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Master's Thesis of Economics

The Effect of the EITC on the Elderly Labor

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The Effect of the EITC on the Elderly Labor

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Abstract

This paper examines the effect of the earned income tax credit (EITC) on elderly labor by using an exogenous quasi-experimental design. This paper exploits an EITC reform in 2013, enabling single-person households older than 60 to be eligible for tax refunds in South Korea. The panel data, Korean Longitudinal Study of Aging, is used for the main analysis. This paper uses a dynamic binary panel regression and shows that there exists strong state dependency of the elderly's labor market participation. After controlling for such dependency, it is shown that the EITC increases wage workers, about 6.4%, but not significantly affects the number of self-employments. In addition, this paper evaluates the effect of the EITC on income by panel quantile regression and stochastic dominance approach. This paper finds that the EITC helps older ages in low quantile of the income distributions, which highlights the function of the EITC as a social safety net.

Keyword: EITC, Elderly labor, Employment, State Dependency

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Chapter 1. Introduction

There are growing concerns regarding the poverty status of older ages as aging society leads to a labor market reform in many countries. Policymakers seek an effective anti-poverty policy targeting this group and are particularly interested in the prolonged labor market participation. Regarding these interests, how the elderly population responds to an economic incentive for labor market participation should be highlighted and examined thoroughly.

This paper evaluates the impact of the earned income tax credit (EITC) on the extensive margin response of elderly labor by using an exogenous quasi-experimental design. The key criterion evaluating the EITC is whether the EITC induces unemployed poor households to get a job in the labor market, which mitigates the welfare trap. This paper exploits an EITC reform in 2013 Korea, enabling single-person households older than 60 to be eligible for tax refunds, and then evaluates the intend-to-treat (ITT) effect of the EITC.

This paper distinguishes an employment status as paid employment, self-employment and not working. Self-employment is an attractive option for older ages wishing to work and should not be ignored in analyzing the elderly labor force. Choosing to be a self-employee depends on several factors such as individual preference valuing to be a boss, flexible workhour schedule, and expected future earnings.

This paper highlights the persistency of the labor market participation of older ages. In particular, self-employment is essentially a dynamic decision based on future expectations.[①] To consider dynamic aspects of self-employment decision, this paper follows the spirit of Heckman (1981a, 1981b) and takes a dynamic binary panel model approach. Through this approach, this paper suggests evidence that (1) state dependency significantly affects the labor market participation of the elderly, and (2) the EITC increases the number of employed elderly workers but does not significantly affect that of the elderly self-employee. This emphasizes the fact that the overall employment effect of the EITC on the elderly depends on the composition of work types of the elderly labor.

To examine whether the EITC is practically helpful for low-income households and reduces income inequality, this paper also evaluates the effect of the EITC on income distributions of older ages. For this purpose, this research takes the panel quantile regression and stochastic dominance approach. To summarize my findings, the EITC significantly improves the income status of older ages via pushing the low-quantile distribution rightward. This finding suggests that the EITC acts as a social safety net.

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① There are papers considering self-employment and dynamic decision makings. See Pardo and Ruiz-Tagle (2017) and Dillon and Stanton (2017)

The data used in this paper is the Korean Longitudinal Study of Aging (KLoSA), which is biyearly panel data tracking older ages in Korea. KLoSA has multiple advantages for analyzing the elderly labor force. First, KLoSA contains detailed survey responses about labor market participation, so it is possible to distinguish employed and self-employed. In addition, KLoSA provides the health history of an individual, which enables us to exclude or control for disability and bad health conditions. Furthermore, KLoSA contains key variables allowing me to control for covariates affecting the labor market outcomes of older ages.

This paper is organized as follows. First, I review related literature in Chapter 2. In Chapter 3, I introduce the institutional background of the EITC in Korea. In Chapter 4, I introduce the main data KLoSA and descriptive statistics. In Chapter 5, I examine the employment effect of the EITC by both static- and dynamic-binary response models. In Chapter 6, the effect of the EITC on income distribution is examined. Concluding remarks are in Chapter 7.

Chapter 2. Literature Review

This paper contributes to large literature evaluating the effectiveness of the EITC. The EITC is one of the most examined anti-poverty policies in the economics literature. There has been wide consensus on the positive employment effect of the EITC (Eissa and Liebman, 1996; Meyer and Rosenbaum, 2001; Hotz and Scholz, 2006; Meyer, 2010), which mainly focuses on single mothers. In contrast to the consensus, Kleven (2020) suggests the counter-argument against this consensus. He points out that the positive impact of the EITC is mainly driven by welfare reforms and a favorable macroeconomic condition. In addition, Chetty, Friedman and Saez (2013) suggest that EITC knowledge among people has a significant impact on the effectiveness of the EITC. This paper contributes to these mixed arguments by pointing out that the impact of the EITC may differ, depending on the employment status.

This paper also contributes to the literature about the effect of the EITC on income and poverty. There are papers studying the impact of the EITC on earnings (Grogger, 2003; Neumark and Wascher, 2001, 2011), and on income and poverty (Bollinger et al, 2009; Grogger 2003; Gunderson and Ziliak, 2004). Hoynes and Patel (2015) study the effect of the EITC on the entire distribution and conclude that there exist positive poverty reductions due to the EITC benefits. This paper also suggests evidence that the EITC is an effective anti-poverty policy even for older ages by examining the whole income distribution.

This paper's main contribution is analyzing the impact of EITC on elderly labor. Despite the growing number of the elderly labor force, there is surprisingly little literature dealing with the effect of the EITC on the elderly's labor market participation. Most studies examining the EITC exclude samples older than a certain age, so their scope of analysis does not contain the elderly labor force. To the best of my knowledge, there is only one paper, Laun (2017), which investigates the impact of income credits on older ages' labor supply and income by using Swedish administrative data. My paper additionally provides empirical evidence and is distinguishable in the sense of identifying the significant state dependency of the elderly labor market participation.

This paper is related to the literature about policies regarding self-employment. LaLumia (2009) and Kuka (2013) argue that generous EITC increases the number of taxpayers reporting income to the IRS. Lim and Michelmore (2018) report that the EITC leads to an increase in real hours spent as self-employed by the low-income, non-college-educated married mothers.[②] However, these papers do not include older ages as a subject. There are also papers evaluating a training program targeting self-employment (Benus, 1995; Michaelides and Benus 2012). They emphasize the fact that the small

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② There are studies about the effect of tax rates on increase in self-employment. Results of these studies are mixed. Robson and Wren (1999), Schuetze (2000), and Cullen and Gordon (2007) report that increase in marginal tax rates leads to increase in self-employment. However, Bruch and Moshin (2006) argue that self-employment is not significantly affected by income tax rates.

amount of financial assistance encourages the unemployed to become self-employed. Abraham, Hershbein and Houseman (2019) survey the determinants of becoming self-employed and point out the heterogenous preference on flexibility, the labor market condition, life-cycle considerations as potential factors.

In addition, this study contributes to the literature about the elderly labor supply, which mainly focuses on the retirement decision (Hanoch and Honig, 1983; Honig and Hanoch, 1985; Honig, 1996). Haider and Loughran (2001) study reasons for the labor supply decision of the elderly. They find that wealth and health conditions play an important role in the decision. Vere (2011) estimates the effects of Social Security income on elderly labor supply in the 1990s and early 2000s and conclude that reductions in benefits let elderly workers work more hours. Kaushal (2014) studies the impact of public pension on elderly labor supply and welfare using Indian data and shows that public pension has a negative impact on the employment of the elderly.

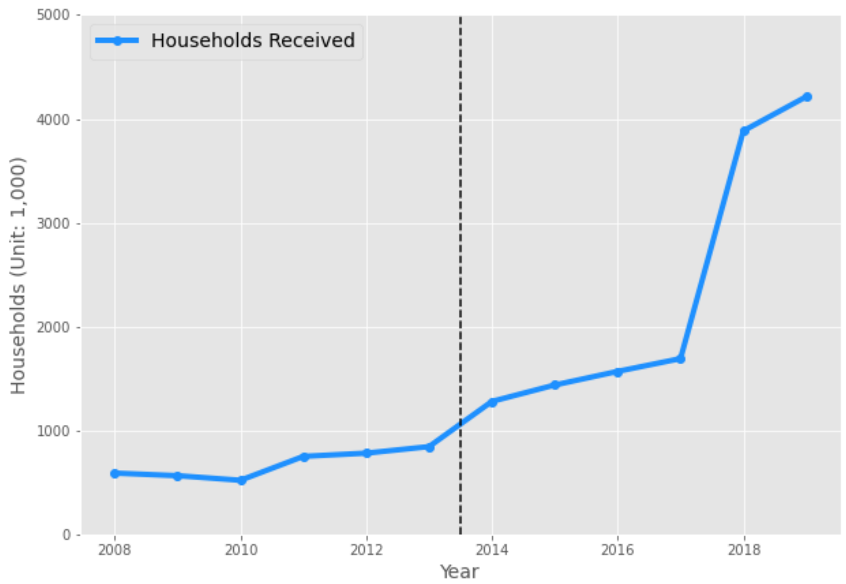
Lastly, this paper also contributes to the literature about state dependency and labor market participation. Since Heckman (1981a, 1981b) studied married women's labor market participation, state dependence has been highlighted as one of the key factors for labor market participation. Hyslop (1999) investigates intertemporal labor market participation of women and emphasizes heterogeneity and significant state dependence. There are subsequent studies about the dynamic labor market behaviors of women (Haan, 2005 2010; Eckstein and Lifshitz, 2011). Different from previous papers, this paper studies the state dependence of older ages' labor market behaviors.

Chapter 3. Institutional Background

3.1. The Earned Income Tax Credit in Korea

In Korea, the EITC was first discussed in 2003 and legislated in 2006. The first credit refund was done in 2009. An eligible household applies for tax credits in May and gets refunds in October for every year. There are multiple conditions for being eligible: number of children, marital status, age, income, and assets. A household meeting all these conditions is eligible for application. Figure 1 shows the number of Korean households that received credits each year. The number of households in South Korea is around 20 million, which means a substantial portion of households has received the EITC benefits.

Figure 1. The number of households receiving credits in Korea



Notes The solid blue line indicates the number of households receiving tax credits each year. The data is from the *Statistical Yearbook of National Tax* by the National Tax Service

A single-person household had not been eligible for income credits until 2012 and became possible to apply for the credit in 2013. In 2012, a single-person household, who is equal to or older than 60 and meets certain criteria, became eligible for tax credits. After 2012, there have been the EITC reforms that amend the eligibility conditions and the EITC benefit structure. Table 1 summarizes changes in eligibility conditions for a single-person household.

The income condition is based on the total income, the sum of earned income and business income that is adjusted differently among the business sectors, of the last year (imputed income). The amount of benefits is determined by the total income of a household. There are three sections regarding credit. Figure 2 shows the EITC benefit structure. The first is the incremental section, where the amount of refund increases as income increases. The second is the plateau section, where the amount of refund is the same regardless of income. The last is the decremental section, where the amount of refund decreases as income decreases. The maximum benefit from 2012 to 2014 is 0.70 million KRW, that from 2015 to 2016 is 0.77 million KRW, that in 2017 is 0.85 million KRW and that from 2018 is 1.50 million KRW.

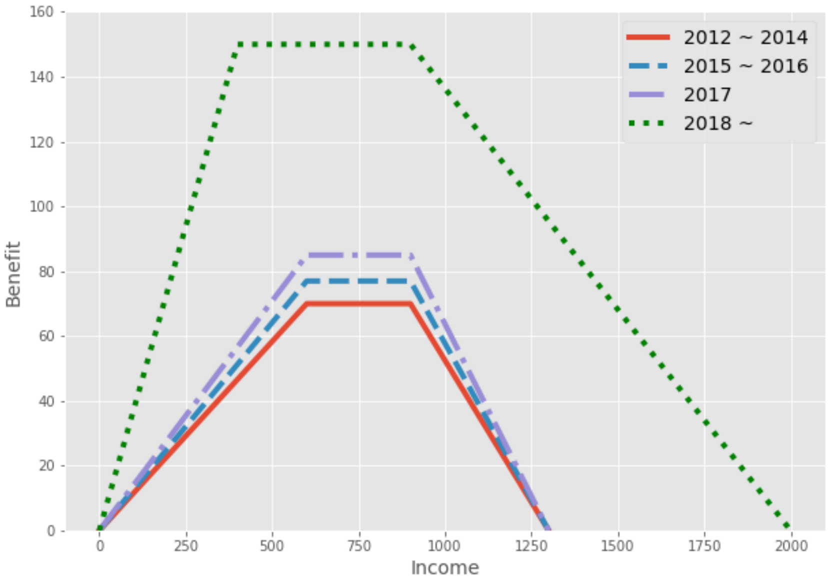
For being eligible, a household must meet asset conditions in which there were major revisions on the criterion. For example, a household's amount of total assets must not exceed 100 million KRW from 2008 to 2013, 140 million KRW from 2014 to 2017, and 200 million KRW after 2018 (in here and hereafter, year denotes imputed year).

Table 1. EITC Reforms and Eligibility Conditions for a Single-Person Household

<table>
<tr><th rowspan="2">Imputed Year
(Application Year)</th><th colspan="6">Eligibility Conditions</th></tr>
<tr><th>Age</th><th>Income</th><th>Wealth</th><th>House</th><th>Basic Livelihood Earning</th><th>Work Type</th></tr>
<tr><td>2008
(2009)</td><td colspan="6" rowspan="2">Single-person household is not available</td></tr>
<tr><td>2011
(2012)</td></tr>
<tr><td>2012
(2013)</td><td rowspan="3">60 ~</td><td rowspan="6">~ 13 million KRW</td><td rowspan="2">~ 100 million KRW</td><td rowspan="2">Own no house or a house cheaper than 60 million KRW</td><td>Do not receive basic security earnings more than three months in imputed year</td><td rowspan="2">Paid Employment</td></tr>
<tr><td>2013
(2014)</td><td>Do not receive basic security earnings in March of application year</td></tr>
<tr><td>2014
(2015)</td><td rowspan="5">~ 140 million KRW</td><td rowspan="3">Own no more than one house</td><td rowspan="5">Abolished</td><td rowspan="5">Paid Employment and Self-Employment</td></tr>
<tr><td>2015
(2016)</td><td>50 ~</td></tr>
<tr><td>2016
(2017)</td><td>40 ~</td></tr>
<tr><td>2017
(2018)</td><td>30 ~</td><td rowspan="2">Abolished</td></tr>
<tr><td>2018
(2019)</td><td>Abolished</td><td>~ 20 million KRW</td></tr>
</table>

Notes This table shows years when EITC reforms happen and corresponding changes in eligibility conditions for a single-person household in Korea. From 2008 to 2011 (year denotes the imputed year in these notes), a single-person household could not apply for the tax credit. However, from 2012, a single-person household older than or equal to 60 meeting certain conditions becomes eligible. An age standard has been lowered and eventually abolished in 2018. From 2012 to 2017, an income condition requires a household should earn income no more than 13 million KRW. In 2018, an income requirement is expanded to 20 million KRW. From 2012 to 2013, a wealth condition requires a household to hold assets no more than 100 million KRW. From 2014, the maximum asset an eligible household could hold has been changed to 140 million KRW. From 2012 to 2013, a house ownership condition requires a household to own no house or a house cheaper than 60 million KRW. From 2014 to 2016, a house ownership condition requires a household to own no more than one house. Since 2017, a house ownership condition has been abolished. In 2012, a household, who receives basic security earnings for more than three months, is not eligible for EITC. In 2013, a household, who receives basic security earnings in March of the application year, is not eligible for EITC. This condition has been abolished since 2015. Until 2013, only a worker having paid employment job had been eligible for the EITC. Since 2014, a self-employment worker has been also eligible for the EITC.

Figure 2. The EITC Benefit Structure for a Single-Person Household



Notes The red solid line indicates the amount of tax credit an eligible household with a certain income can receive from 2012 to 2014. The blue dash line indicates that from 2015 to 2016. The purple dash-dot line indicates that in 2017. The green dot line indicates that from 2018. Years are imputed years.

In addition to the total assets, a household must meet conditions about ownership and price of a house property. From 2012 to 2013, a household should not own any house or own only up to one house cheaper than 60 million KRW. In 2014, the price criterion was abolished, and a household having less than or equal to one house became eligible. In 2018, a condition for house ownership was abolished.

There have been also changes in conditions regarding basic living security earnings, which acts as one of the main social safety nets in Korea. A household earning basic living security for more than 3 months in the imputed year had not been eligible from 2009 to 2013. In 2014, A household earning basic living security at March application year was not eligible. After 2015, a condition of basic living security income was removed.

Lastly, demographic conditions have been mitigated and eventually abolished. In 2012, a single-person household older than 60 became eligible. In 2015, a single-person household older than 50 also was added to the eligible group. The age standard for a single-person household had been lower and was abolished in 2018.

Chapter 4. Data

4.1. Korean Longitudinal Study of Aging

In this paper, I use Korean Longitudinal Study of Aging (KLoSA) data. KLoSA is a nationally representative sample of more than 10,000 persons who are older than 45 years old in South Korea (except residents in Jeju-island). It is first conducted in 2006 and tracks samples biennially. The survey is conducted from September to November of the corresponding year. I use the data from 2008 to 2016. This is because the data in 2006 do not have information on household size, so I am not able to identify single-person households.

There are three reasons the KLoSA is suitable for empirical research. First, the KLoSA allows us to check eligibility for EITC. For example, the KLoSA contains information about house ownership, house price, total assets, and basic living security recipient at last year. Using this information, we can construct indicators for eligibility. Second, the KLoSA provides data about the dynamics of labor market participation. By exploiting this information, it is possible to identify the effect of the EITC and the state dependency on labor market participation. Last, there are data, including each individual's education, gender, age, health conditions, so we can properly control for factors affecting labor market behaviors of the elderly.

In this research, I define a single-person household as a household whose size is equal to one and marital status is not married.[③] I only remain single-person households in KLoSA and exclude an individual with a disability. Then, I define employment status by using answers to the following questionnaire:

"I will ask you about the most important jobs you currently do. Which of the following are your most important jobs?"

(1) Employed by another person or company to work for wages

(2) Self-Employed

(3) Helping family members or relatives for more than 18 hours a week

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[③] I also exclude a household whose marital status is "living apart from the partner."

without receiving money

(4) Helping family members or relatives for less than 18 hours a week without receiving money

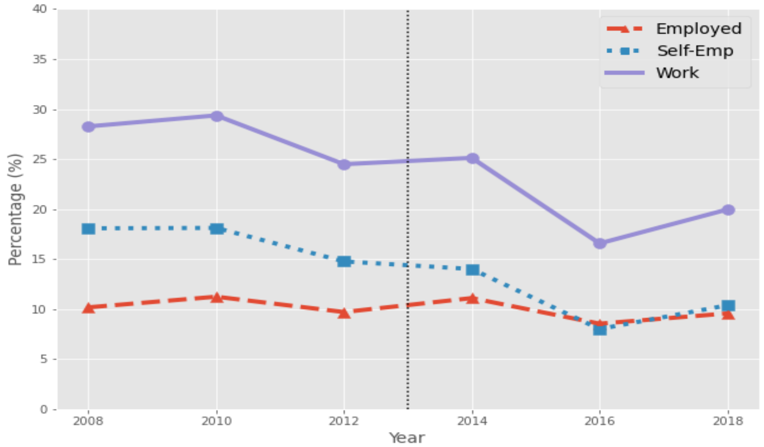
If an answer of a respondent is (1) and (2), then I define her employment status as an employee and self-employed, respectively.

Figure 3. shows the yearly share of workers. In Figure 3. (a), there is a downward trend in the share of workers and self-employed. In contrast, the share of employees is stable during the whole sample period. Figure 3. (b) reveals the ratio of employees to workers has increased from 36.02% to 47.97% in 2018.

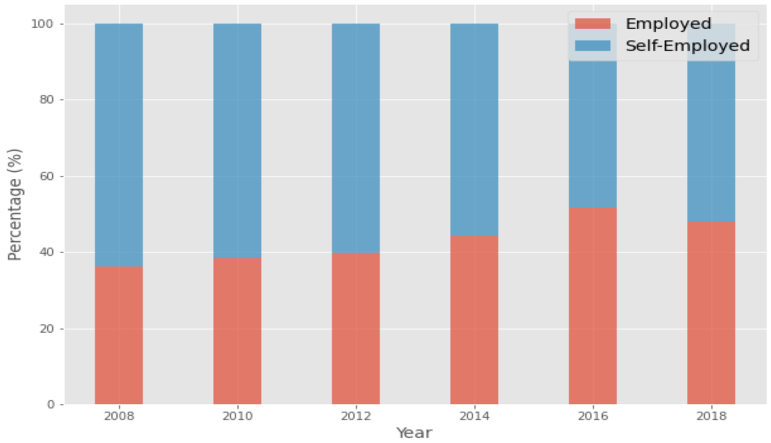
Figure 4 shows the histogram of the annual nominal income[④] for whole sample periods. Single-person elderly households in Korea are mostly a low-income household and meets income conditions for EITC. About 88% of the sample has an income of no more than 13 million KRW which is the maximum total income for receiving benefits.

[④] The income in the KLoSA is the sum of earned income, asset income, public transfer, transfer from others, personal pension, and other income.

Figure 3. Single elderly workers in KLoSA



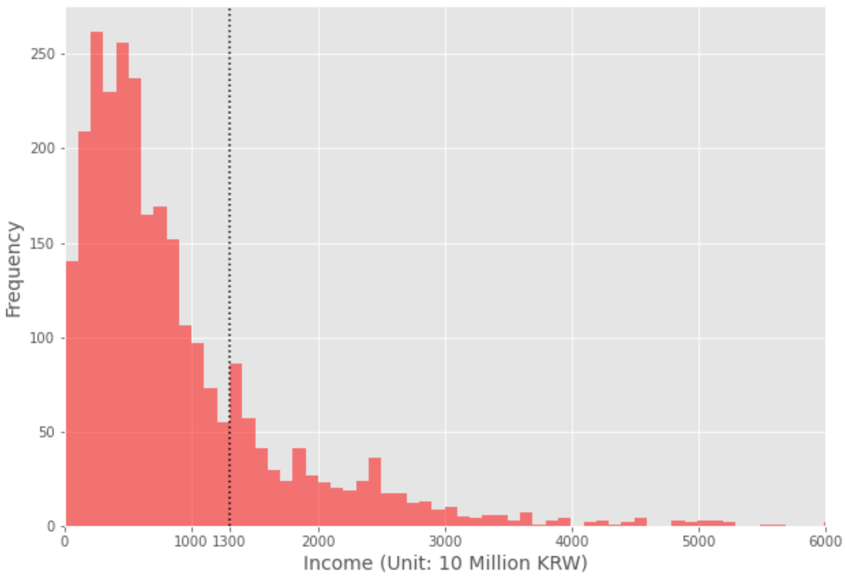
(a) Yearly trend of working households



(b) Yearly composition of working households

Notes Figure 3. (a) shows the share of working elderly to single-person households. The solid purple line indicates the share of workers, the dotted blue line indicates that of the self-employed, and the dashed red line indicates that of employees. For each year, the summation of the share of the self-employed and the share of employed is equal to the share of workers. Figure 3. (b) shows the yearly composition of workers. The red bar indicates the share of the employed and the blue bar indicates that of the self-employed.

Figure 4. Income Distribution



Notes This figure shows the histogram of annual income for whole sample periods. The horizontal axis indicates income and the unit is 10 million KRW. The interval between each bin is 1 million KRW. The vertical axis indicates the frequency of each bin.

To identify the ITT effect of the EITC, I define a dummy variable D_{it} which indicates whether an individual (a single-person household) i meets eligibility conditions, excluding the income condition, at year t. To be specific, D_{it} is a product of the following four dummy variables: D_{hit}, D_{bit}, D_{wit} and D_{ait}. I introduce the definition of these dummy variables as:

$D_{hit} = 1$ if (1) an individual i does not own a house or owns a house cheaper than 60 million KRW year $t = 2014$ or (2) $t = 2016$,

2018[5] Otherwise, $D_{hit} = 0$.

$D_{bit} = 1$ if (1) an individual i does not receive basic living security income at $t = 2014$[6] or (2) $t = 2016, 2018$ Otherwise, $D_{bit} = 0$.

$D_{wit} = 1$ if an individual i has the amount of total asset lower than 140 million KRW at year $t = 2014, 2016.$ Otherwise, $D_{wit} = 0$.

$D_{ait} = 1$ if (1) a birth year of an individual i is before or equals to 1953 at year $t = 2014$, (2) a birth year of an individual i is before or equals to 1965 at year $t = 2016$ or (3) a birth year of an individual i is before or equals to 1977 at year $t = 2018.$ Otherwise, $D_{ait} = 0$.

Then, we define $D_{it} = D_{hit} \times D_{bit} \times D_{wit} \times D_{ait}$. In Figure 5, the share of the eligible single-person household elderly for the EITC is presented. Among single-person households, around 35% of households are eligible for application in 2014 and 65% of households are eligible in 2016. This increase is mainly due to mitigated eligibility of house ownership and age standards.

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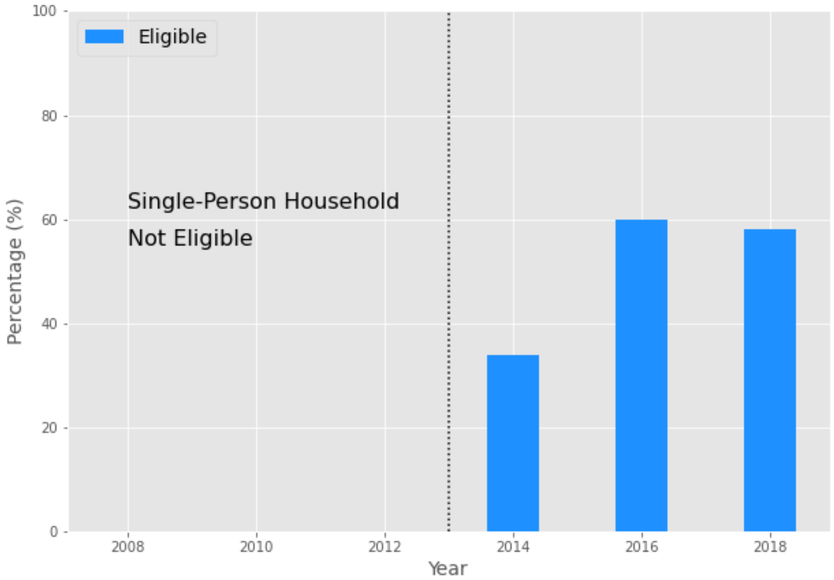
[5] Even though a household owns only up to one house is eligible in 2016, we are unable to check how many houses a household owns in data. Therefore, we construct D_{hit} by checking the ownership of a house.

[6] An individual i must not receive basic living security income at March in 2014. However, it is not possible to exactly identify when an individual received basic living security income. Therefore, we use whether an individual received the income last year as a proxy variable.

Figure 5. The Share of the Eligible



Notes This figure shows the share of the eligible persons each year. The horizontal axis indicates the year the vertical axis indicates the percentage of eligible households each year.

4.2. Descriptive Statistics

Table 2 shows descriptive statistics of variables. The 'Eligible' column is descriptive statistics of treated samples ($D_{it} = 1$) and the 'Not Eligible' column is those of samples not treated ($D_{it} = 0$).

Although the eligible experience poorer economic conditions than not eligible, the eligible households who work are fewer than the not eligible on average. However, both the eligible and not eligible households have a similar share of paid employees. The most notable difference in economic variables is assets. The eligible households have fewer assets than not eligible households. In addition, the share of house owners among eligible households is smaller than that of house owners among not eligible households. Over half of the eligible households reside in a rural region.

Most of the individuals are women and experienced bereavement. This might be due to the longer life expectancy of women. Most individuals are low educated. The share of the eligible households whose highest degree is elementary school graduation is bigger than that of not eligible households. The number of eligibles who regard themselves as having bad health conditions is larger than that of not eligible households.

Table 3 contains the correlation coefficients of variables. Aging negatively affects labor market participation. Residing in a rural region is positively correlated with self-employment, but negatively correlated with employment. This might be related to labor market opportunities because living in a city can offer more job options than living in a rural town. In Table 3, except age, most variables are not greatly correlated with employment variables. This calls for considering unobserved heterogeneity affecting the labor market participation of the elderly.

Table 2. Descriptive Statistics

Variables	All	Eligible	Not Eligible
Employment			
– Work	0.245 (0.430)	0.189 (0.392)	0.261 (0.439)
– Employed	0.101 (0.301)	0.098 (0.297)	0.101 (0.301)
– Self-Employed	0.144 (0.351)	0.091 (0.289)	0.160 (0.366)
Gender			
– Man	0.152 (0.358)	0.126 (0.332)	0.159 (0.366)
Education			
– Elementary School	0.749 (0.433)	0.853 (0.354)	0.719 (0.450)
– Middle School	0.106 (0.308)	0.068 (0.252)	0.118 (0.322)
– High School	0.112 (0.316)	0.062 (0.240)	0.127 (0.333)
– College	0.032 (0.176)	0.017 (0.131)	0.036 (0.187)
Age	74 (9)	77 (8)	73 (8)
Marital Status			
– Divorced	0.050 (0.219)	0.043 (0.202)	0.053 (0.223)
– Bereaved	0.935 (0.247)	0.946 (0.225)	0.932 (252)
– Not Married	0.015 (0.120)	0.011 (0.105)	0.016 (0.124)
Economic Variables (Unit: 10 Mil KRW)			
– Income	920 (1108)	759 (591)	968 (1216)
– Public Transfer	272 (500)	315 (384)	259 (529)
– Assets	15438 (22172)	5429 (3996)	18367 (24350)
House Ownership	0.853 (0.354)	0.680 (0.467)	0.904 (0.296)
Region			
– Big city	0.320 (0.467)	0.191 (0.393)	0.358 (0.480)
– Small city	0.286 (0.452)	0.271 (0.445)	0.290 (0.454)
– Rural	0.394 (0.489)	0.538 (0.499)	0.352 (0.478)
Bad Health Condition	0.315 (0.465)	0.397 (0.490)	0.291 (0.454)
Observations	2,801	634	2,167

Notes The number in cells of 'All', 'Eligible' and 'Not Eligible' columns is mean (standard deviation). The 'Eligible' column is descriptive statistics of samples with $D_{it} = 1$ and the 'Not Eligible' column is those of samples with $D_{it} = 0$.

Table 3: Correlation Matrix

	Eligible (D_{it})	Employee	Self-Employed	Man	Elementary School	Middle School	High School	College	Age	Income	Public Trans	Assets	House	Big City	Small City	Rural	Bad Health
Eligible (D_{it})	1.00																
Employee	0.00	1.00															
Self-Employed	−0.08	−0.14	1.00														
Man	−0.04	0.08	0.08	1.00													
Elementary School	0.13	−0.08	−0.02	−0.26	1.00												
Middle School	−0.07	0.00	0.01	0.12	−0.60	1.00											
High School	−0.09	0.07	0.04	0.15	−0.61	−0.12	1.00										
College	−0.05	0.07	−0.04	0.17	−0.32	−0.06	−0.06	1.00									
Age	0.24	−0.30	−0.25	−0.02	0.28	−0.17	−0.18	−0.07	1.00								
Income	−0.08	0.14	0.14	0.08	−0.23	0.05	0.19	0.14	−0.21	1.00							
Public Trans	0.05	−0.05	−0.11	0.07	−0.21	0.09	0.14	0.11	0.05	0.37	1.00						
Assets	−0.24	−0.02	0.01	0.04	−0.33	0.11	0.26	0.15	−0.09	0.25	0.07	1.00					
House	−0.26	0.03	−0.01	0.06	−0.09	0.05	0.06	0.02	−0.12	0.03	0.00	0.20	1.00				
Big City	−0.15	−0.06	−0.12	−0.04	−0.12	0.06	0.09	0.03	−0.02	0.07	0.04	0.20	0.11	1.00			
Small City	−0.02	0.11	−0.10	0.07	−0.16	0.12	0.07	0.05	−0.06	0.04	0.02	0.06	−0.01	−0.43	1.00		
Rural	0.16	−0.04	0.20	−0.02	0.26	−0.16	−0.15	−0.07	0.08	−0.10	−0.06	−0.25	−0.10	−0.55	−0.51	1.00	
Bad Health	0.10	−0.08	−0.09	−0.07	0.19	−0.08	−0.14	−0.07	0.21	−0.15	−0.04	−0.14	−0.04	−0.09	0.00	0.09	1.00

Notes Table 3 shows correlation coefficients of variables. The number of observations is 2,801.

Table 4, correlation coefficients between current employment variables and past employment variables are shown. The correlation coefficient between current and lagged variables is greatly positive; the correlation coefficient between being paid employees at t and $t-1$ is 0.66 and the correlation coefficient between being self-employed at t and $t-1$ is 0.79. This is descriptive evidence indicating the strong persistency of the labor market participation of older ages. It seems that the transition from one type to another type is not usual. The correlation coefficient relating to such transition is relatively small.

Table 4. Correlation Matrix with Lagged Employment Variables

	Employee at t	Employee at $t-1$	Self-Employed at t	Self-Employed at $t-1$
Employee at t	1			
Employee at $t-1$	0.66	1		
Self-Employed at t	−0.14	−0.10	1	
Self-Employed at $t-1$	−0.10	−0.16	0.79	1

Notes Table 4 shows the correlation between current employment variables and lagged employment variables. The number of observations is 1,296.

Chapter 5. Employment Effect

This chapter investigates the impact of the EITC on elderly labor's labor market participation by both static and dynamic models. This chapter first introduces a static and dynamic model. Then, I show and compare regression results, then discuss policy implications.

5.1. Static Binary Response Model

Consider the following binary response panel model with unobserved heterogeneity:

$$y_{it} = 1\{y_{it}^* \geq 0\},$$
$$y_{it}^* = c_i + \gamma D_{it} + X_{it}\beta + \epsilon_{it} \quad (1)$$

for $i = 1,2,\ldots,N_t, t = 0,1,\ldots,T$. In this model, $1\{\cdot\}$ is the indicator function, y_{it} is the labor market participation and y_{it}^* is the latent variable that determines labor market participation. c_i is unobserved heterogeneity such as time-invariant human capital and personal preference. X_{it} are covariates that affect labor market participation. As a covariate, I control for gender, age, education, the number of kids, residential place, house ownership, health condition, and yearly dummies.

In this paper, ϵ_{it} is an error term and assumed to be independent of X_{it}.

From (1) we can obtain the following equation:

$$P(y_{it} = 1 | X_{it}, D_{it}, c_i) = \Phi(c_i + \gamma D_{it} + X_{it}\beta) \quad (2)$$

where Φ is linear function or a cumulative distribution function of the standard normal or logistic distribution, which depends on the model specification.

In this paper, my quantity of interest is the average treatment effect (ATE) of EITC which is expressed as:

$$E[\Phi(c_i + \gamma + X_{it}\beta) - \Phi(c_i + X_{it}\beta)] \quad (3)$$

where E denotes expectation. This can be estimated by estimating the average partial effect (APE) of the EITC. I estimate the quantity by using several approaches. The first model is the fixed-effect linear probability model (LPM FE) which sets Φ as a linear function. This approach is advantageous to directly estimate and control for c_i, so is robust to unobserved heterogeneity (Hyslop, 1999). However, it might be too restrictive to set Φ as a linear and allowing the predicted probability out of unit interval might result in the poor fitting. ⑦

⑦ However, it is known that LPM FE would provide reasonable estimates for the average partial effects (Wooldridge, 2010).

In addition to the linear model, I estimate parameters via nonlinear models such as the random-effect probit model (Probit RE), random-effect logit model (Logit RE). Although these models specify the distributions of c_i and ϵ_{it}, these nonlinear models can provide a better fit via restricting predicted values in the unit interval and are known to provide stronger identification.[⑧]

I first estimate models, setting y_{it} as a dummy variable $Employee_{it}$ which indicates whether an individual i is a wage worker at year t or not. In addition to paid employment, I analyze the impact of the EITC on self-employment. After setting y_{it} as a dummy variable $Self-Employed_{it}$ which indicates whether an individual i is self-employed at year t, I estimate the same models.

5.2. Dynamic Binary Response Model

In this section, I describe the model for testing whether state dependency has a significant impact on the labor market participation of older ages and identify the employment effect of the EITC after controlling for such state dependency. For estimation, I consider the dynamic binary response model with unobserved heterogeneity as:

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⑧ For checking the robustness, population-averaged probit model and population-averaged logit model are also used. The estimation result is qualitatively similar.

$$y_{it}^* = c_i + \delta y_{i,t-1} + \gamma D_{it} + X_{it}\beta + \epsilon_{it} \quad (4)$$

for $i = 1,2,\ldots,N, t = 1,\ldots,T$.

Through this specification, it is possible to test the state dependency of older workers' labor market participation, which corresponds to testing $\delta = 0$. In addition to testing, I am interested in whether the size of the coefficient γ increases after controlling for the state dependency. This is because the inflexible adjustment due to the state dependency might cause a limited effect of the policy.

For nonlinear models, estimation via simple probit or logit regression is not valid in a dynamic context, due to the initial conditions problem (Heckman 1981b). This problem has been widely discussed in econometrics literature, and there are mainly two approaches: a dynamic conditional logit model with fixed effects by Honore and Kyriazidou (2000) and a dynamic random effect probit model proposed by Wooldridge (2005). Despite several advantages, the method by Honore and Kyriazidou (2000) cannot identify partial effects and is not suitable for this research. Therefore, even though I need to specify conditional distributions of c_i given y_0, I apply the method proposed by Wooldridge (2005). A similar approach has been used in Michaud and Vermeulen (2004), Michaud and Tatsiramos (2008), Lee and Tae (2005), and Haan (2010).

5.3. Regression Result

Table 5 and Table 6 show regression results on paid employment and self-employment, respectively. The full estimation result is contained in Appendix Table A1 and Table A2. In Table 5, the estimated coefficient of the EITC eligibility, $\hat{\gamma}$, is positive and statistically significant for all models. The regression results show that the EITC leads to a positive employment effect around 4.8% ~ 5.1% for static models. Even after controlling for the state dependency, $\hat{\gamma}$ is positive and statistically significant. The APE of the EITC is estimated at 6.4%, which is larger than static models. This is consistent with most of the literature which reports the positive employment effect of the EITC (Eissa and Liebman, 1996; Meyer and Rosenbaum, 2001; Hotz et al., 2006; Meyer, 2010). In addition to the impact of the EITC, the dynamic probit regression result shows strong state dependency of the employment and improved fitting of the data. When using dynamic regression, the percentage of correct predictions, that is predicting whether an individual i is an employee at time t, increases by about 3%p.

Table 5. Regression Result (Employee)

Model	(1) LPM FE	(2) Static Probit	(3) Static Logit	(4) Dynamic Probit
EITC (D_{it})	0.051***	0.686***	1.201***	0.668**
	(0.018)	(0.226)	(0.404)	(0.273)
Past Employment				
y_{it-1}				1.471***
				(0.318)
y_{i0}				1.069**
				(0.522)
APE of EITC (D_{it})	0.051***	0.049***	0.048***	0.064**
	(0.018)	(0.017)	(0.017)	(0.029)
Number of Individuals	1,112	1,112	1,112	578
Observations	2,801	2,801	2,801	1,296
Correct Predictions (%)	89.97	90.04	90.04	93.29

Notes Table 5 shows regression results setting a dependent variable as a $\boldsymbol{Employee_{it}}$. The number in the cell shows estimated coefficients (standard error). The standard errors are clustered on observations by an individual for the LPM FE model. *, **, and *** indicate the coefficient is statistically significant at the 10%, 5%, and 1% significance level, respectively. The 'Correct Predictions' row shows the percentage of correctly predicted observations, corresponding to each model.

In Table 6, regression results on self-employment are shown. In contrast to regression on paid employment, there exists a notable difference between static and dynamic models. This might be evidence of omitted variable bias in a static regression model on self-employment due to neglecting a dynamic component. For static models, it is estimated that the EITC has a decreasing impact on self-employment, which is shown by the negative $\hat{\gamma}$ that is statistically significant. The estimated APE of the EITC is around −3.5%. However, after controlling for lagged and initial dependent variables, $\hat{\gamma}$ becomes close to zero and is not statistically significant. The APE of the EITC is almost 0 and not statistically significant. In addition to estimates, the percentage of correct predictions greatly increases by about 9%p. This supports the importance of the state dependency of the elderly labor.

Table 6. Regression Result (Self-Employed)

Model	(1) LPM FE	(2) Static Probit	(3) Static Logit	(4) Dynamic Probit
EITC (D_{it})	−0.035*	−0.640**	−1.084**	−0.0517
	(0.020)	(0.262)	(0.465)	(0.243)
Past Employment				
y_{it-1}				2.310***
				(0.254)
y_{i0}				0.583**
				(0.259)
APE of EITC (D_{it})	−0.036*	−0.036***	−0.035**	−0.00
	(0.020)	(0.014)	(0.014)	(0.020)
Number of Individuals	1,112	1,112	1,112	578
Observations	2,801	2,801	2,801	1,296
Correct Predictions (%)	85.58	85.79	85.86	94.75

Notes Table 6 shows regression results setting a dependent variable as a $Self-Employed_{it}$. The number in the cell shows estimated coefficients (standard error). The standard errors are clustered on observations by an individual for the LPM FE model. *, **, and *** indicate the coefficient is statistically significant at the 10%, 5%, and 1% significance level, respectively. The 'Correct Predictions' row shows the percentage of correctly predicted observations, corresponding to each model.

As a confounding factor, we can think of assets. As eligibility conditions have been mitigated or abolished except the wealth condition, the amount of assets almost determines the eligibility. Therefore, it is necessary to check the estimates $\hat{\gamma}$ means the effect of the EITC or the effect of low assets. To check the robustness of the main dynamic model, I try alternative specifications. First, I run dynamic regression of the same model only using the data before 2015. In addition, I run dynamic regression of the same model after controlling for log assets as a covariate.

Table 7. Robustness Check (Employee)

Specification	(1) Main	(2) Before 2015	(3) Including Assets
EITC (D_{it})	0.668**	0.778**	0.522*
	(0.273)	(0.363)	(0.285)
Past Employment			
y_{it-1}	1.471***	1.232***	1.478***
	(0.318)	(0.378)	(0.318)
y_{i0}	1.069**	1.613**	1.020**
	(0.522)	(0.702)	(0.518)
APE of EITC (D_{it})	0.064**	0.069*	0.048*
	(0.029)	(0.036)	(0.029)
Number of Individuals	578	526	578
Observations	1,296	1,094	1,296
Correct Predictions (%)	93.29	93.51	93.13

Notes This table shows regression results setting a dependent variable as a $\boldsymbol{Employee_{it}}$ of main and alternative specifications. Column (1) is the main specification. Column (2) is regression after excluding samples from 2016. Column (3) is regression after adding log assets as a covariate. The number in the cell shows estimated coefficients (standard error). *, **, and *** indicate the coefficient is statistically significant at the 10%, 5%, and 1% significance level, respectively. The 'Correct Predictions' row shows the percentage of correctly predicted observations, corresponding to each model.

Table 8. Robustness Check (Self-Employment)

Specification	(1) Main	(2) Before 2015	(3) Including Assets
EITC (D_{it})	−0.052	0.043	0.134
	(0.243)	(0.289)	(0.261)
Past Employment			
y_{it-1}	2.310***	2.178***	2.284***
	(0.254)	(0.292)	(0.256)
y_{i0}	0.583**	0.680**	0.598**
	(0.259)	(0.301)	(0.262)
APE of EITC (D_{it})	−0.00	−0.004	0.011
	(0.020)	(0.025)	(0.022)
Number of Individuals	578	526	578
Observations	1,296	1,094	1,296
Correct Predictions (%)	94.75	94.42	94.98

Notes This table shows regression results setting a dependent variable as a $\boldsymbol{Self-Employed_{it}}$ of main and alternative specifications. Column (1) is the main specification. Column (2) is regression after excluding samples from 2016. Column (3) is regression after adding log assets as covariates. The number in the cell shows estimated coefficients (standard error). *, **, and *** indicate the coefficient is statistically significant at the 10%, 5%, and 1% significance level, respectively. The 'Correct Predictions' row shows the percentage of correctly predicted observations, corresponding to each model.

In Table 7 and Table 8, regression results via alternative specifications are presented. Full estimation results are shown in Appendix Table A3. It is notable that the estimated APE of $\hat{\gamma}$ is robust even after excluding samples from 2016. Estimated APE of $\hat{\gamma}$ is also qualitatively similar for the specification which includes log assets as a covariate. In Table A3, the coefficient of log assets is not significant when regressing on $\boldsymbol{Employee_{it}}$, but positively significant when regression on $\boldsymbol{Self - Employed_{it}}$. However, overall estimation results are like the main specification even after controlling for log assets.

There are several policy implications from this regression. First, the employment effect of the EITC largely depends on state dependency. Especially, self-employment shows strong state dependency, and controlling for the state dependency drastically changes coefficients of the EITC eligibility dummy. Therefore, it is likely that the share of self-employees in an economy is important for the effectiveness of the EITC policy. Second, the employment effect of the EITC on paid employment and self-employment is different. In contrast to self-employment, the employment effect of the EITC is significantly positive even after adding lagged variables. This is interesting in the sense that the most positive employment effect of the EITC is for wage workers.

Chapter 6. EITC on Income

6.1. Linear Panel Regression

Consider the following linear panel model:

$$Y_{it+1} = c_i + \mu_t + \gamma D_{it} + X_{it}\beta + u_{it} \quad (5)$$

where Y_{it+1} is the log income of the next year. This is because the income data at t means the income of the last year in KLoSA data. For example, in 2014 data, income data means the income in 2013. Therefore, to evaluate the impact of EITC on welfare, I use the income of the next year which is contained in $t+1$ KLoSA data. c_i and μ_t are individual and time-fixed effects, respectively. u_{it} is an error term.

In this model, γ represents ATE of the EITC as shown in:

$$E[(Y_{it+1}|c_i, \mu_t, X_{it}, D_{it} = 1)] - E[(Y_{it+1}|c_i, \mu_t, X_{it}, D_{it} = 0)] = \gamma \quad (6)$$

In addition to log income, I run a regression of which dependent variable is the log public transfer of the next year. The EITC benefits are captured in the public transfer variable so that positive estimates $\hat{\gamma}$ is additional evidence about the EITC benefits of the eligible individuals. Income and public transfer are deflated by CPI.

In Table 8, regression results are shown. It is shown that the EITC increases income by 34.1% and public transfers by 77.4% on average. Both estimates are statistically significant at the 5% level. Living in a rural region is a significant factor for both income and public transfers, in a different direction. It seems that there has been a yearly increase in public transfer, which is shown in yearly dummy estimates. This regression result shows evidence indicating the EITC improves an income situation on average.

6.2. Quantile Panel Regression

Consider the following location-scale model:

$$Y_{it+i} = \alpha_i + \gamma D_{it} + X_{it}\beta + (\eta_i + \zeta D_{it} + X_{it}\xi)U_{it} \quad (7)$$

where Y_{it+i} is the log income of the next year and U_{it} is an unobserved random variable, independent of (X_{it}, D_{it}), with density function bounded away from 0 and satisfies $E(U) = 0, E(|U|) = 1.$ Let $P\big(U < q(\tau)\big) = \tau$, and from eq (7), we can derive the conditional quantiles $Q_Y(\tau|X_{it}, D_{it})$ as:

$$Q_Y(\tau|X_{it}, D_{it}) = c_i(\tau) + \gamma(\tau)D_{it} + X_{it}\beta(\tau) \quad (8)$$

where $c_i(\tau) = \big(c_i + \eta_i q(\tau)\big)$, $\gamma(\tau) = \big(\gamma + \zeta q(\tau)\big)$, and $\beta(\tau) = \big(\beta + \xi q(\tau)\big)$.

Table 9. Regression Results (Average Effect)

Dependent Variable	(1) Log Income	(2) Log Public Transfer
EITC (D_{it})	0.341***	0.774**
	(0.116)	(0.308)
House Ownership	0.021	0.162
	(0.088)	(0.175)
Kids	−0.034	−0.016
	(0.364)	(0.540)
Rural	−0.160***	1.053***
	(0.045)	(0.103)
Bad Health	−0.003	0.156
	(0.062)	(0.158)
Yearly Dummies		
- 2010	−0.037	0.338***
	(0.049)	(0.099)
- 2012	0.111**	1.598***
	(0.053)	(0.135)
- 2014	−0.016	1.368***
	(0.099)	(0.257)
- 2016	0.045	1.924***
	(0.118)	(0.329)
Constant	6.521***	2.353
	(1.365)	(2.036)
Number of Individuals	619	619
Observations	1,366	1,366
R-squared		
- Within	0.032	0.275
- Between	0.011	0.044
- Overall	0.022	0.077
Fixed Effect	Yes	Yes

Notes Table 8 shows regression results. The number in the cell shows estimated coefficients (standard error). The standard errors are clustered on observations by an individual. *, **, *** indicate the coefficient is statistically significant at 10%, 5%, 1% significance level, respectively. The number of observations is 1,366 and that of individuals is 619.

In this model, $\alpha_i(\tau)$ can be interpreted as the quantile−τ fixed effect for individual i. My main parameter of interests is $\gamma(\tau)$ which is equivalent to quantile treatment effect (QTE) as:

$$Q_Y(\tau|c_i, \mu_t, X_{it}, D_{it} = 1) - Q_Y(\tau|c_i, \mu_t, X_{it}, D_{it} = 0) = \gamma(\tau)$$

I estimate this model by using the method of Machado and Silva (2019), which provides fixed-effect panel quantile regression. Table 10 shows quantile regression results.

In Table 10, it is notable that the welfare effect of the EITC is bigger for low-income quantiles. The coefficients of the EITC eligibility dummy for 10% quantile is 0.400 and gradually gets smaller as the quantile gets bigger. The coefficients for 10% and 30% quantiles are statistically significant. This gives evidence that the EITC is an effective anti-poverty policy for older ages by shifting low quantiles of the income distribution to increase. This can be interpreted as the EITC acts as a social safety net.

6.3. Stochastic Dominance Test

This paper applies stochastic dominance testing to identify the distributional improvement on the treated. Stochastic dominance is a widely used welfare comparison criterion that provides the uniform order among different social welfare by comparing the whole distributions.

Table 10. Regression Results (Quantile Effect)

Quantile (τ)	(1) 0.1	(2) 0.3	(3) 0.5	(4) 0.7	(5) 0.9
EITC (D_{it})	0.400*	0.380**	0.341	0.302	0.282
	(0.237)	(0.188)	(0.210)	(0.344)	(0.429)
House Ownership	0.037	0.032	0.021	0.010	0.005
	(0.156)	(0.123)	(0.138)	(0.226)	(0.282)
Kids	−0.104	−0.081	−0.034	0.012	0.037
	(0.681)	(0.540)	(0.603)	(0.988)	(1.235)
Rural	0.023	−0.038	−0.161	−0.281	−0.345
	(0.211)	(0.167)	(0.187)	(0.307)	(0.383)
Bad Health	−0.021	−0.015	−0.003	0.008	0.014
	(0.107)	(0.085)	(0.095)	(0.156)	(0.194)
Yearly Dummies					
- 2010	−0.005	−0.016	−0.037	−0.057	−0.068
	(0.087)	(0.069)	(0.077)	(0.127)	(0.158)
- 2012	0.118	0.116	0.111	0.106	0.104
	(0.092)	(0.073)	(0.081)	(0.133)	(0.166)
- 2014	−0.008	−0.011	−0.016	−0.022	−0.025
	(0.193)	(0.153)	(0.170)	(0.279)	(0.349)
- 2016	0.082	0.070	0.044	0.020	0.006
	(0.218)	(0.173)	(0.193)	(0.316)	(0.395)
Number of Individuals	619	619	619	619	619
Observations	1,366	1,366	1,366	1,366	1,366
Fixed Effect	Yes	Yes	Yes	Yes	Yes

Notes Table 8 shows regression results. The number in the cell shows estimated coefficients (standard error). The standard errors are calculated as in Machado and Silva (2019). *, **, *** indicate the coefficient is statistically significant at 10%, 5%, 1% significance level, respectively. The number of observations is 1,366 and that of individuals is 619.

The hypothesis of interest is whether the next year's income distribution of the eligible individuals s-order stochastically dominates the last year's income distribution of them in year t. The null hypotheses of interest are expressed as:

$$H_{0,s}^{t,1} : Y_{t+1}(1) \ \geq_s \ Y_t(1) \quad (9)$$

where $Y_t(1) \coloneqq Y_t|(D_{it} = 1)$ and $Y_{t+1}(1) \coloneqq Y_{t+1}|(D_{it} = 1)$ and a stochastic dominance order $s = 1, 2$. $Y_t|(D_{it} = 1)$ and $Y_{t+1}|(D_{it} = 1)$ means the log income distributions at t and $t + 1$ of individuals who are eligible at t. The alternative hypothesis $H_{1,s}^{t,1}$ is the negation of the $H_{0,s}^{t,1}$. To identify the stochastic dominance relation, I also test the following hypotheses:

$$H_{0,s}^{t,2} : Y_t(1) \ \geq_s \ Y_{t+1}(1) \quad (10)$$

for $s = 1, 2$. The alternative hypothesis $H_{1,s}^{t,2}$ is the negation of the $H_{0,s}^{t,2}$. If there exists the distributional welfare improving effect of the EITC, $H_{0,s}^{t,2}$ is false and $H_{0,s}^{t,1}$ is true.

In addition, the following null hypotheses are tested to identify the welfare effect of the EITC:

$$H_{0,s}^{t,3} : Y_{t+1}(0) \ \geq_s \ Y_t(0) \quad (11)$$

$$H_{0,s}^{t,4} : Y_{t+1}(0) \geq_s \ Y_t(0) \quad (12)$$

where $Y_t(0) := Y_t|(D_{it} = 0)$ and $Y_{t+1}(0) := Y_{t+1}|(D_{it} = 0)$ for $s = 1, 2$. $Y_t|(D_{it} = 0)$ and $Y_{t+1}|(D_{it} = 0)$ means the log income distributions at t and $t + 1$ of individuals who are not eligible at t. The alternative hypotheses $H_{1,s}^{t,3}$ and $H_{1,s}^{t,4}$ are the negation of $H_{0,s}^{t,3}$ and $H_{0,s}^{t,4}$, respectively.

Figure 6 shows empirical log income distributions. Figure 6. (a) and (c) show empirical log income distributions of the eligible individuals. Notably, there exists a right shift of income distributions for low-income quantile individuals. In contrast, there seems no shift or drastic change of income distributions for not eligible households, which is shown in Figure 6. (b) and (d).

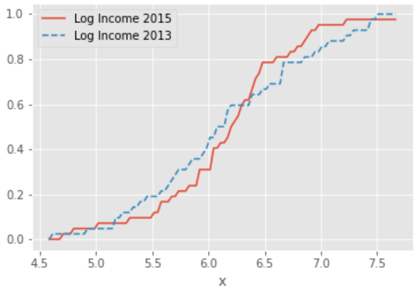
I apply the stochastic dominance test proposed by Linton, Song and Whang (2010), which provides a bootstrap stochastic dominance testing with the improved power property via the 'contact-set' estimation.[9] To allow time-dependency of each individual i, I conduct bootstraps in a pair (Y_{it+1}, Y_{it}). I use the grid of size 100 that is equally spaced on the range of pooled empirical distributions and repeat 200 bootstrapping of 40 bootstrap samples. Tables 11 and 12 provide the stochastic dominance testing results.

In Table 11, stochastic dominance testing for $H_{0,s}^{2014,k}$ $(k = 1,2,3,4)$ is shown. There seems welfare improving transitions of the eligible individuals. This is because $H_{0,s}^{2014,1}$ is not rejected but $H_{0,s}^{2014,2}$ is rejected

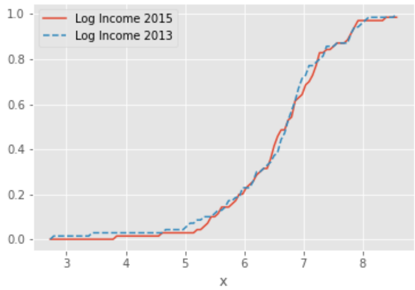
[9] In this paper, I set the tuning parameter c equals to 0.75.

for $s = 2$ at the 1% significance level, which means the next year's log income distribution of the eligible households second-order stochastically dominates the last year's log income distribution of them. Since $H_{0,s}^{2014,1}$ and $H_{0,s}^{2014,2}$ are both rejected for $s = 1$ at the 1% significance level, there is no first-order stochastic dominance relation between two distributions. In contrast to the eligible households, the null hypotheses $H_{0,s}^{2014,3}$ and $H_{0,s}^{2014,4}$ are not rejected for all $s = 1,2$ even at the 10% significance level, which means two distributions are the same in terms of stochastic dominance relation. This can be interpreted as there is no distributional improvement for non-eligible households.

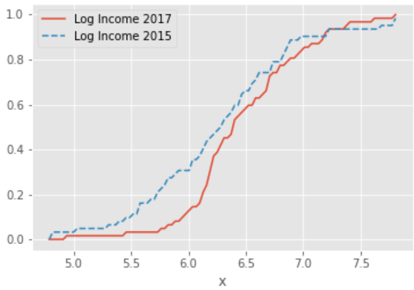
Figure 6. Empirical Log Income Distributions



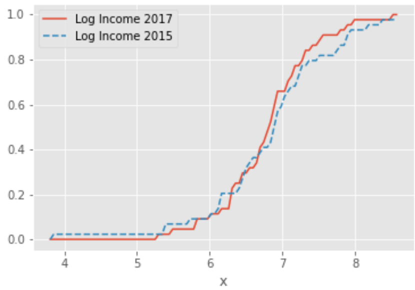
(a) Eligible in 2014



(b) Not Eligible in 2014



(c) Eligible in 2016



(d) Not Eligible in 2016

Notes Figure 6 shows the empirical log income distributions. Figure 6. (a) shows the empirical log income distributions of the eligible in 2013 and 2015. The red solid line indicates the empirical distribution in 2015 and the blue dash line indicates the empirical distribution in 2013. Figure 6. (b) shows the empirical log income distributions of the not eligible in 2013 and 2015. The red solid line indicates the empirical distribution in 2015 and the blue dash line indicates the empirical distribution in 2013. Figure 6. (c) shows the empirical log income distributions of the eligible in 2015 and 2017. The red solid line indicates the empirical distribution in 2017 and the blue dash line indicates the empirical distribution in 2015. Figure 6. (d) shows the empirical log income distributions of the not eligible in 2015 and 2017. The red solid line indicates the empirical distribution in 2017 and the blue dash line indicates the empirical distribution in 2015.

Table 11. Stochastic Dominance Testing Results (2014)

Year	2014			
H_0	$Y_{t+1}(1) \geq_s Y_t(1)$		$Y_{t+1}(0) \geq_s Y_t(0)$	
s	1	2	1	2
P-value	0.000	0.480	0.712	1.000
H_0	$Y_t(1) \geq_s Y_{t+1}(1)$		$Y_t(0) \geq_s Y_{t+1}(0)$	
s	1	2	1	2
P-value	0.000	0.010	0.446	0.263
Observations	42		70	

Notes The stochastic dominance test by Linton, Song and Whang (2010) is used. I conduct bootstraps in a pair (Y_{it+1}, Y_{it}) and repeat 200 bootstrapping. I use the grid of size 100 that is equally spaced on the range of pooled empirical distributions. The row 's' indicates the stochastic dominance order. The row 'P-value' indicates the bootstrap calculated P-value. The row 'Observations' means the number of observations for testing.

Table 12. Stochastic Dominance Testing Results (2016)

Year	2016			
H_0	$Y_{t+1}(1) \geq_s Y_t(1)$		$Y_{t+1}(0) \geq_s Y_t(0)$	
s	1	2	1	2
P-value	0.770	1.000	0.001	0.000
H_0	$Y_t(1) \geq_s Y_{t+1}(1)$		$Y_t(0) \geq_s Y_{t+1}(0)$	
s	1	2	1	2
P-value	0.000	0.000	0.035	0.020
Observations	62		44	

Notes The stochastic dominance test by Linton, Song and Whang (2010) is used. I conduct bootstraps in a pair (Y_{it+1}, Y_{it}) and repeat 200 bootstrapping. I use the grid of size 100 that is equally spaced on the range of pooled empirical distributions. The row 's' indicates the stochastic dominance order. The row 'P-value' indicates the bootstrap calculated P-value. The row 'Observations' means the number of observations for testing.

In Table 12, stochastic dominance testing for $H_{0,s}^{2016,k}$ $(k = 1,2,3,4)$ is shown. The next year log income distribution of the eligible households, $Y_{it+1}(1)$, first-order stochastically dominates the last year log income distribution of them, $Y_{it}(1)$ in 2016. This is equivalent to the fact that $H_{0,s}^{2016,1}$ is not rejected, but $H_{0,s}^{2016,2}$ is rejected for all $s = 1,2$ at the 1% significance level. In contrast to the eligible households, the null hypotheses $H_{0,s}^{2016,3}$ and $H_{0,s}^{2016,4}$ are rejected for all $s = 1,2$ at the 5% significance level. This shows that the two distributions do not show any stochastic dominance relations.

Chapter 7. Conclusion

Because of the aging society, policymakers are greatly concerned with the poverty status of the elderly. This paper examined the effect of the EITC on elderly labor. Even though the EITC is one of the most examined anti-poverty policies in the economics literature, a study of the EITC focusing on older ages has been scarce.

This paper investigated the employment effect of the EITC on the extensive margin, distinguishing a type of work as paid employment and self-employment. To consider the state dependency, a dynamic binary response model was used. The regression results showed that the EITC increases the paid employment but does not significantly affect self-employment. Regression analysis showed strong state dependency for both work types. This implies that the inertia of the elderly labor is strong, which affects the effectiveness of the EITC policy.

This paper also analyzed the effect of the EITC on income by panel quantile regression and stochastic dominance testing. It is shown that the EITC helps low-income older ages by shifting the low quantile of the income distribution. This result highlights the role of the EITC as a social safety net.

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Appendix

Table A1. Full Estimation Results (Employee)

Model	(1) LPM FE	(2) Probit RE	(3) Logit RE	(4) Dynamic Probit
EITC (D_{it})	0.051***	0.686***	1.201***	0.668**
	(0.018)	(0.226)	(0.404)	(0.273)
Past Employment				
y_{it-1}				1.471***
				(0.318)
y_{i0}				1.069**
				(0.522)
Male		0.600**	1.080**	0.223
		(0.281)	(0.495)	(0.236)
Age		0.036	0.078	0.111
		(0.152)	(0.270)	(0.167)
Age Squared		-0.001	-0.003	-0.00119
		(0.001)	(0.002)	(0.00120)
House Ownership		0.098	0.160	0.498
		(0.243)	(0.436)	(0.317)
Education				
- Middle School		-0.314*	-1.261**	-0.317
		(0.163)	(0.617)	(0.323)
- High School		-0.0341	-0.218	-0.0311
		(0.151)	(0.564)	(0.288)
- College +		0.140	0.601	0.902**
		(0.229)	(0.837)	(0.413)
Kids	0.005	-0.025	-0.047	0.0187
	(0.038)	(0.085)	(0.151)	(0.0719)
Rural	0.022	-0.308	-0.559	0.0702
	(0.034)	(0.233)	(0.412)	(0.190)
Bad Health	-0.014	-0.205	-0.395	-0.0752
	(0.014)	(0.180)	(0.323)	(0.193)
Yearly Dummies				
- 2010	0.004	0.393*	0.710**	
	(0.013)	(0.201)	(0.359)	
- 2012	-0.016	0.390*	0.710*	-0.0967
	(0.015)	(0.215)	(0.386)	(0.202)
- 2014	-0.032*	0.544**	0.997**	-0.152
	(0.017)	(0.229)	(0.412)	(0.228)
- 2016	-0.064**	0.281	0.549	-0.214
	(0.026)	(0.349)	(0.629)	(0.366)
- 2018	-0.082***	0.591**	1.041**	0.0545
	(0.022)	(0.280)	(0.505)	(0.341)
Constant	0.099	1.561	2.311	-4.630
	(0.140)	(5.224)	(9.261)	(5.797)
APE of EITC (D_{it})	0.051***	0.049***	0.048***	0.064**
	(0.018)	(0.017)	(0.017)	(0.029)
Number of Individuals	1,112	1,112	1,112	578
Observations	2,801	2,801	2,801	1,296
Log Likelihood		-604.82	-605.27	-231.77
Correct Predictions (%)	89.97	90.04	90.04	93.29
Fixed Effect	Yes	No	No	No

Notes Table A1 shows regression results setting dependent variable as a $Employee_{it}$. The number in cell shows estimated coefficients (standard error). The standard errors are clustered on observations by individual for the LPM FE model. *, **, and *** indicate the coefficient is statistically significant at the 10%, 5%, and 1% significance level, respectively. The 'Correct Predictions' row shows the percentage of correctly predicted observations, corresponding to each model.

Table A2. Full Estimation Results (Self-employee)

Model	(1) LPM FE	(2) Probit RE	(3) Logit RE	(4) Dynamic Probit
EITC (D_{it})	-0.035*	-0.640**	-1.084**	-0.0517
	(0.020)	(0.262)	(0.465)	(0.243)
Past Employment				
y_{it-1}				2.310***
				(0.254)
y_{i0}				0.583**
				(0.259)
Male		1.446***	2.448***	0.171
		(0.353)	(0.582)	(0.193)
Age		0.479***	0.874***	-0.121
		(0.175)	(0.306)	(0.129)
Age Squared		-0.005***	-0.008***	0.000583
		(0.001)	(0.002)	(0.000908)
House Ownership		-0.244	-0.442	0.281
		(0.234)	(0.403)	(0.217)
Education				
- Middle School		0.013	0.034	-0.542*
		(0.416)	(0.685)	(0.278)
- High School		0.037	0.063	-0.219
		(0.430)	(0.700)	(0.272)
- College +		-1.699**	-2.963**	-1.816**
		(0.839)	(1.424)	(0.786)
Kids	-0.025	0.182*	0.317**	-0.0256
	(0.016)	(0.097)	(0.160)	(0.0565)
Rural	0.006	2.387***	4.042***	0.191
	(0.017)	(0.304)	(0.494)	(0.161)
Bad Health	-0.015	-0.280	-0.536	-0.202
	(0.016)	(0.188)	(0.333)	(0.164)
Yearly Dummies				
- 2010	-0.002	0.341*	0.586*	
	(0.012)	(0.197)	(0.341)	
- 2012	-0.045***	0.063	0.087	-0.384**
	(0.016)	(0.216)	(0.373)	(0.183)
- 2014	-0.058***	0.217	0.341	-0.289
	(0.018)	(0.241)	(0.413)	(0.204)
- 2016	-0.084***	-0.070	-0.188	-0.296
	(0.026)	(0.412)	(0.721)	(0.350)
- 2018	-0.092***	0.367	0.512	-0.0328
	(0.025)	(0.303)	(0.523)	(0.331)
Constant	0.290***	-15.790***	-28.850***	3.570
	(0.062)	(6.104)	(10.570)	(4.506)
APE of EITC (D_{it})	-0.036*	-0.036***	-0.035**	-0.00
	(0.020)	(0.014)	(0.014)	(0.020)
Number of Individuals	1,112	1,112	1,112	578
Observations	2,801	2,801	2,801	1,296
Log Likelihood		-685.89	-684.27	-194.65
Correct Predictions (%)	85.58	85.79	85.86	94.75
Fixed Effect	Yes	No	No	No

Notes Table A2 shows regression results setting dependent variable as a $Self-Employed_{it}$. The number in cell shows estimated coefficients (standard error). The standard errors are clustered on observations by individual for the LPM FE model. *, **, and *** indicate the coefficient is statistically significant at the 10%, 5%, and 1% significance level, respectively. The 'Correct Predictions' row shows the percentage of correctly predicted observations, corresponding to each model.

Table A3. Full Estimation Results (Robustness Check)

	(1)	(2)	(3)	(4)
Dependent Variable (y_{it})	Employee		Self-Employed	
Specification	Before 2015	Assets	Before 2015	Assets
EITC (D_{it})	0.778**	0.522*	0.0434	0.134
	(0.363)	(0.285)	(0.289)	(0.261)
Past Employment				
y_{it-1}	1.232***	1.478***	2.178***	2.284***
	(0.378)	(0.318)	(0.292)	(0.256)
y_{i0}	1.613**	1.020**	0.680**	0.598**
	(0.702)	(0.518)	(0.301)	(0.262)
Male	0.284	0.202	0.212	0.184
	(0.277)	(0.233)	(0.197)	(0.194)
Age	0.168	0.139	−0.0717	−0.161
	(0.215)	(0.169)	(0.139)	(0.128)
Age Squared	−0.00163	−0.00140	0.000202	0.000864
	(0.00157)	(0.00122)	(0.000984)	(0.000902)
House Ownership	0.504	0.764**	0.202	0.0899
	(0.414)	(0.376)	(0.228)	(0.237)
Education				
− Middle School	−0.325	−0.258	−0.467	−0.541*
	(0.395)	(0.324)	(0.296)	(0.278)
− High School	−0.0551	−0.0179	−0.158	−0.217
	(0.341)	(0.297)	(0.291)	(0.272)
− College +	1.207**	0.992**	−1.805**	−1.825**
	(0.521)	(0.431)	(0.789)	(0.784)
Kids	0.0159	0.0201	−0.0357	−0.0231
	(0.0889)	(0.0709)	(0.0592)	(0.0570)
Rural	−0.0495	0.000982	0.182	0.286*
	(0.236)	(0.194)	(0.171)	(0.168)
Bad Health	−0.192	−0.130	−0.182	−0.141
	(0.243)	(0.195)	(0.173)	(0.167)
Log Assets		−0.143		0.172**
		(0.096)		(0.079)
Yearly Dummies				
− 2012	−0.114	−0.0774	−0.370**	−0.426**
	(0.217)	(0.201)	(0.182)	(0.184)
− 2014	−0.201	−0.0638	−0.315	−0.426**
	(0.260)	(0.234)	(0.212)	(0.215)
− 2016		−0.0816		−0.526
		(0.376)		(0.371)
− 2018		0.207		−0.246
		(0.354)		(0.348)
Constant	−6.611	−4.539	2.096	3.587
	(7.345)	(5.805)	(4.811)	(4.447)
APE of EITC (D_{it})	0.069*	0.048*	−0.004	0.011
	(0.036)	(0.029)	(0.025)	(0.022)
Number of Individuals	526	578	526	578
Observations	1,094	1,296	1,094	1,296
Log Likelihood	−186.275	−230.650	−174.06	−192.24
Correct Predictions (%)	93.51	93.13	94.42	94.98

Notes Table A3 shows regression results of different specifications. The number in cell shows estimated coefficients (standard error). *, **, and *** indicate the coefficient is statistically significant at the 10%, 5%, and 1% significance level, respectively. The 'Correct Predictions' row shows the percentage of correctly predicted observations, corresponding to each model.

국문초록 (Abstract in Korean)

본 논문은 근로장려세세 (EITC)가 고령 근로자에 미치는 효과를 분석한다. 60세 이상의 1인 가구가 근로장려금을 받을 수 있도록 수정한 2014년 세법 개정을 외생적 준실험적 상황으로 이용하여 분석하였다. 분석을 위하여 고령화연구패널 자료가 사용되었다. 회귀분석 결과, 이전 기간 노동시장참여 여부가 다음 기의 노동시장에 참여에 영향을 미치는 상태의존성이 큰 것으로 나타났다. 이러한 상태의존성을 통제하여 분석한 결과, EITC는 고령 임금 근로자를 약 6.4 % 증가시키는 효과가 있음이 추정됐다. 하지만, 고령 자영업자 증가에는 큰 영향을 미치지 않는 것으로 나타났다. 이 논문은 EITC의 후생증진 효과를 패널 분위수 회귀분석과 확률적 지배관계 검정을 통해 평가하였고, EITC가 소득분포에서 낮은 분위수에 위치한 저소득층의 소득 증진에 효과적임을 밝혔다. 이러한 결과는 사회 안전망으로서 EITC가 기능함을 제시한다.

Keyword: 근로장려세제, 고령노동층, 고용, 상태의존성