Second Digit	Benford	Overall Sample		
		Actual	Bias	Z stat
0	11.96%	13.82%	+	1.72
1	11.38%	11.62%	+	0.19
2	10.88%	10.26%	-	0.56
3	10.43%	9.74%	-	0.65
4	10.03%	8.90%	-	1.11
5	9.66%	8.38%	-	1.29
6	9.33%	9.21%	-	0.07
7	9.03%	8.90%	-	0.08
8	8.75%	10.16%	+	1.48
9	8.50%	9.01%	+	0.50
Number of Observation		955		
Chi-Square		8.91		
Mean Absolute Deviation		0.0080		

* Significance at 5%,

Source: Author calculation using Microsoft Excel (2020)

4.1.2.1 Gender Differences

Next, we will further break down the data based on gender and age differences. Based on the Z-statistic test, the results show that, statistically, the difference between the sample data and Benford's law is not significant. Chi-square values for groups of females and males were 12.14 and 9.06, respectively. Both values are still below the cut off value of 16,919. It means that we do not have enough evidence to reject the null hypothesis; the sample data are consistent with Benford's Law. However, the results are slightly different when using the MAD as female's income shows disagreement with Benford’s Law. The value of 0.0205 falls into the non-conformity category in Nigrini's conclusion table. In contrast, the male's income is categorized as acceptable to Benford's law category.

Table 11 Second Digit Frequencies Based on Gender Differences

Second Digit	Benford	Male			Female		
		Actual	Bias	Z stat	Actual	Bias	Z stat
0	11.96%	13.68%	+	1.40	14.36%	+	0.94
1	11.38%	11.55%	+	0.09	11.88%	+	0.11
2	10.88%	11.02%	+	0.07	7.43%	-	1.46
3	10.43%	9.16%	-	1.08	11.88%	+	0.56
4	10.03%	8.63%	-	1.22	9.90%	-	0.06
5	9.66%	9.03%	-	0.52	5.94%	-	1.67
6	9.33%	8.23%	-	0.97	12.87%	+	1.61
7	9.03%	9.56%	+	0.45	6.44%	-	1.16
8	8.75%	10.62%	+	1.76	8.42%	-	0.04
9	8.50%	8.50%	0	0.00	10.89%	+	1.09
Number of Observation		753			202		
Chi-Square		9.06			12.14		
Mean Absolute Deviation		0.0088			0.0205		

* Significance at 5%

Source: Author calculation using Microsoft Excel (2020)

4.1.2.2 Age Differences

Table 12 Second Digit Frequencies Based on Age Factor

Second Digit	Benford	Young			Old		
		Actual	Bias	Z stat	Actual	Bias	Z stat
0	11.96%	13.89%	+	1.11	13.77%	+	1.26
1	11.38%	12.63%	+	0.70	10.91%	-	0.28
2	10.88%	8.84%	-	1.22	11.27%	+	0.23
3	10.43%	8.33%	-	1.28	10.73%	+	0.17
4	10.03%	7.83%	-	1.37	9.66%	-	0.22
5	9.66%	7.07%	-	1.66	9.30%	-	0.21
6	9.33%	8.08%	-	0.77	10.02%	+	0.49
7	9.03%	9.34%	+	0.13	8.59%	-	0.29
8	8.75%	12.63%	+	2.64*	8.41%	-	0.21
9	8.50%	11.36%	+	1.95	7.33%	-	0.91
Number of Observation		396			559		
Chi-Square		20.95			3.30		
Mean Absolute Deviation		0.0204			0.0063		

* Significance at 5%

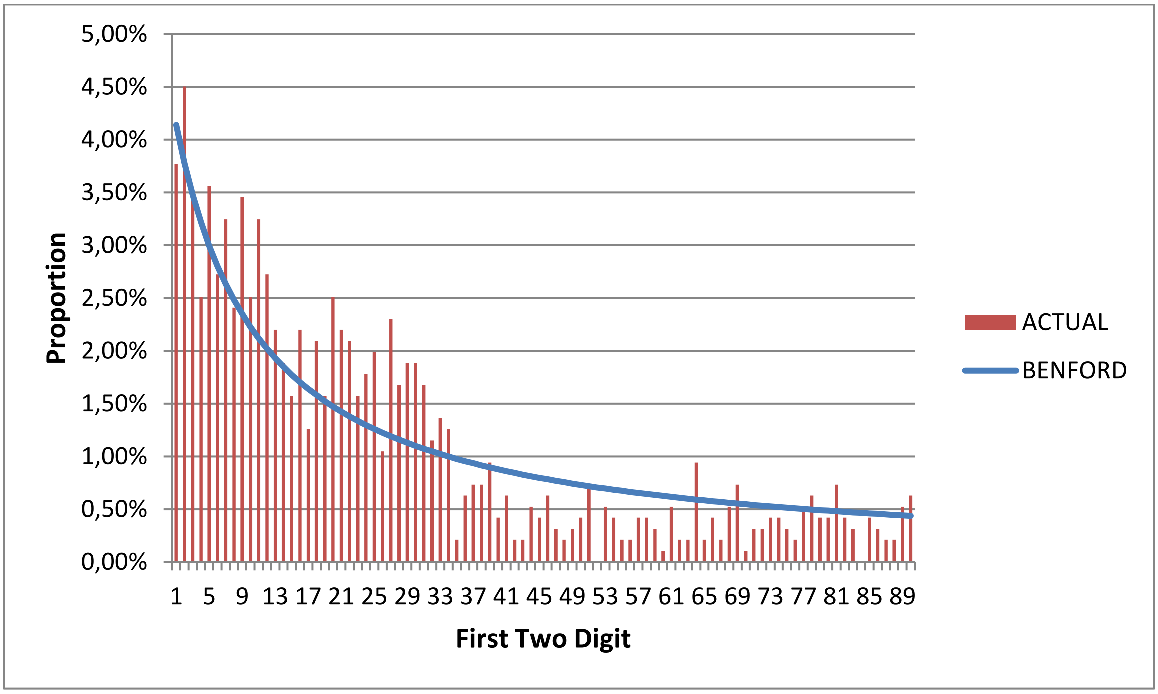
Source: Author calculation using Microsoft Excel (2020)

When we test the data based on age categories, there are some differences in results between the old and young. The result of the chi-square test for younger people is 20.95. This value exceeds the cut-off of 16,919, meaning that we can reject the null hypothesis. It shows that the sample data from the young category does not match with Benford's law. Furthermore, the MAD value is 0.0204. Tests with MAD also indicate that income data from younger people falls into the category of non-conformity with Benford's law. In contrast, the older category shows different results. The chi-square value is 3.30; this value is smaller than the cut-off value of 16,619. We do not have enough evidence to reject the null hypothesis, meaning that the sample data of older people are following Benford's Law. Furthermore, based on the MAD value, which is equal to 0.0063, the sample data for the elderly is close to Benford's law category. In the Z test statistic, there is also no significant difference.

4.1.3 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. 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).

Table 13 First Two Digit Frequencies Overall Data



Source: Author calculation using Microsoft Excel (2020)

A detailed explanation of these digits is as follows: First, taxpayers' income with the first two digits of 18 reported as many as 33 taxpayers with a total value of income of 57.37 billion rupiahs. Second, thirty-one taxpayers reported income with the first two digits of 20, worth 53.59 billion rupiahs. Furthermore, twenty-four taxpayers report their income with the first two digits of 29, with a total income of 62.98 billion rupiahs. Twenty-two taxpayers reported their income with the first two digits 36 with a total income of 60.74 billion rupiahs. Next, 18 taxpayers reported income with the first two digits of 38 with a total income of 65.92 billion rupiahs. Eighteen taxpayers reported income with the first two digits of 39, worth 56.56 billion rupiahs. Finally, only two taxpayers reported income with the first two digits of 44 with a total income of 4.8 billion rupiahs. In total, there were 148 (10.55%) taxpayers who reported income that was not following Benford's law with a total income of 362.07 billion rupiahs. DGT could conduct a further audit of 148 taxpayers. Furthermore, 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 14 First Two Digit Frequencies

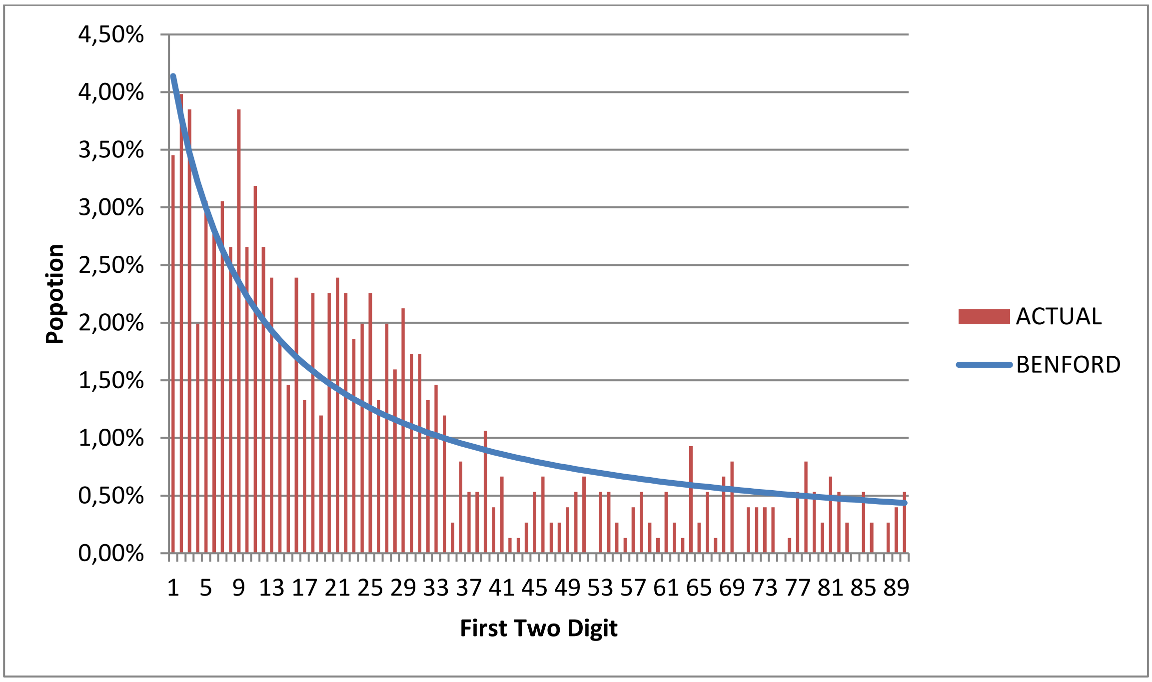
First Two-Digit	Overall Sample	Male	Female	Young	Old
Number of Observation	955	753	202	396	559
Chi-Square	156.61	145.64	88.24	145.65	97.97
Mean Absolute Deviation	0.0036	0.0039	0.0058	0.0055	0.0034

Source: Author calculation using Microsoft Excel (2020)

4.1.3.1 Gender Differences

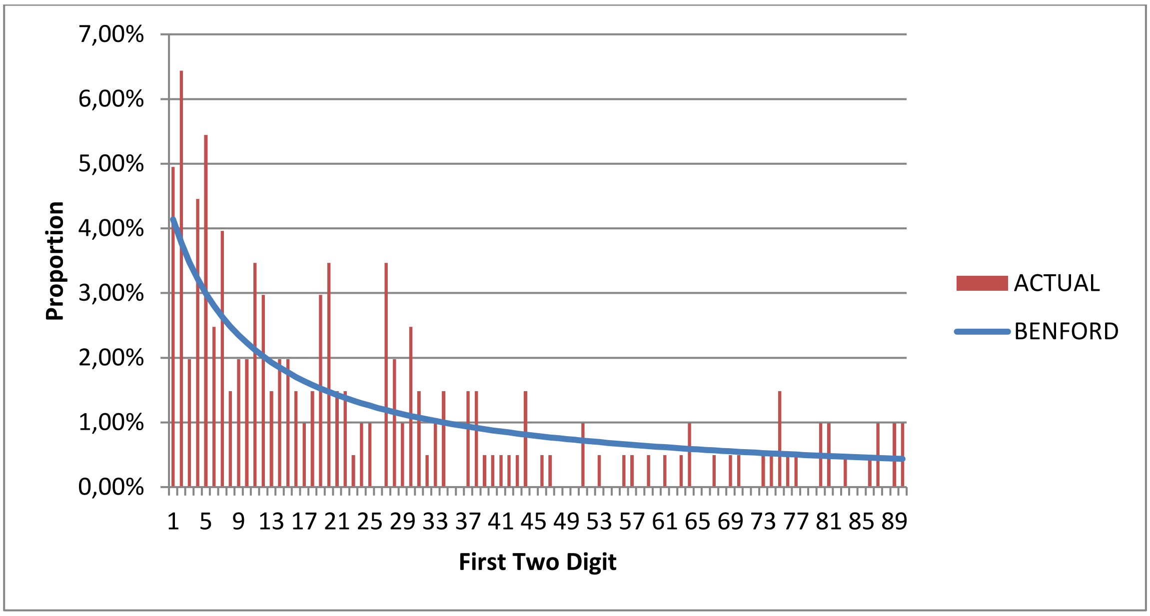
Next, we conduct the first two-digit test based on gender differences. The number of observational data for males and females is 753 and 202, respectively. Accordingly, the MAD is 0.0039 and 0.0058 for males and females. It shows that income data from both males and females are categorized as nonconformity 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.

Table 15 First Two Digit Frequencies of Male Income



Source: Author calculation using Microsoft Excel (2020)

Table 16 First Two Digit Frequencies of Female Income



Source: Author calculation using Microsoft Excel (2020)

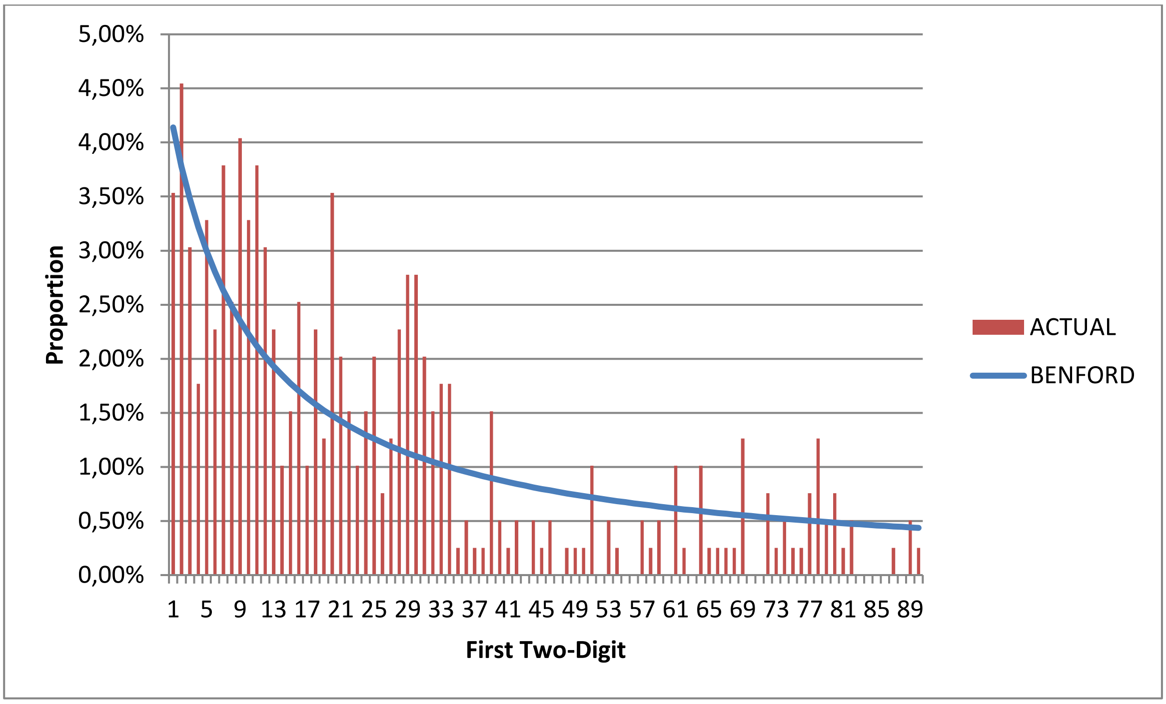
Based on the Z statistic test, there are four digits from 90 digit-groups that are statistically significant on male's income. The numbers are 18, 30, 34 and 38. All the bias sign is positive, meaning that those numbers are overused compared to Benford's law's expected frequencies. In total, there were 80 taxpayers reported income, which was not conformity with Benford's law worth as 206.91 billion rupiahs. On the other hand, only two numbers are statistically significant in the female's income data, 29 and 36. The sign is also positive. We could interpret the use of number 29 and 36 overused compared to the Benford's Set. Fourteen taxpayers reported income with the first two digits of 29 and 36 worth 31.08 billion rupiahs.

4.1.3.2 Age Differences

The MAD values for young and old are 0.0055 and 0.0034, respectively. 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.

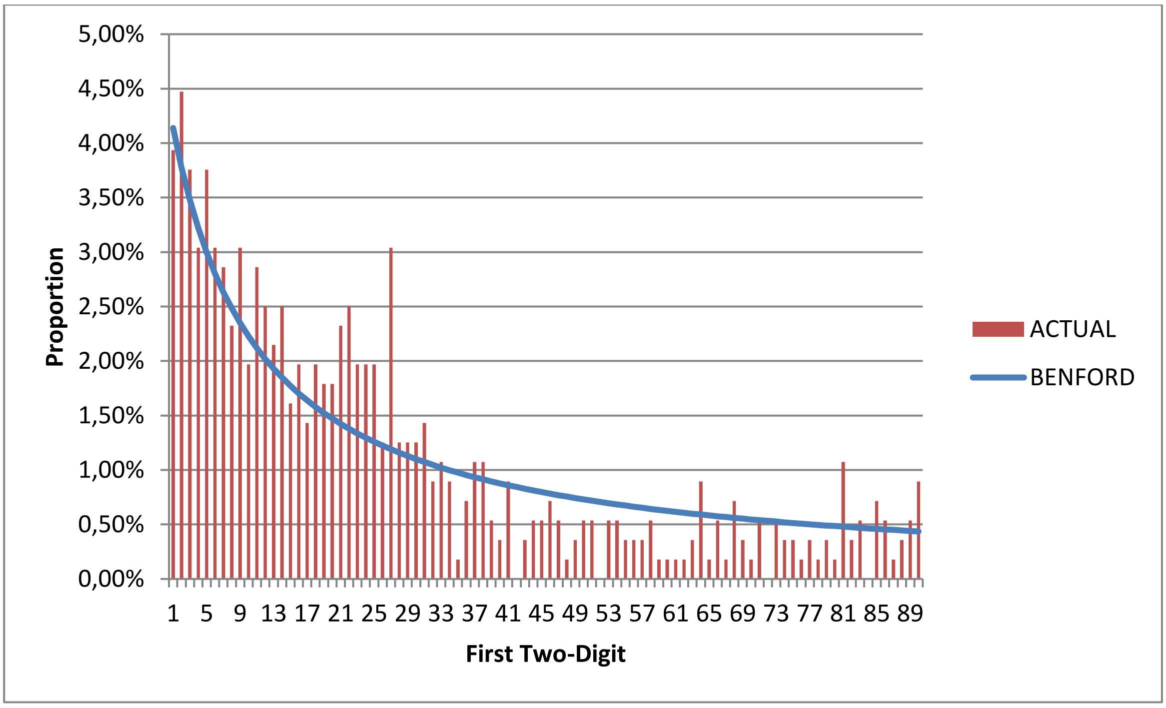
With Z-statistic tests, we can find out the details of groups of digits that have significant differences. The significant difference in the young group is in digit 18, 20, 29, 38 and 39. Sixty-seven taxpayers reported income with those first two digits worth of 167.23 billion rupiahs. All digits have 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. Thirty-four taxpayers reported income with those first two digits worth as 49.14 billion rupiahs. The sign of the bias is also positive means the overuse of these digits in the sample data compares to Benford's law frequency.

Table 17 First Two Digit Frequencies of Younger's Income



Source: Author calculation using Microsoft Excel (2020)

Table 18 First Two Digit Frequencies of Older's Income



Source: Author calculation using Microsoft Excel (2020)

4.1.4 The Distortion Factor

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). In general, the distortion factor compares the actual mean with the expected mean of Benford's Law. The results of the DF model can be seen in Table 19.

Table 19 The Distortion Factor

The Distortion Factor Model	Overall Sample	Male	Female	Young	Old
Number Of Observation	955	753	202	396	559
Actual Mean (AM)	34.676	34.726	34.489	34.591	34.736
Expected Mean (EM)	39.086	39.086	39.086	39.086	39.086
Distortion Factor = (AM - EM)/EM	-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)

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. 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.

4.2 The Effect of Age and Gender on the 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. Based on the regression results of Logit method, all the variables; gender and age, statistically significantly affected the 2019 tax compliance. The dependent variable is compliance 2019, while the independent variables are age and gender. The Model is as follows:

$$\mathrm{Compl_i} = \propto_0 + \propto_1 Age_{\mathrm{i}} + \propto_2 \ Gender_{\mathrm{i}} \ + \varepsilon_{\mathrm{i}} \,) \qquad \ldots\ldots..1$$

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

Table 20 Variable Description

No	Variable		Description
1	Dependent	$Compl_i$	Tax compliance, represented by paying the final tax on the fiscal year 2019.
2	Independent	$\propto_1 Age_i$	Age level, $\propto_1$ is expected to be positive since, in Indonesia, the older people are more as a role model to younger people.
3	Independent	$\propto_2 Gender_i$	Gender, $\propto_2$ is expected to be negative as women in Indonesia are usually more comply with the law.

4.2.1 Goodness of Fit Measure

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. Firstly, we look at the pseudo R-square. The pseudo-R-square of logit method is 0.0091. (see Table 22) 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 21, 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.

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.

Table 21 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)

4.2.2 Analysis of Coefficient

Regression results show that the coefficients in all independent variables have positive value.

Table 22 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	0.0011
Pseudo R2	0.0091

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

Standard Error in parenthesis

Source: Author calculation using STATA 15 (2020)

4.2.2.1 Gender

Regression results of the logit method show that 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.

4.2.2.2 Age

The relationship between age levels and tax compliance is 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.

Looking at the age composition in the Tanah Abang market, most traders are indeed older people. From a total of 1402 observations, there are 55% or 785 people whose are more than 45 years old, while traders whose age are less than 45 years are only 617 people (45%). 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.

The age square variable indicates a parabolic relationship between age and tax compliance. At some point, the relationship between age and tax compliance will turn around. The age variable results that we have discussed earlier show that older people have more probability of compliance. However, at some point, compliance will decrease. From the age square variable, we can calculate when the turning point is. So, we will look for a turning point when the relationship changes direction. By using the formula $-\beta 1/\ (2\beta 2)$ from Wooldridge (2012), where β1 is the linear coefficient of age while β2 is the coefficient of age square variable, we can calculate the turning points. The coefficient of the age variable based on the logit method is 0.0219. The coefficient of age_sq variable is -0.0002. By using the logit method, the extreme point value can be calculated: - (0.0219 / 2x-0.0002)) = 54.75 years.

4.2.3 Analysis of Odds Ratio

Table 23 Odds Ratio Model

Logistic Regression			
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. Furthermore, from the age variable, older people tend to have 1.1 times higher odds ratio to comply with taxes than younger people.

4.3 Summary

Based on the first digit test, income data does not follow the digital frequency of Benford's law and is mostly done by males. The second digit test shows the conformity with Benford's law. Through more detailed results, we can see by using the first two-digit test. Income data shows non-conformity with Benford's law. The use of lower digits is more than expected frequencies from Benford's law, such as digits 18, 20, 29, 36, 38, 39 and 44. Males and younger ages mostly do it. Next, the DF results are - 11.28%. It indicates that UPE exists because the DF value is negative; use of lower digits more than expected frequency. Males mostly do UPE compared to females. Meanwhile, based on age differences, older people tend to do UPE compared to younger ones. This study's results are similar to the study by Nigrini (1996), who found UPE on individual taxpayers in the USA using IRS data. DGT could take out a policy to carry out further supervision for taxpayers in data confirmation or tax audits.

Furthermore, the analysis of the regression result shows that gender affects tax compliance. Men are more likely to comply than women. These results are in line with research from Houston and Tran (2001) that men tended to comply than women. In addition, age has also a significant effect on tax compliance. The effect is positive, meaning that older people tend to be more obedient to their tax obligations. The positive relationship is also found by Jackson and Milliron (1986) and Chung and Trivedi (2003).

Chapter 5
Conclusion and Recommendation

5.1 Conclusion

In the last three years, tax compliance in Indonesia has increased. Nevertheless, the trend of increasing taxpayer compliance is not in line with the trend of achieving the tax revenue target. Tax revenues tended to fluctuate compared to formal tax compliance for corporate and individual non-employee taxpayers (DGT, 2020). Furthermore, the role of the individual non-employee taxpayers is very significant towards compliance. Based on data from the Ministry of Cooperatives, almost 99% of business units in Indonesia are MSMEs, so the compliance of the MSMEs sector is essential for formal compliance in Indonesia. Tanah Abang Market is one of the largest MSMEs centers in Indonesia. Internal factors such as demographic factors become crucial when taxpayers are homogeneous as in the context of the Tanah Abang market.

This study wanted to detect unplanned evasion (UPE) using Benford's law and to determine the effects of gender and age on taxpayer's compliance. If UPE exists, does it vary by age and gender? It aimed to provide an overview to inform policies adopted by DGT in terms of tax compliance.

UPE occurs at a time when taxpayers report or pay taxes (Nigrini, 1996). We assume that if there is no UPE, the digit frequency of the income data will follow the expected frequency of Benford's Law. We use the first digit, second digit and first two-digit test. For each digit test, we use the goodness of fit measure such as Z-statistic tests, Chi-square tests and Mean Absolute Deviation.

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. According to Nigrini (1996), underreported income occurs if the use of lower digits is more than the frequency of Benford's law. Next, we break down data on age and gender differences. The second digit test shows slightly different results. 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.

Finally, 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.

From the description above, 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.

5.2 Recommendations

5.2.1 Policy Recommendations

Several policy recommendations could be carried out by the government. First, DGT continues the "tax outlet" program, such as in Tanah Abang Market, since it was effectively increasing taxpayer compliance. The recommendation is to replicate the tax outlet in other places such as malls and shopping centers. The second recommendation is counseling that focuses on young taxpayers since they tend to be less compliant. The counseling can take the forms of taxation seminars on campuses, opening more tax centers at universities and debate contests on taxes. According to a study from Andriani and Herianti (2016), tax counseling conducted by the DGT in Tanah Abang Market has a significant effect on taxpayer's compliance. Third, DGT could conduct more validity tests of taxpayer income data by tax audits or data confirmation. As the number of taxpayers is vast, Benford's law can be used to detect the existence of UPE at the aggregate. Using the first-two digit test will help to determine tax audit priorities. All these recommendations still need in-depth studies before implemented so that the policies taken are effective. Such policies will result in achieving tax revenue targets, helping in turn to finance development policies.

5.2.2 Future Study

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 and 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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Appendices

Appendix 1 Age Summary

```
. mean age
```

Mean estimation Number of obs = 1,402

	Mean	Std. Err.	[95% Conf.	Interval]
age	48.55136	.3122573	47.93881	49.1639

Appendix 2 Output Logit Regression

```
. logistic comp_2019 gender age age_sq
```

Logistic regression Number of obs = 1,402
LR chi2(3) = 16.01
Prob > chi2 = 0.0011
Log likelihood = -870.38042 Pseudo R2 = 0.0091

comp_2019	Odds Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
gender	1.264291	.1708573	1.74	0.083	.9700962	1.647703
age	1.107691	.0371293	3.05	0.002	1.037258	1.182907
age_sq	.9990918	.0003308	-2.74	0.006	.9984436	.9997404
_cons	.1203251	.0990362	-2.57	0.010	.0239749	.603888

Note: _cons estimates baseline odds.

Appendix 3 Output Marginal Effect Logistic Regression

```
. margins, dydx(gender age age_sq)
```

Average marginal effects Number of obs = 1,402
Model VCE : OIM

Expression : Pr(comp_2019), predict()
dy/dx w.r.t. : gender age age_sq

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
gender	.0503903	.0289293	1.74	0.082	-.0063101	.1070906
age	.0219768	.0071154	3.09	0.002	.0080308	.0359228
age_sq	-.0001952	.0000705	-2.77	0.006	-.0003333	-.0000572