경제학박사학위논문

경기동행적 또는 경기역행적?

소득집단별 경기변동이 개인의 건강에 미치는 차별적 효과

Pro-cyclical or Counter-cyclical?

Heterogeneity Effects of Business Cycle on the Individual Health Status across Income Groups

2016 년 2 월

서울대학교 대학원

경제학부 경제학 전공

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English Abstract

Pro-cyclical or Counter-cyclical?
Heterogeneity Effects of Business Cycle on the Individual Health Status across Income Groups

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Though the impact of long-term growth on individual health has been actively studied, research on the health effects of short-term economic fluctuations has only recently begun with Ruhm(2000). The literature mostly uses mortality as the proxy for individual health but does not yet provide a consistent answer as to how business cycle affects health. With an aggregate variable such as mortality, we can only identify the average effect on the entire group. Such analysis may not be accurate when business cycle has different implications for different individuals with different levels of income.

We suggest a theoretical model to show that business cycle has different health effects across income groups, and estimate these differential effects with actual data. Empirical analysis shows that the effect of business cycle on the entire sample is insignificant. However, if we divide the sample according to household income, health is pro-cyclical for low income groups and counter-cyclical for high income groups.

We contribute to the literature by suggesting a theoretical framework to explain the relationship between economic fluctuation and health, and also by providing novel empirical results that differ from existing studies.

Key Words: Business cycle, health, income group, differential effect, welfare cost

Student Number: 2010-20193

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Chapter 1. Introduction

Various works have studied the relationship between a country's long-term economic growth and the health of its citizens, mostly with data from developing countries. The interaction between health and short-term business cycles, on the other hand, have only recently received attention, starting from Ruhm (2000). The literature mostly agrees that economic growth improves individual health through higher incomes. [1] However, a consensus is yet to be reached on how business cycle affects health.

For developed countries whose economies have reached maturity, it may be more relevant to examine the health impacts of the business cycle than those of growth. This is especially true for Korea, which has experienced large economic fluctuations such as the Asian financial crisis of 1997 and the global financial crisis of 2008, but does not have a strong social security system compared to other developed countries.

Most studies of business cycle and health have used mortality as the proxy for individual health status. But this approach entails a few problems. First, since mortality is an aggregate variable, it is only possible to know how business cycle affects health on average, across the entire group. If business cycle has different effects on different social or economic groups, we are unable to distinguish these effects. For example, business cycle may have a significant effect on each income group, while its effect on all the groups combined is insignificant. Second, the literature focuses on empirical analyses and does not provide a theoretical model to describe the mechanism through which business cycle changes health. Finally, mortality may not be a good proxy of individual health. Mortality may be related to health for people with bad health conditions, but not so much for many who have few health problems to begin with. We may thus only discern the effect of business cycle on those with bad health. Also, even if mortality is related to health, there could be a significant delay before deterioration of health conditions leads to death.

We provide a simple model of consumption and health with a lower bound on consumption level to show that business cycle can have different effects according to income. We also conduct an

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[1] For example, see Pritchett and Summers (1996).

empirical analysis using panel data on individual levels. Instead of mortality, we use self-reported health status, which we deem more relevant, as the proxy variable for individual health conditions.

The paper proceeds as follows. Chapter 2 reviews the literature on the relationship between business cycle and individual health. Chapter 3 introduces a model of optimal choice between consumption and health and shows that the health impacts of business cycle can differ according to income levels. We also provide a simple simulation to examine policy implications of such income effects with regards to the welfare costs of business cycle. We explain our empirical analyses in Chapter 4. Chapter 5 concludes.

Chapter 2. Literature Review

Grossman (1972) provides a theoretical model in which an individual's health is determined not by exogenous factors, but by his optimal choice of endogenous factors. Grossman assumes that health is a durable good that depends on investment, such as expenditure on medical care or time spent on health-relevant activities. His model implies that short-term economic fluctuations, which cause relatively less change in exogenous factors, can still affect individual health.

Ruhm (2000) uses unemployment rates and mortality rates of U.S. states from 1972 to 1991 to analyze the health effect of business cycle. He concludes that a rise in unemployment by 1%p leads to a decrease in mortality by 0.5 to 0.6% (or equivalently, a decrease in death toll by 11,000), so that the business cycle has a counter-cyclical impact on individual health[2]. The effect was greatest for those aged 20 to 44, while for those aged 45 to 64 and those aged 65 or more, the effect was either small or not significant. The effect was greater for external factors generally unrelated to individual health, such as traffic accident, other accident, suicide, or murder. For deaths due to factors more relevant to health, including cancer or disease of the heart, lung, or liver, there was little effect. To explain the counter-cyclicity, the paper uses cross-sectional data at the individual level from 1987 to 1995 to observe how health-relevant lifestyle changes with the business cycle. The result shows that change in the optimal lifestyle of individuals explains the adverse relationship to some degree; during recessions, people smoke less, are less obese, and improve their diets and exercise habits. Finally, business cycle has long-term as well as short-term effects, even though the long-term effects are smaller.

Various follow-up studies have found that health is counter-cyclical[3]. But Stevens et al. (2011), McInerney and Mellor (2012), and Ruhm (2013) extend the analysis of Ruhm (2000) to include data from the 2000s, to find that in recent years the relationship has become less counter-cyclical, or even pro-cyclical. McInerney and Mellor (2012)[4], using micro data on beneficiaries of Medicare and

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2 Since health generally has an inverse relationship with mortality, health is counter-cyclical when mortality is pro-cyclical. We use pro-cyclicity and counter-cyclicity to refer to the properties of health, unless stated otherwise.

3 Some papers such as Sullivan and von Wachter (2009), in contrast, have reported pro-cyclicity.

4 The authors also conduct an analysis with self-reported health status, which results in pro-cyclicity.

Medicaid in the U.S, find that health-relevant lifestyle does not explain the counter-cyclical relationship. Also, Stevens et al. (2011) and McInerney and Mellor (2012) use additional data to show that rather than demand-side factors such as employment or lifestyle, supply-side factors such as the quantity and quality of medical service can be more important to an individual's health.

These studies mostly use mortality rate to examine the average effect on the whole population. In contrast, Haaland and Telle (2014) use vital statistics of Norway from 1977 to 2008 in order to discern the effects on various social and economic groups. The authors divide the sample into high-status and low-status groups according to education, income, and asset levels, and marital status, and estimate the effect on each group[5]. For all criteria except marital status, the high-status group showed a more counter-cyclical relationship between health and business cycle. The authors also note that disability, traffic accident, and obesity rates decrease during recessions. This implies that changes in vital statistics are actually due to changes in individual health conditions.

There have been relatively few works that use Korean data. Hong et al. (2010) use mortality and epidemic prevalence rate from 1983 to 2008[6]. They take real GDP per capita, unemployment rate, and economic activity participation rate as proxies for business cycle. For these variables, the authors make use of data from a year before, in consideration of the time it takes for the business cycle to affect mortality. Health is found to be pro-cyclical in estimations with mortality, as well as with prevalence rate. However, the study does not control variables other than the business cycle that may affect mortality. Lee and Kim (2011) use regional mortality data and national unemployment data from 1991 to 2009 and follow the method of Ruhm (2000). As in Ruhm (2000), mortality decreases during recessions. But Korea displays a larger effect of business cycle; while data from U.S. and OECD show that an increase in unemployment rate by 1%p leads to decrease in mortality by 0.5 ~ 0.6%, in Korea mortality is found to decrease by 1.8 ~ 2.8%.[7] In terms of age, those with vulnerable health, i.e. children, middle-aged men, and the elderly were particularly susceptible to economic

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[5] The authors generate high school diploma dummy, above-median income dummy, above-median asset dummy, and marriage dummy. They then use the interaction term of unemployment rate and each dummy variable to estimate the effect on each group.

[6] They use national data in general, and utilize regional data for a few models.

[7] Gerdtham and Ruhm(2006) uses data of OECD countries.

fluctuation. In terms of cause of death, certain infectious and parasitic diseases, diseases of the nervous system, diseases of the respiratory system, diseases of the genitoruinary system, fall, and suicide were affected the most.

Chapter 3. Theoretical Model

We provide a theoretical model to show that business cycle can have heterogeneous health effects on individuals with different levels of income. Our model describes how an individual with a budget constraint, a time constraint, and minimum consumption-level constraint chooses optimal levels of consumption and health.

We consider a static model in which the agent's utility at each period is determined solely by consumption C and health H of that period. We assume a logarithmic utility function, so that

$$U = U(C, H) = \log(C) + \log(H) \quad (1)$$

At each period, the agent faces the following budget and time constraint[8].

$$P \cdot C = T_w \cdot W + A, \;\; 0 \leq T_w, T_h \leq 1 \quad (2)$$

$$T_w + T_h = 1 \quad (3)$$

The parameters P, A, and W represent the price of consumption good, the amount of asset that the agent holds, and wage per hour, respectively[9]. The variables T_w and T_h are time spent on labor and health, respectively. At each period, the health status of the agent, H, is determined by the following health investment function h.

$$H = h(T_h) = T_h^{\alpha}, \;\; 0 < \alpha < 1 \quad (4)$$

Finally, the minimum consumption-level constraint takes the following form.

$$0 < \underline{C} \leq C \quad (5)$$

Here, $\underline{C}$ is the minimum consumption-level.

The optimal consumption level C^* and health status H^* can be solved for via the Lagrangian function,[10]

$$\mathcal{L}(C, T_h) = \log(C) + \alpha \cdot \log(T_h) + \lambda \cdot [W - W \cdot T_h + A - C] + \delta \cdot [C - \underline{C}], \quad (6)$$

[8] The amount of time available in each period is normalized to 1.

[9] Below, we normalize the price of consumption good to P=1.

[10] Solving the Lagrangian gives the optimal time spent on health, T_h^*. We can use this value to derive H^*.

where λ and δ are the Lagrangian multipliers for the budget constraint and the minimum consumption-level constraint, respectively.

The form of optimal health status H^* depends on whether the minimum consumption-level constraint is binding. For those in the low-income group, for whom the constraint is binding ($\underline{C} = C$, $0 < \delta$) because they have low wages and own small amounts of asset, H_1^* can be solved as

$$H_1^* = [1 - \frac{1}{W}(\underline{C} - A)]^{\alpha} \tag{7}$$

For those in the high-income group with high wages and large amounts of asset, the constraint is not binding ($\underline{C} < C,\ \delta = 0$), so that H_2^* is written as

$$H_2^* = [(\frac{\alpha}{1+\alpha}) \cdot (1 + \frac{A}{W})]^{\alpha} \tag{8}$$

Differentiating H^* with respect to wage W gives the effect of business cycle on the optimal individual health status[11]. The effect on the low-income group is

$$\frac{dH_1^*}{dW} = \alpha \cdot \left[1 - \frac{1}{W}(\underline{C} - A)\right]^{\alpha} \cdot \frac{\underline{C}}{W^2} > 0 \tag{9}$$

According to Equation (9), business cycle has a pro-cyclical effect on the health of low-income group; as wage drops, so does optimal health status. The effect on high-income group, on the other hand, is

$$\frac{dH_2^*}{dW} = -\alpha \cdot A \cdot \left(\frac{\alpha}{1+\alpha}\right)^{\alpha} \cdot \frac{1}{[W^{1+\alpha} + (W+A)^{1-\alpha}]} < 0 \tag{10}$$

We see that the impact of business cycle is now counter-cyclical, since lower wage leads to better health.

Why does business cycle have different effects on health according to income levels? Intuitively, the opportunity cost of investing in health decreases for both income groups when wages fall during a recession. A high-income agent can consume more than the minimum consumption-level even with the lower wage (income), so he works fewer hours and invests more time to obtaining better health. However, for a low-income agent, lower wage means that she has to work more hours to achieve the minimum consumption-level. Even though the opportunity cost of health investment has decreased, she spends less time on health and is left with worse health conditions.

[11] We assume that wages increase during booms and decreases during recessions.

Our results may have important policy implications. If health is counter-cyclical, income and health move in opposite directions. This means that the actual welfare cost of the business cycle in terms of both income and health may be smaller than the cost in terms of income (consumption) only. If health is pro-cyclical, the welfare cost would be larger.

We conduct a simple simulation to examine the welfare costs of economic fluctuation. Specifically, we compute the percentage change in average utility levels according to variation of the business cycle, in terms of consumption only and in terms of both consumption and health (when health is pro-cyclical or counter-cyclical). Refer to Table 9 in the Appendix for the details of the simulation. Figure 1 depicts the welfare costs when consumption changes by 10%.

[Figure 1] Welfare costs of business cycle when consumption changes 10%

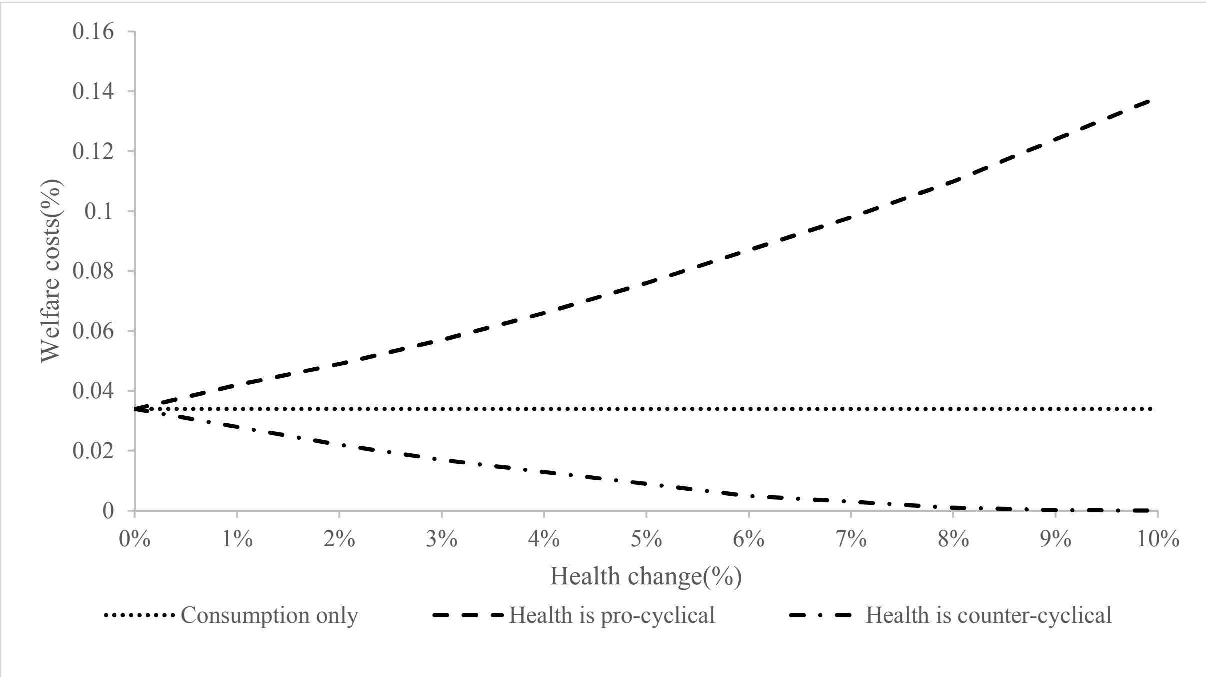

Figure 1 shows that if health is pro-cyclical, the welfare cost is larger than if we only consider consumption. In contrast, if health is counter-cyclical, looking at consumption only overestimates the welfare cost. Even when we take into account both consumption and health, the average cost of the whole population underestimates the cost for the pro-cyclical group and overestimates that of the counter-cyclical group.

Chapter 4. Empirical Analysis

In this chapter, we use actual data to estimate the effects of the business cycle on individual health. We describe the data in Section 1. In Section 2, we explain our estimation methods and provide the results. We first estimate by using information on death, and consider the shortcomings of such an approach. We then use self-reported health status as proxy for individual health to determine how business cycle affects the health of individuals with different income levels. Section 3 provides various sensitivity analyses.

Section 1. Data

This paper uses Korean Longitudinal Study of Aging (KLoSA), provided by Korea Labor Institute[12]. KLoSA is a panel data similar to HRS(Health and Retirement Study) in the U.S., ELSA(English Longitudinal Study of Ageing) in Britain, or SHARE(Survey of Health, Ageing and Retirement in Europe) in Europe and provides diverse information on the middle-aged and elderly population. The first survey of KLoSA, conducted in 2006, collected data from 10,254 adults aged 45 or higher, across the country except Jeju Province. The study has been conducted biennially ever since, so that data is currently available for 4 separate surveys.[13] KLoSA provides data on a variety of variables for individual characteristics such as age, sex, and education level, as well as variables related to individual health, including self-reported health status. Also, it provides information on the dead since the second survey (2008), so that it is possible to analyze the impact of economic fluctuation on death as done in the literature.

Our proxy for individual health is self-reported health status. This variable is a self-reported evaluation of the responder's own health conditions, and takes values 1 (very bad), 2 (bad), 3 (fair), 4 (good), or 5 (very good). Although this is a subjective measure, we believe that it is in general more

[12] Korea Labor Institute is a national research institute that specializes in labor policies.

[13] Korea Labor Institute conducted the survey up to 2008. Since that time, Korea Employment Information Service has conducted the survey.

closely related to an individual's health conditions than mortality rate. Moreover, while mortality is an aggregate variable, self-reported health status is a variable at the individual level and therefore better satisfies our purpose of discerning different effects on income groups. For the business cycle, we follow the convention and use annual unemployment rate as proxy. We use the national unemployment rate, but note that our results do not change much when we use regional unemployment rate[14] instead. Per capita household income[15] is used divide the sample into income groups. We elaborate on the income group classification in the next section. We also use age, sex, education level, marital status, and economic activity to control individual characteristics. The data for variables we use is summarized below.

[Table 1] Summary statistics

	2006		2008		2010		2012	
	AVERAGE	S.E.	AVERAGE	S.E.	AVERAGE	S.E.	AVERAGE	S.E.
Death dummy(death=1)	0	0	0.02	0.14	0.04	0.19	0.04	0.20
Self-reported health status(1~5)	3.03	1.00	3.02	0.94	2.99	0.93	2.95	0.89
National unemployment(%)	3.50	0	3.20	0	3.70	0.04	3.21	0.04
Regional unemployment(%)	3.36	1.01	3.06	0.76	3.51	0.88	3.04	0.87
Age dummy	61.7	11.1	63.9	11.1	65.7	10.8	67.3	10.5
Sex dummy(male=1)	0.44	0.50	0.44	0.50	0.43	0.50	0.43	0.50
Education dummy(high school diploma=1)	0.26	0.44	0.26	0.44	0.26	0.44	0.26	0.44
Education dummy(college diploma or above=1)	0.10	0.30	0.10	0.29	0.10	0.29	0.10	0.30
Marital status dummy(married=1)	0.78	0.42	0.77	0.42	0.76	0.43	0.75	0.43
Economic activity dummy(working=1)	0.38	0.49	0.42	0.49	0.42	0.49	0.38	0.49
Per capita household income(million KRW)	6.58	8.91	9.07	14.9	8.90	9.45	10.8	11.8
Per capita household asset(million KRW)	73.0	143	86.2	150	86.4	138	109	164
Individual financial asset(million KRW)	0.02	0.12	0.03	0.17	0.04	0.19	0.07	0.24
Employment type dummy(paid worker=1)	0.18	0.39	0.19	0.39	0.19	0.39	0.18	0.38
Employment type dummy(self-employed=1)	0.17	0.37	0.18	0.39	0.18	0.39	0.17	0.38
Average work hour per month	194	73.5	193	67.2	181	69.1	181	66.4
Observations	10,254		8,864		8,228		7,811	

The above statistics include data for the dead. For those who have died during the survey, some variables (education level, marital status, economic activity, per capita household asset) are unavailable. We therefore make use of the last values before death. Also, the unemployment rates for the dead are the rates of the year of death, not the year of survey. We omit data with missing values.

[14] In Korea, unemployment data is available for 17 regions (metropolitan cities and provinces).

[15] KLoSA only provides the household income of the year before the survey, and not of the survey year. We therefore use the household income of the previous year as our variable for income.

We note that while unemployment shows a fluctuation of around 10% during the survey period, self-reported health status decreases through the years, probably due to aging effect. Hence the above summary is insufficient to determine the effect of business cycle on individual health. For an accurate analysis, we need to control for age, as well as other factors that affect health.

Section 2. Estimation method and results

1. Effect of business cycle on death

When a responder dies, KLoSA provides this information as well as the year of death. We use this data to examine how economic fluctuation affects death, and consider the problems of using a death-related variable as proxy for individual health[16].

Since all respondents were alive at the time of the first KLoSA survey(2006), we use the data from the second survey(2008) and thereafter. We generate a death dummy variable, which takes the value of 0 if the responder was dead at the time of the survey and 0 if otherwise. The proxy for business cycle is the unemployment rate. If the responder is alive, we use the unemployment rate of the survey year, while if the responder has died, we take the rate of the year of death. We estimate the Linear Probability Model, taking the death dummy as the dependent variable and unemployment, age, age squared, sex, education level, marital status, economic activity, and log-per capita household income as the independent variables. [17] The result is shown below.

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[16] We analyze the impact of unemployment on the probability of death, not the actual mortality rate. Hence a direct comparison with works that use mortality is not feasible.

[17] Though we do not provide the results, all of our models include regional dummies to control regional fixed-effect.

[Table 2] The effect of business cycle on probability of death

	(1)	(2)	(3)	(4)	(5)	(6)
	Whole sample				Self-reported health status	
					good, very good	very bad, bad, fair
dependent var.: death dummy						
age	-0.02*** (0.00)	-0.02*** (0.00)	-0.02*** (0.00)	-0.02*** (0.00)	-0.02*** (0.00)	-0.03*** (0.00)
age squared	0.00*** (0.00)	0.00*** (0.00)	0.00*** (0.00)	0.00*** (0.00)	0.00*** (0.00)	0.00*** (0.00)
sex(male=1)	0.03*** (0.00)	0.03*** (0.00)	0.03*** (0.00)	0.03*** (0.00)	0.01*** (0.00)	0.03*** (0.00)
education(high school diploma=1)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	0.00 (0.00)	-0.00 (0.00)
education(college diploma or above=1)	-0.01* (0.00)	-0.01* (0.00)	-0.01* (0.00)	-0.01* (0.00)	-0.00 (0.00)	-0.00 (0.01)
marital status(married=1)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	-0.01 (0.00)	0.00 (0.00)
economic activity(working=1))	-0.02*** (0.00)	-0.02*** (0.00)	-0.02*** (0.00)	-0.02*** (0.00)	-0.00 (0.00)	-0.03*** (0.00)
(log) per capita household income(million KRW)	-0.01*** (0.00)	-0.01*** (0.00)	-0.01*** (0.00)	-0.01*** (0.00)	-0.01** (0.00)	-0.01*** (0.00)
national unemployment	0.02*** (0.00)				-0.00 (0.00)	0.03*** (0.01)
national unemployment(prev. year)		0.05*** (0.01)				
regional unemployment			0.02*** (0.00)			
regional unemployment(prev. year)				0.01* (0.00)		
observations	24,579	24,579	24,579	24,579	7,767	16,812

The result for regional dummies is omitted. Values in parentheses are Huber-White standard errors. *** p<0.01, ** p<0.05, * p<0.1.

Model (1) shows that when national unemployment rate increases by 1%p, the probability of death increases by 2%p. Hence with death as the proxy, individual health is pro-cyclical. Models (2) through (4) tell us that considering the time delay of unemployment or looking at regional rates of unemployment do not change our result. Models (5) and (6) divide the sample into those with self-reported health status of fair or below and those with good or above, in order to check if death is related to health regardless of health status. Model (5) shows that for those with low self-reported health status, the probability of death increases with unemployment. In Model (6), however, the coefficient of unemployment rate is very small and not significant. These results imply that while death may be related to health for those with bad health, for most individuals with no health risks it is not. Using a variable related to death, such as mortality rate, as proxy for health may only represent the effect of business cycle on those with bad health.

2. Health effect of business cycle on the entire group

We now use self-reported health status as the dependent variable. First, we do not divide the sample according to income and examine how business cycle affects health on average across the entire group.

Recall that self-reported health status is an ordered categorical variable; only the order of the values, not the absolute values themselves, has any meaning. Therefore, if we use a classical linear regression model, we can interpret the sign of coefficients but not their sizes. One solution for this problem is grouping; we can divide the values from 1 to 5 into two groups, so that we have a dummy variable taking values 0 or 1, and then use the Linear Probability Model or the Logit Model. But grouping necessarily entails loss of information, and the size or even sign of coefficients may differ according to the grouping criterion.[18]

This paper uses the Ordered Logit Model[19], which does not suffer from the above defects and is known to be the most suited for analyzing ordered categorical variables. In this model, although we cannot interpret the estimated coefficients themselves, with appropriate transformation we can obtain estimates of the average marginal effect on the probability of each category of the dependent variable[20]. With self-reported health status as the dependent variable, we therefore get average marginal effect estimates on the probabilities of the 5 categories, for each independent variable.

Another issue with self-reported health status is that individuals may differ in their criteria of evaluating one's health. When we estimate by comparing different individuals, such unobserved individual fixed effect can lead to bias. Unfortunately, there is no method for controlling individual fixed effects in the Ordered Logit Model. Therefore, below we always provide the results of the Fixed

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[18] This method is widely used to study the effect of retirement on health. See, for example, Coe and Zamarro (2011).

[19] Refer to Wooldridge (2010) for a detailed explanation of the Ordered Logit Model.

[20] The coefficient of the Ordered Logit Model has the opposite sign as the average marginal effect on the probability of the lowest category, and the same sign as the highest category. Therefore, when we use unemployment rate as proxy for business cycle, a negative coefficient means health is pro-cyclical and a positive coefficient implies counter-cyclicity.

Effect Model in tandem with those of the Ordered Logit Model, so that we may determine if individual fixed effect is problematic. The Fixed Effect Model is free from the abovementioned bias because it estimates the effect of business cycle by comparing self-reported health status of each individual at different points in time, instead of comparing different individuals. However, being a linear regression model, it admits interpretation only of coefficient sign, not size. Therefore, we use the Fixed Effect Model only for the purpose of comparing its results with those of the Ordered Logit to check if not controlling for individual fixed effect is problematic[21].

As we have done with death probability, unemployment rate is the proxy for business cycle. The control variables are age, age squared, sex, education level, marital status, economic activity, and log-per capita household income[22]. The result is shown below.

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[21] Specifically, we compare the unemployment rate coefficients from the Ordered Logit and the Fixed Effect. If both coefficents are negative, health is pro-cyclical. If both coefficients are positive, it is counter-cyclical.

[22] The Fixed Effect Model does not include age squared, per capita household income, and regional dummy variables. Age squared and regional dummies have been omitted because they are insignificant in most of the models. We exclude per capita household income because the change in income with time is likely to explain a substantial part of the business cycle effect. Controlling these variables do not change our result very much.

[Table 3] Average effect of business cycle on self-reported health status

	(1)		(2)		(3)		(4)		(5)	(6)	(7)	(8)
	Ordered Logit Model								Fixed Effect Model			
	coef.	marginal effect	coef.	marginal effect	coef.	marginal effect	coef.	marginal effect	coef.	coef.	coef.	coef.
dependent var.: self-reported health status												
national unemployment	0.07 (0.05)	-0.00 (0.00) -0.01 (0.01) -0.00 (0.00) 0.01 (0.01) 0.00 (0.00)							-0.00 (0.02)			
regional unemployment			0.06* (0.03)	-0.00* (0.00) -0.01* (0.00) -0.00* (0.00) 0.01* (0.01) 0.00* (0.00)						0.01 (0.01)		
national unemployment (prev. year)					0.09* (0.05)	-0.00* (0.00) -0.01* (0.01) -0.00 (0.00) 0.01* (0.01) 0.00* (0.00)					- 0.04** (0.02)	
Regional unemployment (prev. year)							0.06 (0.04)	-0.00 (0.00) -0.01 (0.00) -0.00 (0.00) 0.01 (0.01) 0.00 (0.00)				-0.01 (0.01)
observations	33,194	33,194	33,194	33,194	33,194	33,194	33,194	33,194	34,339	34,339	34,339	34,339

Results are omitted for other control variables. Values in parentheses are Huber-White standard errors. *** p<0.01, ** p<0.05, * p<0.1. The marginal effects of the Ordered Logit are written in the order of very bad, bad, fair, good, and very good.

In Model (2) and (3), the coefficients of unemployment rate are small but significant, so that health is counter-cyclical. In Models (1) and (4), the coefficients are not significant. With the Fixed Effect Model, the unemployment coefficients are not significant in all models except Model (7), where the sign is negative, implying pro-cyclicity. These mixed results imply that analyzing the whole sample at once cannot accurately identify the health impacts of economic fluctuation.

3. Health effects of business cycle on different income groups

The ambiguity we have seen may be because business cycle has different effects on different income groups. We therefore divide the sample into a number of groups according to income, and examine how business cycle affects each group.

We use per capita household income to classify sample. We use household income instead of individual labor income (hourly wage) because of the following reason. According to our theoretical model, asset as well as labor income affects the individual's time allocation. If the income of household members acts as a sort of asset, household income encompasses both an individual's labor income and his assets and is thus better fir for our analysis. In addition, labor income is insufficient to classify the sample because data is available only if the individual is currently working.

To construct income groups, we first calculate for each individual the average per capita household income over the years he has participated in the survey. We then use these individual data to calculate the percentiles of per capita household income, and generate dummy variables $\mathrm{D}_{10,\mathrm{i}}$, $\mathrm{D}_{20,\mathrm{i}}$, … , $\mathrm{D}_{90,\mathrm{i}}$, $\mathrm{D}_{100,\mathrm{i}}$. The variable $\mathrm{D}_{10,\mathrm{i}}$ takes value 1 if the per capita household income of individual i is in the 1st to 10th percentile, and 0 if otherwise. Similarly, $\mathrm{D}_{100,\mathrm{i}}$ is 1 if and only if the income of i is in the 90th to 100th percentile. To sum up, we divide the sample into 10 income groups according to per capita household income percentile.

Again, we use unemployment rate as proxy for business cycle, and control for age, age squared, sex, education level, marital status, economic activity, and log-per capita household income. Unlike our analysis for the whole sample, we now use the interaction term of unemployment rate and the dummies instead of the rate itself. What we have done above is estimate the coefficient γ of $\gamma \cdot \mathrm{unemployment}_\mathrm{t}$ to calculate the average effect on the whole sample. Now we estimate the coefficients γ_1, … , γ_{10} in $\gamma_1 \cdot (\mathrm{D}_{10,\mathrm{i}} \cdot \mathrm{unemployment}_\mathrm{t})$, … , $\gamma_{10} \cdot (\mathrm{D}_{100,\mathrm{i}} \cdot \mathrm{unemployment}_\mathrm{t})$ to estimate the effects on each income group. If these effects differ as predicted by our theoretical model, the γ_1 and γ_{10} will have opposite signs. Table 4 summarizes the result[23].

[23] From now on, we only provide the results for coefficients and omit those for marginal effects.

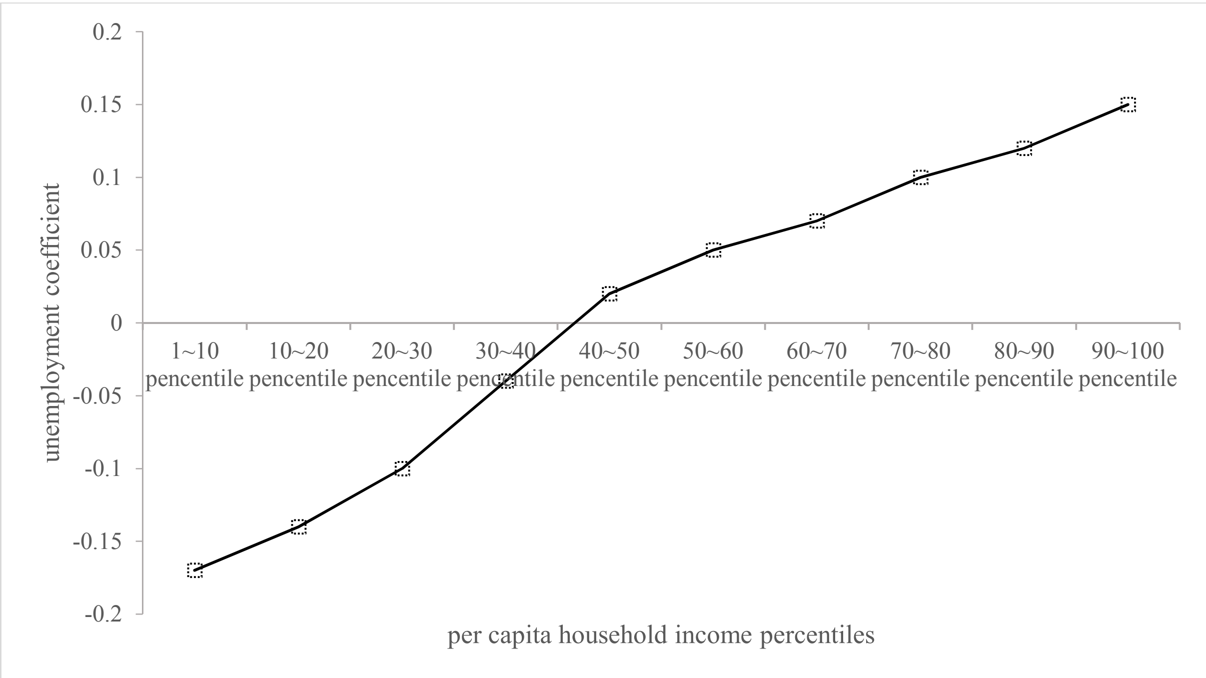
[Table 4] Effect of business cycle on health according to income groups

	(1)	(2)	(3)	(4)	(5)	(6)
	Ordered Logit Model			Fixed Effect Model		
	coef.	coef.	coef.	coef.	coef.	coef.
dependent var.: self-reported health status						
national unemployment*1~10 percentile dummy	-0.17*** (0.05)			-0.15*** (0.06)		
national unemployment*10~20 percentile dummy	-0.14*** (0.05)			0.00 (0.05)		
national unemployment*20~30 percentile dummy	-0.10* (0.05)			-0.08 (0.05)		
national unemployment*30~40 percentile dummy	-0.04 (0.05)			0.01 (0.05)		
national unemployment*40~50 percentile dummy	0.02 (0.05)			-0.05 (0.05)		
national unemployment*50~60 percentile dummy	0.05 (0.05)			0.01 (0.05)		
national unemployment*60~70 percentile dummy	0.07 (0.05)			0.01 (0.05)		
national unemployment*70~80 percentile dummy	0.10** (0.05)			0.05 (0.05)		
national unemployment*80~90 percentile dummy	0.12** (0.05)			0.07 (0.05)		
national unemployment*90~100 percentile dummy	0.15*** (0.05)			0.07 (0.05)		
national unemployment*1~30 percentile dummy		-0.11** (0.05)			-0.07** (0.03)	
national unemployment*30~70 percentile dummy		0.04 (0.05)			-0.00 (0.03)	
national unemployment*70~100 percentile dummy		0.12** (0.05)			0.06** (0.03)	
national unemployment (prev. year)*1~30 percentile dummy			-0.14** (0.06)			-0.10*** (0.03)
national unemployment (prev. year)*30~70 percentile dummy			0.00 (0.06)			-0.06* (0.03)
national unemployment (prev. year)*70~100 percentile dummy			0.09 (0.06)			0.01 (0.03)
observations	33,194	33,194	33,194	33,194	33,194	33,194

Results are omitted for other control variables. Values in parentheses are Huber-White standard errors. *** p<0.01, ** p<0.05, * p<0.1.

Model (1) shows that for the 1st to 30th percentiles with low income, the unemployment coefficient is negative and significant, implying that health is pro-cyclical. On the other hand, for the 70th to 100th percentile groups, the coefficient is positive and significant, so that health is counter-cyclical. For those in between, the 30th to 70th percentiles, the coefficients are small in size and not significant. Based on this result, Model (2) reclassifies the sample into 3 groups by combining groups with similar business cycle effects. The result shows a clearer difference between income groups. Model (3) shows that introducing a time delay of a year for unemployment does not change our result very much. Model (4) to (6) show that although the counter-cylicity of the high income group disappears with time delay, individual fixed effect is not problematic. Figure 2 below plots the unemployment coefficient of each income group estimated in Model (1).

[Figure 2] Unemployment coefficient according to per capita household income percentiles



4. Sensitivity analysis

In this section, we perform various sensitivity analyses.

Our theoretical model implies that not only income (hourly wage) but also the amount of asset affects an individual's decision. Therefore, the health effect of the business cycle may also differ according to asset groups. To classify asset groups, we use per capita household assets. As we have done with income, we divide the sample into 10 groups based on percentiles and estimate the effect on each group. Household assets include diverse types, including real estate as well as financial assets. But illiquid assets such as real estate may have little relevance to an individual's consumption level. We therefore perform the same estimation with financial assets only. Because KLoSA does not provide data on household financial assets, we use individual financial assets. Finally, since those under the 50th percentile do not own any financial assets, we divide the sample into three groups - 1st to 50th percentile, 50th to 75th percentile, and 75th to 100th percentile.

[Table 5] Health effects of business cycle on different asset groups

	(1)	(2)	(3)	(4)	(5)	(6)
	Ordered Logit Model			Fixed Effect Model		
	coef.	coef.	coef.	coef.	coef.	coef.
dependent var.: self-reported health status						
national unemployment*1~10 percentile dummy (per capita household asset)	-0.14*** (0.05)			-0.12** (0.06)		
national unemployment*10~20 percentile dummy (per capita household asset)	-0.05 (0.05)			-0.03 (0.05)		
national unemployment*20~30 percentile dummy (per capita household asset)	-0.01 (0.05)			-0.03 (0.05)		
national unemployment*30~40 percentile dummy (per capita household asset)	0.04 (0.05)			-0.06 (0.05)		
national unemployment*40~50 percentile dummy (per capita household asset)	0.04 (0.05)			-0.02 (0.05)		
national unemployment*50~60 percentile dummy (per capita household asset)	0.05 (0.05)			-0.06 (0.05)		
national unemployment*60~70 percentile dummy (per capita household asset)	0.07 (0.05)			0.15*** (0.05)		
national unemployment*70~80 percentile dummy (per capita household asset)	0.10** (0.05)			0.02 (0.05)		
national unemployment*80~90 percentile dummy (per capita household asset)	0.14*** (0.05)			0.05 (0.05)		
national unemployment*90~100 percentile dummy (per capita household asset)	0.16*** (0.05)			0.06 (0.05)		
national unemployment*1~10 percentile dummy (per capita household asset)		-0.13** (0.05)			-0.12** (0.06)	
national unemployment*10~70 percentile dummy (per capita household asset)		0.03 (0.05)			-0.04* (0.02)	
national unemployment*70~100 percentile dummy (per capita household asset)		0.12** (0.05)			0.07*** (0.03)	
national unemployment *1~50 percentile dummy (individual financial asset)			-0.03 (0.05)			-0.04 (0.02)
national unemployment *50~75 percentile dummy (individual financial asset)			0.09* (0.05)			0.02 (0.03)
national unemployment *75~100 percentile dummy (individual financial asset)			0.13*** (0.05)			0.05 (0.03)
observations	31,941	31,941	32,341	32,798	32,798	33,337

Results are omitted for other control variables. Values in parentheses are Huber-White standard errors. *** p<0.01, ** p<0.05, * p<0.1.

As did income groups, asset groups are influenced by the business cycle in different ways. Models (1) and (2) show that for the 1st to 10th percentile group with low asset value, the unemployment coefficient is negative and significant, so that health is pro-cyclical. For the 70th to 100th percentile group, the coefficient is positive and significant, implying that health is counter-cyclical. For the 10th to 70th percentile, the coefficient is small and insignificant. However, Models (3) and (6) show that the differential effects on asset groups are not so noticeable when we use individual financial assets.

Next, we use both household income and assets to determine if the effect on each income group also differs by asset level. Intuitively, those with low income and small amount of assets will be the most pro-cyclical, while those with high income and large amount of assets is likely to be the most counter-cyclical. We also expect that the relative importance of income is higher, and therefore the differential effect according to income more evident, for those with less assets. We first divide the sample according to per capita household assets into 1st to 70th percentile group and 70th to 100th percentile group, and then test the income effects for each group. The result is as shown below.

[Table 6] Income effects according to asset levels

	(1) Per capita household asset 1~70 percentile	(2) Per capita household asset 70~100 percentile	(3) Per capita household asset 1~70 percentile	(4) Per capita household asset 70~100 percentile
	Ordered Logit Model		Fixed Effect Model	
	coef.	coef.	coef.	coef.
dependent var.: self-reported health status				
national unemployment*10~30 percentile dummy (per capita household income)	-0.15** (0.06)	-0.01 (0.08)	-0.08** (0.04)	0.03 (0.06)
national unemployment *30~70 percentile dummy (per capita household income)	-0.01 (0.06)	0.09 (0.08)	-0.04 (0.03)	0.06 (0.05)
national unemployment *70~100 percentile dummy (per capita household income)	0.05 (0.06)	0.17** (0.08)	0.05 (0.05)	0.05 (0.04)
observations	19,231	12,710	19,231	12,710

Results are omitted for other control variables. Values in parentheses are Huber-White standard errors. *** p<0.01, ** p<0.05, * p<0.1.

In Models (1) and (2), we see that pro-cyclic effect is the largest for the group with low asset and low income (-0.15), and counter-cyclic effect is the largest in the group with high asset and high income (0.17). Also, the groups with low asset (Model (1)) show a slightly larger income effect compared to the groups with high asset (Model (2)). Models (3) and (4) show that controlling for individual fixed effects does not change the nature of our result.

We also check if the income effects differ according to economic activity and employment types. A worker participating in the labor market will face steeper changes in income due to changes in the business cycle, compared with a non-participant. This means that the income effect will be greater for those participate in the labor market. In addition, the incomes of self-employed workers will fluctuate more than those of paid workers. We therefore divide the sample according to economic activity and employment types, and then examine income effects for each group.

[Table 7] Income effects according to for economic activity and employment type

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Worker	Non-worker	Paid worker	Self-employed	Worker	Non-worker	Paid worker	Self-employed
	Ordered Logit Model				Fixed Effect Model			
	coef.	coef.	coef.	coef.	coef.	coef.	coef.	coef.
dependent var.: self-reported health status								
national unemployment*10~30 percentile dummy (per capita household income)	-0.09 (0.08)	-0.10 (0.06)	-0.01 (0.12)	-0.10 (0.12)	-0.16** (0.07)	-0.04 (0.04)	-0.01 (0.11)	-0.15 (0.09)
national unemployment*30~70 percentile dummy (per capita household income)	0.06 (0.08)	0.03 (0.06)	0.12 (0.12)	0.07 (0.12)	-0.01 (0.04)	0.01 (0.04)	-0.04 (0.06)	-0.05 (0.06)
national unemployment*70~100 percentile dummy (per capita household income)	0.12 (0.08)	0.13** (0.06)	0.16 (0.12)	0.14 (0.12)	0.06 (0.04)	0.08* (0.05)	0.03 (0.06)	0.11* (0.06)
observations	13,738	19,456	6,246	5,944	13,738	19,456	6,246	5,944

Results are omitted for other control variables. Values in parentheses are Huber-White standard errors. *** p<0.01, ** p<0.05, * p<0.1.

Models (1) and (2) show that workers and non-workers do not show different income effects when not controlling for individual fixed effects. When we do control for fixed effects, however, the workers show a greater income effect compared to non-workers (Models (5) and (6)). Models (3) and (4) show that the self-employed are influenced to a greater degree by income compared to paid workers. This difference is clearer when we control for individual fixed effects (Models (7) and (8)).

Finally, we test if the different effects on income groups are in fact due to changes in working hours as our theory predicts. We use the Fixed Effect Model to examine how the business cycle affects average monthly working hours for three different income groups.

[Table 8] Change in working hours according to business cycle

	(1) Paid worker	(2) Self-employed
	Fixed Effect Model	
	coef.	coef.
dependent variable: average work hours per month		
national unemployment*10~30 percentile dummy(per capita household income)	-15.16 (9.26)	-5.43 (8.43)
national unemployment*30~70 percentile dummy(per capita household income)	2.12 (4.06)	-23.72*** (5.02)
national unemployment*70~100 percentile dummy(per capita household income)	-2.89 (3.18)	-17.98*** (4.91)
observations	6,239	5,940

Results are omitted for other control variables. Values in parentheses are Huber-White standard errors. *** p<0.01, ** p<0.05, * p<0.1..

For paid workers, the unemployment coefficient is not significant in any income group, as shown in Model (1). However, Model (2) shows that in the case of the self-employed, those with per capita household income in 30^{th} to 70^{th} percentiles and 70^{th} to 100^{th} percentiles significantly work fewer hours during recessions. Therefore, for self-employed individuals with high income, change in working hours does explain the counter-cyclicity of health.

Chapter 5. Conclusion

This paper shows that the business cycle can have differential effects on individual health according to income groups. We use a model of optimal choice between consumption and health under minimum consumption-level constraint. The analysis reveals that when the opportunity cost of health investment decreases during recessions, the high income group invests more time on health and obtains better health status. In contrast, the low income group, despite the lower opportunity cost, is forced to invest less on health and spend more time on labor in order to meet the minimum consumption-level constraint. As a result, the low income group has a lower health status during recessions.

We then test these insights with empirical data. When we do not differentiate between income groups, business cycle does not show a significant relationship with health. When we divide our sample according to household income, however, health is pro-cyclical for low income groups counter-cyclical for high income groups. These results suggest that we cannot adequately characterize the health effects of business cycle by using an aggregate variable such as mortality rate.

Our results have important policy implications with regards to the welfare costs of the business cycle. For high income groups, income and health move in opposite directions, so that the actual welfare cost of the business cycle may be smaller than the cost purely in terms of income. But for low income groups, since income and health move together, the actual welfare cost of the business cycle may be greater than one might have expected.

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Appendix

[Table 9] Simulation of the welfare cost(%) of business cycle

	2 periods (period 1: boom, period 2: recession), $U_t = \sqrt{C_t \cdot H_t}$, Discount Factor = 1					
	1. Consumption only		Consumption and health			
			2.Health is pro-cyclical		3. Health is counter-cyclical	
	Period 1(boom)	Period 2(recession)	Period 1	Period 2	Period 1	Period 2
Consumption	C_1	$C_2 = \lambda \cdot C_1$ $(0 < \lambda < 1)$	C_1	C_2	C_1	C_2
Health	H_{11}	$H_{12} = H_{11}$	H_{21}	$H_{22} = \delta \cdot H_{21}$ $(0 < \delta < 1)$	$H_{31} = \delta \cdot H_{32}$	H_{32}
Average utility with business cycle	$\overline{U_{1Y}} = \frac{\sqrt{C_1 \cdot H_{11}} + \sqrt{\lambda \cdot C_1 \cdot H_{11}}}{2}$		$\overline{U_{2Y}} = \frac{\sqrt{C_1 \cdot H_{21}} + \sqrt{\lambda \cdot \delta \cdot C_1 \cdot H_{21}}}{2}$		$\overline{U_{3Y}} = \frac{\sqrt{\delta \cdot C_1 \cdot H_{32}} + \sqrt{\lambda \cdot C_1 \cdot H_{32}}}{2}$	
Average utility without business cycle	$\overline{U_N} = \sqrt{\frac{C_1 \cdot H_{11} + \lambda \cdot C_1 \cdot H_{11}}{2}} = \sqrt{K}$ (Normalization)		$\overline{U_N} = \sqrt{\frac{C_1 \cdot H_{21} + \lambda \cdot \delta \cdot C_1 \cdot H_{21}}{2}}$ $= \sqrt{K}$		$\overline{U_N} = \sqrt{\frac{\delta \cdot C_1 \cdot H_{32} + \lambda \cdot C_1 \cdot H_{32}}{2}}$ $= \sqrt{K}$	
Welfare cost of business cycle(%)	$(\frac{U_{1Y} - U_N}{U_N}) \cdot 100$		$(\frac{U_{2Y} - U_N}{U_N}) \cdot 100$		$(\frac{U_{3Y} - U_N}{U_N}) \cdot 100$	

요약(국문초록)

경기동행적 또는 경기역행적?
소득집단별 경기변동이 개인의 건강에 미치는 차별적 효과

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정 재 원

장기적인 경제성장이 개인의 건강에 미치는 효과에 대한 연구는 기존에 활발히 진행되어 온 반면 단기적인 경기변동이 개인의 건강에 미치는 효과에 대한 연구는 Ruhm(2000)의 연구를 시작으로 비교적 최근에 와서야 시작 되었다. 기존 선행연구들의 경우 주로 사망률을 개인의 건강에 대한 대리변수로 이용하여 경기변동이 개인의 건강에 미치는 효과를 분석 하였으나 현재까지 일관된 결론을 제시하지 못하고 있다. 사망률과 같이 집계변수를 이용하여 분석하는 경우 경기변동이 개인의 건강에 미치는 집단 전체에 걸친 평균적인 효과만을 식별하게 된다. 따라서, 경기변동이 소득집단 별로 개인의 건강에 차별적인 효과를 미치는 경우 집단 전체에 걸친 분석을 통해서는 경기변동의 효과가 정확히 식별되지 않는 문제가 있을 수 있다.

본 연구에서는 이론모형을 통해 소득집단 별로 경기변동이 개인의 건강에 차별적인 효과를 미칠 수 있음을 보이고 이러한 소득집단 별 차별적인 효과를 실제 자료를 이용하여 추정 하였다. 실증분석 결과, 소득집단을 구분하지 않고 집단 전체에 대한 분석을 하는 경우 경기변동의 효과가 유의하게 나타나지 않았다. 반면, 가구소득을

기준으로 전체 집단을 구분하여 분석하는 경우 저소득집단에서는 건강이 경기동행적으로 나타난 반면 고소득집단에서는 건강이 경기역행적인 것으로 나타났다.

본 연구는 경기변동과 개인의 건강간의 관계를 설명할 수 있는 이론적 틀을 제공하고 기존 선행연구들과는 구분되는 새로운 실증분석 결과를 제시했다는 점에서 이 분야의 연구에 기여를 할 것으로 판단된다.

주요어: 경기변동, 건강, 소득집단, 차별적 효과, 후생비용

학　번: 2010-20193