



# Income volatility, household leverage, and consumption in Korea

Daesun Jung<sup>a</sup>, Young Sik Kim<sup>b,\*</sup>

<sup>a</sup> Samsung Economic Research Institute, Seoul, Republic of Korea

<sup>b</sup> Department of Economics & SIRFE, Seoul National University, Seoul, Republic of Korea



## ARTICLE INFO

### JEL classification:

D14  
D12  
E21

### Keywords:

Income volatility  
Household debt  
Consumption  
Precautionary saving  
Consumption smoothing

## ABSTRACT

Using the micro household data in Korea, we examine the effects of income volatility changes on households' leverage and consumption. We found that households who faced increased income volatility lowered their leverage ratio. A one standard deviation increase in income volatility was associated with 1.3 ~ 1.5 percentage point decrease in the leverage ratio. The effects of income volatility changes on households' leverage choices varied with households' borrowing constraints and other socioeconomic backgrounds. We also found that when faced with enlarged income uncertainty, households' income coefficients on consumption were lowered. The income coefficient of average households was estimated to be around 0.16, while households with increased income volatility were around 0.12. In particular, similar to the relations in leverage ratio changes, consumptions among potentially borrowing-constrained households and those with 'net-short' position in real estate assets were more affected by increases in income volatility. This can be understood that households smoothed their consumption during the periods of increased income volatility, and this was shown in the smaller consumption elasticity on income. This can be attributed to the fact that faced with increased income volatility, households lower the risk exposure of their financial net wealth by lowering their leverage ratio.

## 1. Introduction

Huge household debt has become one of the most significant risks in the Korean economy. Korean household debt compared to its GDP rose from 79.7 % at the end of 2011 to 97.7 % in 2018. Gu (2007) argued that after the 1997 financial crisis, the volume and proportion of bank financing has grown as a result of risk-focused management of financial institutes. More recently, coincided with record-low interest rate and the self-fulfilling expectations of rising house prices, household debts have grown remarkably. Households' borrowing rate from commercial banks decreased from 9.88 percent in 2010 to in 2010 were 9.88 percent to 3.14 percent in 2016, accompanied by global low interest rate environment, and the average house prices doubled during the same periods (Fig. 1).

Many studies examined the relationships among household debt, income and consumption in Korea. Choi et al. (2015), using micro data obtained from the credit bureau, found that the magnitude of wealth effects from rising house prices was greater in high income and older households. Park (2019) found similar relations that households with 'net-long' in real estate assets had bigger wealth effects. Song (2018) studied the relationship of household leverage and consumption. The author argued that in economic circumstances where households are

highly in debt and have insufficient liquid assets, household consumption is likely to be vulnerable to negative income shocks, which could hamper aggregate spending growth.

There also exist many important researches with Japanese household micro data. Abe and Yamada (2009) found a strong relation between income risks and household consumption with detailed micro household data from the National Survey of Family Income and Expenditure (NSFIE), which is one of the largest household surveys in the world. They confirmed the standard precautionary saving motives were found in the consumption behaviors in Japanese households. Zhou (2003) also examined the impacts of household earning uncertainty on household consumption and savings, and reported that about 5.6 percent of total saving of salaried worker are related to precautionary savings. Ogawa and Wan (2007) empirically examined the influences of household debt on consumption during and after the financial bubble in Japan with NSFIE, and found that high debt-asset ratio had negative effects on household consumptions.

However, few studies focused on the relationships between households' income uncertainty, leverage and consumption, especially with Korean household micro data. Considering the rapidly changing socioeconomic environment, including demographic changes and adverse external demand caused by major economies' trade tensions, Korean

\* Corresponding author.

E-mail addresses: [ds99.jung@samsung.com](mailto:ds99.jung@samsung.com) (D. Jung), [kimy@snu.ac.kr](mailto:kimy@snu.ac.kr) (Y.S. Kim).

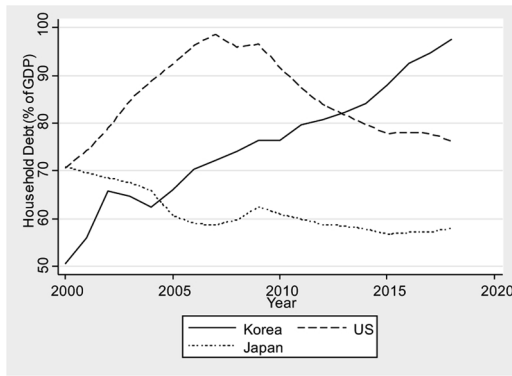


Fig. 1. Household debt to GDP ratio.

households face substantial changes in income uncertainty.

Chang et al. (2019), which furnished the main motivation for our research, analyzed the relations between household income uncertainty and household’s asset portfolio choices using detailed Norwegian household micro-level data. They found that if households face enlarged income uncertainty, they adjust overall risk exposure by lowering other risks such as price risks in asset choices.

Considering Korean households’ small share of financial assets and huge amount of debt, we focus on households’ leverage and consumption choices when income uncertainty changes. According to the Bank of Korea (2017), the share of financial assets in households’ total assets was 37.2 percent, which is only the half of United States’ 69.9 percent. Other major advanced economies, such as Japan (63.5 percent), United Kingdom (52.8) and Germany (42.9) also showed a relatively larger share of financial assets.

A risk averse household would decrease his/her overall risk stemming from assets and liabilities, if the risk from human wealth increases, indicating households manage their overall risk exposure of human wealth and ‘tangible’ wealth. This ‘risk management incentive’ is the starting point of our analysis. And we further consider other aspects that can exert influences on the relationship of changes of income uncertainty and household leverage/consumption.

First, borrowing-constraints are thought to be a crucial factor in examining the effects of income volatility changes on the leverage ratio. As Deaton (1992) noted, if a person faces or expects to face a borrowing constraint, he or she would save more in order to guarantee the minimum consumption levels in future periods, since increased income volatility is associated with the probability increase of being borrowing-constrained.

Second, life-cycle theory suggests that old households’ leverage ratio would be less affected by increased income volatility, since their remaining life-time income is smaller than that of young households.

Third, as Brunnermeier and Nagel (2008) noted, households’ risk aversion may differ with their wealth level. Considering that real estate assets account for the largest share in Korean households’ wealth, households who do not own houses would be more risk-averse, indicating their leverage and consumption would be more affected by changes in income uncertainty.

Fourth, distinguishing permanent and transitory income shock is also a crucial factor in examining households’ leverage and consumption responses. If households perceive the changed income uncertainty as a permanent one, they would adjust their leverage and consumption more actively.

Finally, considering households’ leverage and consumption choices at a same time, one can expect the possibility that changes in income volatility ‘directly’ affect consumption through income changes and ‘indirectly’ affect consumption through changes in debt-servicing burden. Standard consumption theory suggests that, by precautionary saving motives, increased income volatility would be associated with

higher income growth rate, which is the result of the decrease of current periods’ consumption. At the same time, since increased income volatility affects households’ leverage choices, changes of debt-servicing burden also indirectly affect consumption.

## 2. Household income volatility and leverage

### 2.1. Data

The panel dataset in this research is obtained from “the Survey of Household Finances and Living Conditions (SFLC)” conducted annually by Statistics Korea, the Financial Supervisory Service of Korea, and the Bank of Korea jointly since 2012. This comprehensive dataset is selected to represent all South Korean households with about twenty thousand household sample. As the samples of this dataset were modified markedly in 2018, we restrict the analysis period to 2012–2017. From 2012–2017, a total of 33,694 individual households were surveyed in SFLC for at least one year. We restrict our sample to 6151 households who were included in the sample for 6 consecutive years. In order to delete outliers, we exclude 87 households who reported total liabilities were 10 times bigger than their total assets. In sum, we use a perfectly balanced panel dataset composed of 6064 households over 6 years. Since in many cases we use log-transformed value of variables, we replace those variables into 1 if they were 0, making the log-transformed value 0. In case of current income, total 23 households reported their current income were zero for 1 year, and 2 households reported their income were zero for 2 years.

### 2.2. Household income volatility change

We construct a measure of household income volatility change. Let  $y_{i,t}$  denote the logged value of annual income of household  $i$  at time  $t$ , after controlling for a common age profile and the number of family members. We use current income as a primary measure for household income. Other definitions of household income gave us similar results.

$$SD_{i,T-} \equiv SD_i [y_{i,t} | t < 2015]$$

$$SD_{i,T+} \equiv SD_i [y_{i,t} | t \geq 2015]$$
(1)

Then, the change in income volatility before and after the threshold year 2015,  $\Delta SD_i$  is:

$$\Delta SD_i \equiv SD_{i,T+} - SD_{i,T-}$$
(2)

Table 1 shows the summary statistics for  $y_{i,t}$  after control (residual) and our measure of income volatility  $SD_i [y_{i,t}]$ . On average, the household income volatility  $SD_i [y_{i,t}]$  is 0.312 with a standard deviation of 0.291.

By imposing a certain threshold, we identify the households who experienced a substantial increase(decrease) in household income volatility. We consider two types: a significant increase or decrease in household income volatility.

$$I\{\text{Volatility Increase}\}_i = \begin{cases} 1, & \text{if } \Delta SD_i > \bar{SD} \\ 0 & \text{otherwise} \end{cases}$$

Table 1  
Summary statistics for income and volatility.

	Mean	S.D.	Percentiles				
			10 %	25 %	50 %	75 %	90 %
$y_i$	0.003	0.814	-1.072	-0.465	0.103	0.541	0.927
$SD_i$	0.312	0.291	0.105	0.163	0.255	0.379	0.535
$SD_{i,T-}$	0.254	0.306	0.051	0.098	0.187	0.322	0.503
$SD_{i,T+}$	0.230	0.286	0.040	0.083	0.164	0.290	0.461
$\Delta SD_i$	-0.021	0.394	-0.309	-0.142	-0.018	0.104	0.261

$$I\{\text{Volatility Decrease}\}_i = \begin{cases} 1, & \text{if } \Delta SD_i \leq \underline{SD} \\ 0 & \text{otherwise} \end{cases}$$

Some households' income volatility may be bigger persistently. However, by differencing the volatility in two sub-periods in same household, we can measure the changes in households' income uncertainty with the consideration of households' idiosyncratic characteristics. For our benchmark analysis, two thresholds,  $\underline{SD}$  and  $\overline{SD}$ , are respectively, the 25 and 75 percentiles of the pooled cross-sectional distribution of  $\Delta SD_i$  (-0.142 and 0.104). With these thresholds, we have 25 % of the sample in each category. The rest of the sample is classified as 'no big change' in income volatility.

### 2.3. Leverage ratio

In order to consider the liability side of households' portfolio choices, we adopt 'leverage ratio', which captures households' debt-financing activities. 'Risky share' in asset side and 'leverage ratio' in debt side have a similar aspect, since both measures evaluate the risk exposure of household. Risky share captures the risk created from the price changes of households' assets. Leverage ratio measures households' solvency risk. As the leverage ratio goes up, the default risk for households rises. We use 'leverage ratio (LR)' as debt to asset ratio, as Song (2018) did.

$$\text{Leverage Ratio (LR)}_{i,t} = \frac{\text{Total Debt}_{i,t}}{\text{Total Asset}_{i,t}}$$

where  $\text{Total Debt}_{i,t}$  is household  $i$ 's total debt, including either financial debt or tenancy deposits in period  $t$ .  $\text{Total Asset}_{i,t}$  is total assets of household  $i$  at period  $t$ .

Table 2 reports the descriptive statistics of the leverage ratio with three different demographic factors: renters vs. homeowners, high school vs. college graduates, and singles vs. married. The variation in the leverage ratio is biggest in home ownership, and in other groups, the variations are relatively small.

Fig. 2 shows the participation rate and the conditional leverage ratio over the age of the head of the household, for both the SFLC and Korean Labor and Income Panel Study (KLIPS). KLIPS is a survey conducted by Korea Labor Institute. KLIPS also provides similar micro-level household data with different samples in Korea. The participation rates (A in (Fig. 2)) are hump-shaped with a peak around the age of 40. It increases from around 55 percent at age 20 to almost 80 percent at age 40, and decreases to about 50 percent at age 60. The conditional leverage ratio (B in (Fig. 2)) also features a hump-shape. We do not show the leverage ratio in KLIPS for simplicity. Although we do not directly compare leverage ratio with KLIPS data, average debt levels show a similar shape, with peak at around age 50. The conditional leverage ratio peaks around age 40, but the debt level still increases until age 50.

**Table 2**  
Average leverage ratio and the amount of debt (unit: ratio, 10k Korean Won).

	Participation	Leverage Ratio (Amount of Debt)	
		Conditional	Total
All Sample	0.659	0.316 (9,402)	0.208 (6,203)
Homeowner	0.708	0.229 (10,610)	0.162 (7,519)
Renter	0.580	0.488 (7,004)	0.283 (4,064)
Less than college	0.595	0.339 (7,562)	0.201 (4,499)
College degree	0.763	0.288 (11,689)	0.219 (8,918)
Single	0.517	0.360 (4,710)	0.182 (2,436)
Married	0.672	0.313 (9,714)	0.210 (6,529)

Note: "Participation" represents the participation rate in debt financing activity. "Conditional Leverage Ratio" represents the leverage ratio conditional on participating in debt financing activity. The "Total" means unconditional leverage ratio, that is, the average leverage ratio of whole sample, no matter whether household has debt or not.

### 2.4. Response of leverage ratio

We examine the links between the income volatility change and household's leverage choice. First, we regress household's leverage ratio on age, age squared and year dummies to obtain the residual leverage ratio net of the average age profile and time effects. Second, we subtract the household-mean leverage ratio to control for each households' unobserved effects (such as different preferences for debt). Fig. 3 shows a negative relationship between income volatility changes and leverage ratios. Households who experienced a big increase in the income volatility (small-dotted line), which corresponds to top 25 percentile in  $\Delta SD_i$  steadily reduced their leverage ratio: which decreased about 1~2 percentage points during the sample period. Households with decreased income volatility increased their leverage ratio by approximately more than 2 percentage points until 2016 and reduced it somewhat in 2017. Households with no big changes in income volatility decreased their leverage ratio slightly.

We now estimate the response of the leverage ratio to income volatility change using the following equation:

$$LR_{i,t+k} - LR_{i,t} = \beta_V \Delta SD_i + \beta_X X_i + \varepsilon_i \tag{4}$$

where  $LR_{i,t}$  is household  $i$ 's leverage ratio at year  $t$ ,  $\Delta SD_i$  is the income volatility change as defined earlier, and  $X_i$  is household  $i$ 's other socioeconomic variable. Here, we use households' age, age square and the number of family members, as we did in previous analysis. In order to capture the time-gap of households' debt-financing activity, we estimated the regression with varying time periods gaps. First, we take leverage ratio changes between 2014 and 2015 ( $LR_{i,2015} - LR_{i,2014}$ ) as a dependent variable, and we denote this as  $k = 1$ , since the year gap in leverage ratio change is one year. Next, we use leverage ratio changes from 2013 to 2016 ( $LR_{i,2016} - LR_{i,2013}$ ), and this case is  $k = 3$ . Next, we compare 2012~2017, which is  $LR_{i,2017} - LR_{i,2012}$ , and this case is  $k = 5$ . Finally, we use the changes of the period average leverage ratio between first three year to the last three year, that is,  $LR_{i,T+} - LR_{i,T-}$  as dependent variable.

Table 3 reports the regression results. This supports the hypothesis that households adjust their leverage ratio to decrease risk exposure if they face enlarged uncertainty in human wealth. A one-unit increase in income volatility was associated with one to five percentage point decrease in the leverage ratio over time. The magnitude of leverage response was biggest in  $k = 5$ , and smallest in  $k = 1$ , indicating households' leverage adjustment in response of income volatility change takes some time. The relationship between income volatility change and leverage ratio holds even after controlling other variables, such as households' income, age and number of family members. For simplicity, we only report regression results with household income. One percent point increase in household income was associated with 0.01~0.035 percent point decrease in leverage ratio. This implies that household saves more if income increases. The magnitude of leverage ratio response was enlarged as the time gap( $k$ ) increases. In Table 1, we saw the average and median of  $\Delta SD_i$  were negative, indicating the overall income uncertainties have declined. Therefore, the recent dramatic increase of Korean household debts could be understood as the consistent results of our income volatility and leverage analysis. However, to investigate the determinants of the changes of aggregate household debts in Korea, further analysis is needed.

In Table 3, we saw income level changes are important in the determination of households' leverage ratio. Here, we compare the average leverage ratio in first three years (2012~2014) to the average in last three years (2015~2017). we apply similar definition to income level changes. We use lower(upper) 25 percent threshold to divide households whose income level 'significantly' decreased(increased).

In Table 4, those whose leverage ratio showed biggest decrease was the households with 'no big change in income volatility' and 'income level increased'. They lowered their leverage ratio by 1.7 percentage points from first 3 years to later 3 years. Households with 'volatility

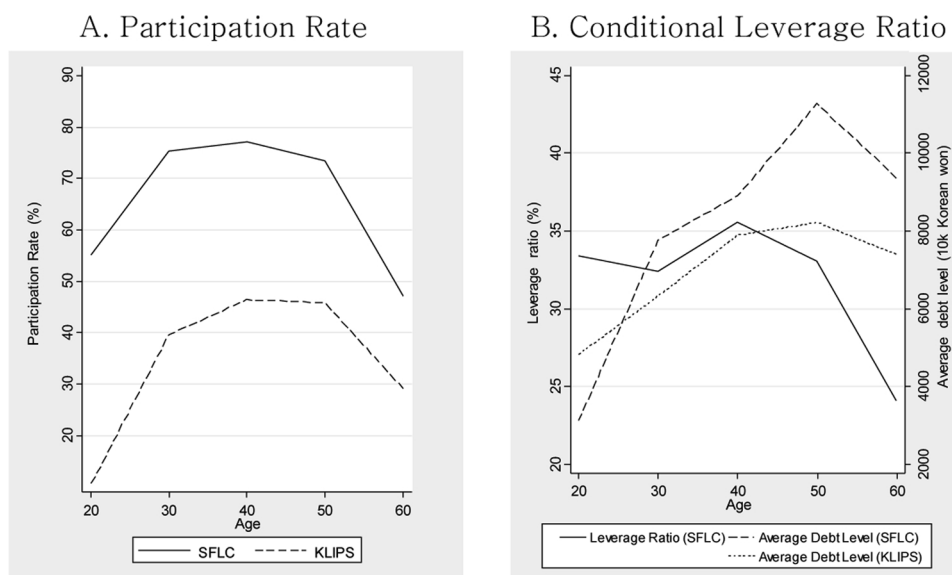


Fig. 2. Leverage ratio over the life cycle.

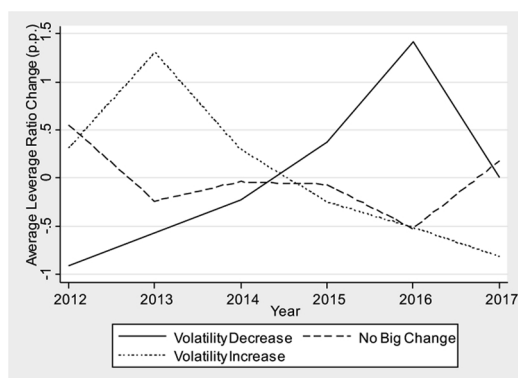


Fig. 3. Leverage ratio change by volatility groups.

Table 3  
Response of Leverage Ratio over Time.

Dependent Variable: Leverage Ratio change ( $LR_{i,t+k} - LR_{i,t}$ )				
	$k = 1$		$k = 3$	
$\Delta SD_i$	-0.006 (0.010)	-0.007 (0.012)	-0.033* (0.018)	-0.048** (0.021)
$\Delta y_i$		-0.000 (0.010)		-0.024 (0.017)
Obs.	6,064	6,064	6,064	6,064
$R^2$	0.000	0.000	0.000	0.000
	$k = 5$		$\bar{L}R_{i,T+} - \bar{L}R_{i,T-}$	
$\Delta SD_i$	-0.025* (0.020)	-0.046* (0.024)	-0.022* (0.012)	-0.034** (0.014)
$\Delta y_i$		-0.035* (0.020)		-0.020* (0.011)
Obs.	6,064	6,064	6,064	6,064
$R^2$	0.000	0.000	0.000	0.000

Note:  $F_S$  is the number of family members. Numbers in parenthesis are standard errors. The \*\*\*, \*\*, \* denote the statistical significance at 1 %, 5 %, 10 % respectively.

decreased' and 'income level increased' also lowered their leverage ratio by 0.5 percentage points. Those can be thought as savings by households with increased income volatility. The row-total (lowest row) supports this relation. On average, households with increased income level lowered their leverage ratio by 0.9 percentage points, while households with decreased income level increased leverage ratio

by 1.2 percentage points. Households with decreased income level might be in need of borrowing more money in order to smooth their consumption.

But households with 'volatility increased' and 'decreased income level' showed big drops of leverage ratio, around 1.4 percentage points during 6 years. For consumption smoothing purpose, households with increased income volatility and decreased income level would need more debts in order to smooth current periods' spending. But they lowered their leverage ratio even in the unfavorable income situation. This suggest the possibility that they might face a 'borrowing-constraint' and de-leveraged their debt 'forcedly'. We will address this issue in a later section further.

2.5. Borrowing constraints and leverage response

On the demand side, households would need more debt in order to smooth their consumption, in response of income shocks, or pay back their debt (save) by precautionary motives. On the supply side, borrowing constraints are crucial in determining households' debt-financing activities. Even if households need more debt, if a household is credit-constrained, raising more debt is not possible. But as Deaton (1992) and Jappelli and Pistaferri (2017) noted, it is not easy to find evidence for liquidity constraints. Since households anticipate 'potential' future borrowing-constraints by saving more, so the standard estimation on the Euler equation may not violated. Most of the time the tests regarding borrowing constraints do not find any violation of the Euler equation, not because credit markets are perfect but because households allow for the probability of future constraints. The main hypothesis of this section is that, if credit-constrained households face enlarged income uncertainty, they will deleverage quickly and save more, in order to ensure the minimum consumption spending for their current and future periods. Thus, borrowing-constrained households will de-leverage more sharply in response to increased income volatility.

However, in our micro household data, we cannot directly observe whether households face borrowing-constraints. Accordingly, we adopt various measures of borrowing-constraints, such as LTV and effective borrowing rates.

The loan regulations in Korea had many changes during our sample period, varied with regions and financial sectors. The main change was that until 2015, the LTV regulation was the primary tool in household debt prudential policy. From 2015, the authority began to consider DSR



**Table 4**  
Leverage ratio change by groups.

		Income Level			
		Dec.	Mid.	Inc.	Total
Income Volatility	Dec.	0.16 → 0.23 (+0.064)	0.20 → 0.21 (+0.014)	<b>0.24 → 0.24</b> <b>(-0.005)*</b>	0.21 → 0.22 (+0.017)
	Mid.	0.19 → 0.20 (+0.008)	0.20 → 0.20 (+0.009)	<b>0.24 → 0.23</b> <b>(-0.017)*</b>	0.20 → 0.21 (+0.004)
	Inc.	<b>0.18 → 0.17</b> <b>(-0.014)*</b>	<b>0.20 → 0.20</b> <b>(-0.004)*</b>	0.29 → 0.29 (+0.000)	<b>0.21 → 0.21</b> <b>(-0.008)*</b>
	Total	<u>0.18 → 0.19</u> (+0.012)	0.20 → 0.20 (+0.008)	<b>0.25 → 0.24</b> <b>(-0.009)*</b>	0.21 → 0.21 (+0.004)

Note: The first number in each cell refers to the average leverage ratio during the first 3 years (2012~2014), the second refers to the average of last 3 years (2015~2017), and numbers in parenthesis are the changes in leverage ratios between these two periods, with a bold star if negative. "Dec" in Income volatility means income volatility change( $\Delta SD_i$ ) was in the low 25 %, "Inc" is in the upper 25 %, and "Mid" is the remaining middle 50 %. "Dec" in Income level means income level change between these two periods was in the lower 25 % percentile, "Inc" is in the upper 25 % percentile, and "Mid" is the remaining middle 50 %.

(Debt-Service Ratio), and these days, LTV and DSR regulations stand for the two primary polity tool. The ratio in the LTV regulations is around 40~70 percent to its collateral real estate assets. Until August 2014, an LTV of 50 percent for the Seoul metropolitan area and 60 percent for other area was applied. The LTV ratio was then relaxed to 60 percent for the entirety of Korea. In the case of the DSR regulation, the authority defined 'high-DSR' as households with a DSR higher than 70 percent.

However, since the sample selection criteria in this section are closely related to households' leverage ratio, which is the dependent variable in our regression analysis, we are not free from sample selection bias. That is, since 'potentially' borrowing constrained households tend to have higher leverage ratio, and this would result more sensitive reaction to income volatility changes. In other words, potentially borrowing constrained households would have bigger coefficient of  $\Delta SD_i$  in equation (3), not because of their borrowing-constraints, but because of their high leverage ratio itself. We will deal with the sample selection bias in the end of this section.

### 2.5.1. LTV ratio

We define two different LTVs, a narrow definition, and the other is a wider one. The first one, denoted  $LTV^N$ , 'N' stands for 'narrow', is more suitable and exact definition, since we use collateral debt as numerator. The second definition,  $LTV^B$ , 'B' stands for 'broader', for the consideration of the overall debt-burden compared to households' assets, uses total debt as numerator. Therefore, by definition,  $LTV^B$  is higher than,  $LTV^N$ .

$$LTV_{i,t}^N = \text{Collateral debt}_{i,t} / \text{Real estate asset}_{i,t}$$

$$LTV_{i,t}^B = \text{Total debt}_{i,t} / \text{Real estate asset}_{i,t}$$

We compare leverage ratio changes of potentially borrowing-constrained households. We define a LTV regulation constrained households as households with LTV are higher than 0.6 at 2014, since 2014 is the end of first 3 years in our sample. As of 2014, 11.31 percent of households had  $LTV^N$  higher than 0.6, and 17.73 percent of households had  $LTV^B$  higher than 0.6. LTV-constrained households with increased income volatility showed relatively bigger deleveraging.

In Table 5, for households with increased income volatility,  $LTV^N$ -constrained households lowered their leverage ratio by 2.5 percentage points, and  $LTV^B$ -constrained households lowered their ratio 5.4 percentage points, while total households with increased income volatility lowered their leverage ratio by 0.8 percentage points on average. Potentially borrowing-constrained households deleveraged more in response to increased income volatility.

We also estimate simple regressions to find the relationship between income volatility changes and leverage ratio. The dependent variable is the changes of leverage ratio between the first 3 years and the second 3 years, and the independent variables include  $\Delta SD_i$  and  $\Delta y_i$  only, for

**Table 5**  
Leverage ratio change by groups: LTV-constrained.

		Total	$LTV^N > 0.6$	$LTV^B > 0.6$
Income Volatility	Dec.	0.207 → 0.224 (+0.017)	0.506 → 0.631 (+0.125)	0.485 → 0.536 (+0.051)
	Mid.	0.203 → 0.207 (+0.004)	0.572 → 0.585 (+0.013)	0.503 → 0.507 (+0.004)
	Inc.	<b>0.214 → 0.206</b> <b>(-0.008)*</b>	<b>0.532 → 0.507</b> <b>(-0.025)*</b>	<b>0.536 → 0.482</b> <b>(-0.054)*</b>
	Total	0.207 → 0.211 (+0.004)	0.545 → 0.580 (+0.035)	0.507 → 0.509 (+0.002)

Note: The first number in the table is the average leverage ratio in the first 3 years, the second number is the average in the second 3 years, and numbers in parentheses are the difference between the two periods.

**Table 6**  
Response of leverage ratio: LTV constrained.

	Total	$LTV^N \geq 0.6$	$LTV^B \geq 0.6$
$\Delta SD_i$	-0.034**	-0.118	-0.081
$\Delta y_i$	-0.020*	-0.018	-0.005
Obs.	6,064	219	535

Note: Each number in the first and second row of the table refers to the coefficient of explanatory variables. The \*\*\*, \*\*, \* denote the statistical significance at three p-values: 1 %, 5 %, 10 % respectively.

simplicity. We saw those two variables had statistically significant relations with the leverage ratio changes in the previous section. (see Table 4) However, the regression results in Table 6 indicate that for LTV-constrained households, the relationship between income volatility changes and leverage ratio were insignificant.

### 2.5.2. Net wealth

Following Park (2019), we use households' net wealth as a measure that determines whether a household is borrowing-constrained. In light of the prevalent loan-approval process in Korea, it is reasonable to postulate that collateral assets are important factors. According to the Bank of Korea's Economic Statistics System (ECOS), 58.5 percent of household loans from depository corporations were collateral loans at the end of 2018. Low or negative net wealth means households' overall financial conditions are weak and have little assets that can be provided as collaterals, so they may face difficulty in borrowing money from financial institutions.

As of 2014, 2.3 percent of households had net wealth less than zero, and 22.0 percent of households had net wealth less than 5000 10k Korean won. Low net wealth group households were more sensitive in income volatility changes. A one-unit increase in income volatility was

**Table 7**  
Response of leverage ratio: net wealth constrained.

	Total	NW < 0	NW < 50,000,000	NW ≥ 50,000,000
$\Delta SD_i$	-0.034**	-0.831**	-0.085	-0.017**
$\Delta y_i$	-0.020*	0.319	-0.065	-0.001
Obs.	6,064	137	1,405	4,659

Note: NW refers to 'net wealth'.

associated with a 0.83-unit decrease in the leverage ratio. This indicates the possibility that households with low (or negative) net wealth are vulnerable to income shocks. It is also interesting that households with net wealth greater than 5000 10k Korean won had a smaller coefficient of  $\Delta SD_i$ , implying that their leverage ratio were less sensitive to income volatility changes. This result would mean that households with relatively abundant net wealth did not alter their liability choices, since they could smooth their consumption with their assets. However, the statistical relationship between income volatility changes and leverage ratio was not significant for households with net wealth of less than 5000 10k Korean won (Table 7).

### 2.5.3. HDRI (household debt risk index)

Here, we employ the household debt risk index (HDRI) introduced by the Bank of Korea. This index was developed to assess household debts' riskiness with balanced consideration of risks in households' cash flow (DSR) and stock (DTA). (For more explanation and interpretation about HDRI, see the Bank of Korea, 2015). Previous measures only considered households' assets and liabilities. However, as the financial authority emphasizes the importance of DSR, it is appropriate to take the cash flow side of households into account. The definition of HDRI is as follows.

$$HDRI_{i,t} = ((1 + (DSR_{i,t} - \alpha)) \times (1 + (DTA_{i,t} - \beta))) \times 100$$

$DSR_{i,t}$  is household  $i$ 's interest and principal payments divided by disposable income. Here, the disposable income in the denominator refers to income before subtracting interest payments.  $DTA_{i,t}$  is the well-known 'Debt to Asset' ratio, but is different from the conventional LTV ratio. The Bank of Korea applied "hair-cut" ratios to each category of assets, in terms of liquidity, but the exact hair-cut ratio was not disclosed. Accordingly, we use the haircut ratio for each asset category as follows: Demand deposit for 0.00, since it can be liquidated without any transaction costs, installment deposit for 0.05, other savings for 0.10, down payments for 0.40, and real estate assets for 0.40. We use a very conservative (high) hair-cut ratio for real estate assets, since instant sale of those assets is accompanied by substantial transaction costs.

The Bank of Korea used  $\alpha$  and  $\beta$  for 0.40 and 1.00 respectively. We adopted the same threshold. The Bank of Korea assessed DSR higher than 0.40 as 'high-DSR,' meaning risky in cash-flow, and DTA higher than 1.00 as 'high-DTA,' meaning risky in asset and liability conditions. If HDRI exceeds 100, the Bank of Korea judged those households as 'highly risky households' (Table 8).

In Table 9, we compare the leverage ratio changes over time by

**Table 8**  
Risky households according to HDRI (unit: percent).

	2014	2015	2016	2017
High DSR	20.7	22.6	26.4	24.4
High DTA	5.1	4.7	4.3	8.9
HDRI > 100 (A)	6.4	6.8	8.4	11.1
HDRI > 100 (B)	1.6	1.4	1.7	3.2

Note: DSR cannot be calculated in 2012 and 2013, since interest payments are not available before 2014 for the Household Welfare Survey. HDRI > 100 (A) refers to households with HDRI > 100. HDRI > 100 (B) refers to households with HDRI > 100, DSR > 0.4 and DTA > 1.0.

**Table 9**  
Leverage ratio change by groups: HDRI.

	Total	HDRI > 100	HDRI ≤ 100	
Income Volatility	Dec.	0.207 → 0.224 (+0.017)	0.979 → 0.954 (-0.025)*	0.161 → 0.181 (+0.020)
	Mid.	0.203 → 0.207 (+0.004)	1.201 → 1.089 (-0.112)*	0.166 → 0.173 (+0.007)
	Inc.	0.214 → 0.206 (-0.008)*	1.289 → 0.803 (-0.486)*	0.166 → 0.180 (+0.014)
	Total	0.207 → 0.211 (+0.004)	1.150 → 0.974 (-0.176)*	0.165 → 0.177 (0.012)

Note: The first number in the table is the average leverage ratio for the first 3 years, the second number is the average for the last 3 years, and the numbers in parentheses are the difference between the two periods.

household groups divided by HDRI with a threshold of 100. On average, the 'high HDRI' group lowered their leverage ratio about 17.6 percentage points. The 'high HDRI' with 'income volatility increased' group decreased their leverage ratio by 48.6 percentage points, which is a substantial change. However, households with HDRI equal to or below 100 showed little difference among volatility change groups. This indicates that income volatility change for 'high HDRI' households caused some difficulty in borrowing extra money, and made them to pay back their debts rapidly.

In Table 10, households with HDRI higher than 100 showed more sensitivity to income volatility changes, compared to the average group (total). A one-unit increase in the standard deviation of income was associated with a 25.3 percentage points decrease in the leverage ratio for them, which is about 8 times greater than the average households. At the same time, we also checked households with high DSR and high DTA separately, and found that household with high DTA were more sensitive to income volatility changes. Though the statistical relation was estimated to be insignificant in LTV criteria, DTA criteria reported a statistically significant relationship between income volatility changes and leverage ratio. DSR criteria also reported statistically significant coefficient, but the value of coefficient was relatively small in absolute terms.

In order to further investigate the different relations with leverage response, we checked the relationship between  $\Delta SD_i$  and leverage ratio with a varying threshold of DSR and DTA. We started with DSR higher than 0.3, and increased the threshold by 0.3 until DSR reaches 0.9, which means households spend more than 90 percent of income to debt-servicing. For DTA, we started from DTA higher than 0.6, and increased the threshold by 0.3 until it reaches 1.2, which means households' total debts are 'underwater'. As the threshold increases, the sample size decreases. For DSR higher than 0.3, there were a total of 1136 observations, but for DSR higher than 0.9, there only left 275 observations. As the DSR criteria increases, the coefficient of  $\Delta SD_i$  slightly increased, staying around 0.1. But the coefficient of  $\Delta SD_i$  rapidly increased as DTA threshold increases, from 0.177 to 0.847. This results support the strong relation with leverage response and DTA measures (Table 11).

### 2.5.4. Borrowing rate

The HDRI criterion in the previous section has several short falls. As mentioned earlier, HDRI's purpose is not to measure the borrowing-constraints, but to assess households' overall solvency risk or

**Table 10**  
Response of leverage ratio: HDRI.

	Total	HDRI > 100	DSR > 0.4	DTA > 1.0
$\Delta SD_i$	-0.034**	-0.253**	-0.063*	-0.762**
$\Delta y_i$	-0.020*	-0.264*	-0.033	-0.309
Obs.	6,064	257	868	202

**Table 11**  
Response of leverage ratio: DSR and DTA.

threshold	DSR Coef.	Obs.	Threshold	DTA Coef.	Obs.
> 0.3	-0.099***	1,136	> 0.6	-0.177**	594
> 0.6	-0.095**	514	> 0.9	-0.560***	254
> 0.9	-0.101**	275	> 1.2	-0.847**	136

Note: The regression specification is the same as in the previous analysis in (Table 14). ‘Coef’ refers to the estimated coefficient of  $\Delta SD_i$ . The coefficient of  $\Delta y_i$  is not reported for simplicity.

vulnerability of financial conditions. Here, we try to tackle households’ borrowing constraints with more direct and objective measures.

A strong definition of borrowing-constrained household is that an individual or household is unable for whatever reason to borrow against future earnings or assets. (Attanasio, 1995) A weak definition is that an individual or household is considered to be borrowing-constrained if the borrowing rate differs from the rate at which they can lend. (Crook, 2003) If a household faces infinitely high borrowing rate, its budget constraint becomes vertical in the area above current net wealth plus earnings. Therefore, we construct an effective borrowing rate from our micro data. Song (2018) classified collateral loans and unsecured loans separately, and defined each households’ effective borrowing rate of collateral and unsecured loans as annual interest payments divided by loan balance. For simplicity, we do not distinguish collateral and unsecured loan, and use following definition as households’ effective borrowing rate.

$$r_{i,t}^L = \frac{\text{annual interest payment}_{i,t}}{\text{loan balance}_{i,t}}$$

where the loan balance is  $(\text{financial debt}_{i,t-1} + \text{financial debt}_{i,t})/2$ . Current periods’ interest payments are from the annual average loan balance. In order to consider that, we use period average loan balance as denominator. We replace the borrowing rate with the legal interest limit if it exceeds the limit. According to Financial Services Commission (FSC), the legal limit was 34.9 percent in 2012~2016, and from March 2016, it changed to 27.9 percent. After January 2018, it changed to 24.0 percent, but our sample period only includes the 2012~2017 period, so technically, the theoretically highest borrowing rate in our sample is 34.9 percent. However, there may be some errors in the derived borrowing rates. First, if households’ principal payments were not even and concentrated at the end (beginning) of the year, the derived borrowing rates may have a upward (downward) bias since the actual average loan balance would be larger (smaller) than the simple average of  $t - 1$  and  $t$ . Second, since in the SFLC dataset, every stock-related variable, such as loan balances, are as of the end of March each year, and every flow-related variable, such as interest payments and incomes, are as of the calendar year (from Jan. 1<sup>st</sup> to Dec. 31<sup>st</sup>), there exists 3 months time gap between our derived borrowing rates’ numerator and denominator. Therefore, one should be aware that our derived borrowing rates of households are not flawless, and should be understood as one of proxy variables measuring households’ ‘real’ borrowing rates with available data.

Since it is difficult to pin-point the exact threshold that distinguishes borrowing-constrained households and not-constrained households, we used various thresholds. First, households with borrowing rate higher than the average borrowing rate in depository institutes, second, borrowing rates higher than 1.5 times the average, thirdly, higher than 2.0 times higher, and finally, borrowing rate higher than 2.5 times higher than the average are used. We are aware that the ‘real’ borrowing-constrained households would have ‘infinitely high’ borrowing rates, so one can neither observe it nor calculate it from the data. However, still, we believe the effective borrowing rate derived from the interest payments and loan balances provides a good measure to distinguish potentially borrowing-constrained households.

**Table 12**  
Response of leverage ratio: borrowing rates.

	Total	> 1.0	> 1.5	> 2.0	> 2.5
$\Delta SD_i$	-0.034**	-0.082***	-0.108***	-0.152**	-0.183*
$\Delta y_i$	-0.020*	-0.065***	-0.119***	-0.199***	-0.211**
Obs.	6,064	1,681	888	454	266

Note: ‘> 1.0’ refers to households with borrowing rates higher than 1.0 times of depository institutes’ average loan rate.

In Table 12, it is found that potentially borrowing-constrained households in terms of their borrowing rates, had a more sensitive leverage response to income volatility changes. Roughly, for households with borrowing rates higher than two times the average banks rate, a one-unit increase in income volatility change was associated with a 15.2 percentage points decrease in leverage ratio. This negative relationship strengthened as the threshold of borrowing rate rises.

This result is somewhat odd. In the previous analysis, we saw that the asset-liability related measures, such as net-wealth and DTA, had statistically significant explanatory powers in linking the relationship between income volatility changes and leverage ratio. DSR, which contains the debt-burden in cash flow, had less explanatory power. In this sense, one can guess the borrowing rate would also have less explanatory power. However, we found a statistically significant relation in households’ borrowing rates. This indicates the possibility that borrowing costs affect households leverage choices in response to income volatility changes; but DSR, which measures households’ free cash-flow after interest and principal payments of debts, has lesser effects.

2.5.5. Sample selection bias and asymmetric effects

As mentioned earlier, the criteria for borrowing constraints are closely related to leverage ratio itself, which is used as dependent variable. Purely exogenous variables are appropriate to be used as the sample classification criteria, but in our analysis, this was not. Therefore, the results in earlier analysis are not free from ‘sample selection bias’. That is, potentially borrowing-constrained households’ bigger coefficient of  $\Delta SD_i$  would be not because they were borrowing-constrained, but because of their high leverage ratio.

Fig. 4 shows the estimated coefficient of  $\Delta SD_i$  with a varying degree for minimum leverage ratio threshold. Leverage ratio minimum threshold ‘0’ means all samples were included, and ‘0.2’ means households with leverage ratio higher than 0.2 were included in the sample.

It seems obvious that households with higher leverage ratio are more sensitive to income volatility changes. Note that as the minimum threshold of leverage ratio increases, the sample sizes rapidly decreases. Now, let us check the changes of estimated coefficient in borrowing-

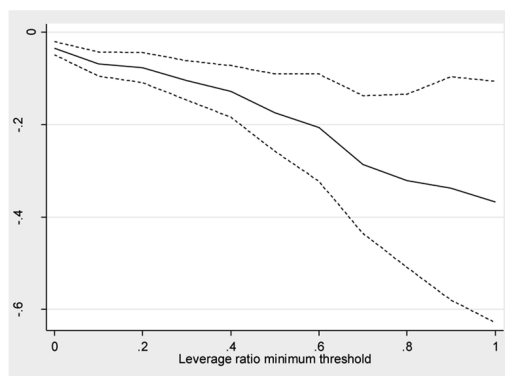
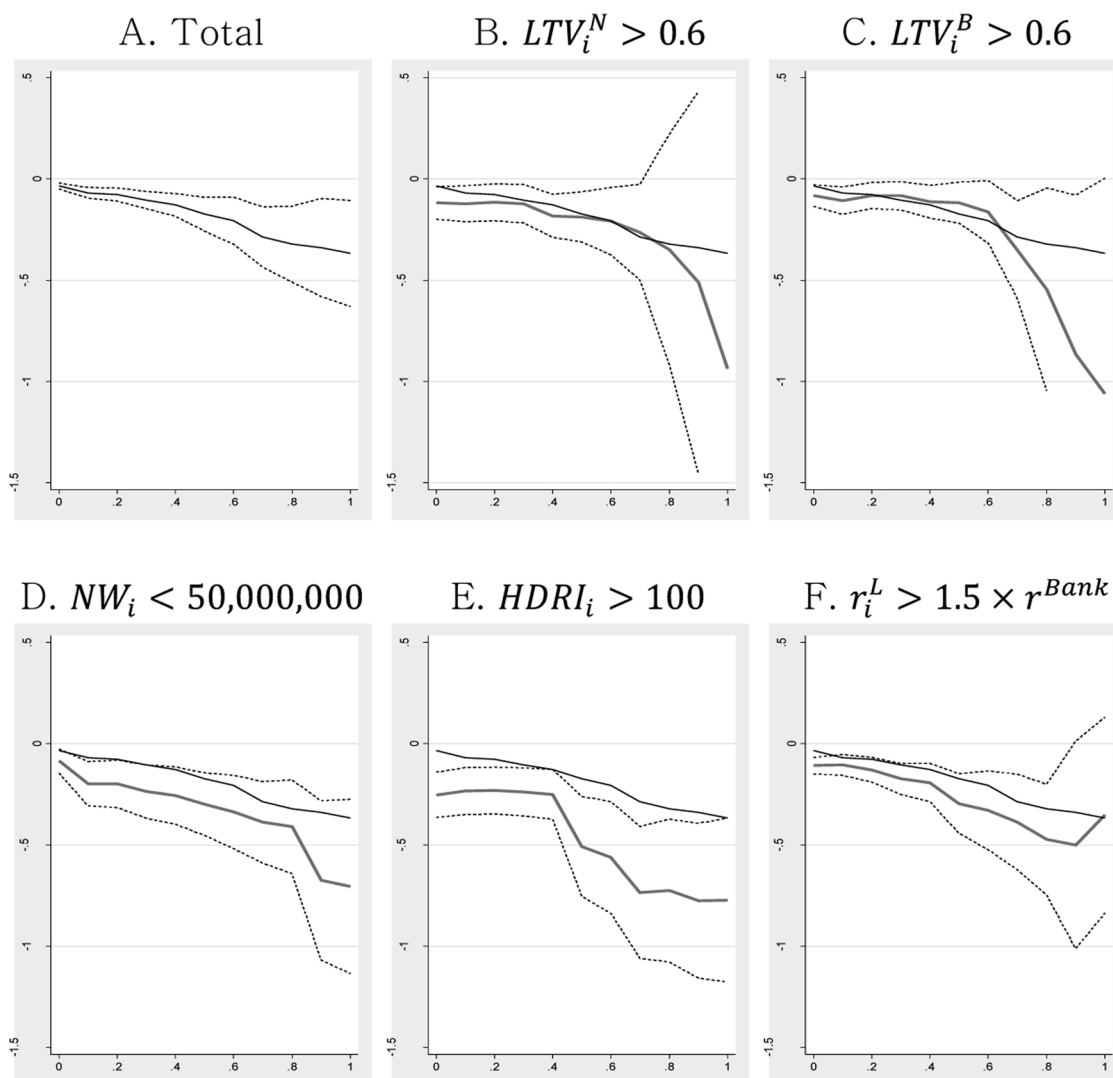


Fig. 4. Coefficient of  $\Delta SD_i$  with varying leverage ratio.  
Note: The solid line refers to the estimated coefficient with the leverage ratio as the dependent variable and  $\Delta SD_i$ ,  $\Delta y_i$  as explanatory variables. Two dotted lines refer to the estimated coefficient +/- one standard error.



**Fig. 5.** Coefficient of  $\Delta SD_i$  in borrowing constraints criteria.  
 Note: For easier comparison, we draw the coefficients in a baseline model with a thin black line in each graph. The thick gray line is the changes of coefficient in each borrowing constraint measures with dotted lines  $\pm$  one standard deviation.

constrained households with varying degree of minimum leverage ratio thresholds. Fig. 5 shows changes of coefficients of  $\Delta SD_i$  with various measure of borrowing constraints.

We find coefficients in LTV related measures are little different from that of baseline model. Therefore, it is difficult to say that more sensitive response in high LTV households were due to their borrowing constraints. However, the coefficients of households with small net wealth, high HDRI, and high borrowing rates had lower coefficients than that of baseline model. Households with small net wealth or high HDRI had persistently lower coefficient of  $\Delta SD_i$  than that of baseline model, as the minimum threshold of leverage ratio increases. Households with high borrowing rates also had lower coefficients, however the statistical significance rapidly dissipated as leverage ratio increases. This may due to the rapidly decreasing sample size as the minimum threshold of leverage ratio rises.

Several measures of borrowing constraints seem to support the possible effects of borrowing constraints on leverage ratio changes as even after considering higher leverage ratio, potentially borrowing-constrained households were more sensitive to changes of income volatility. However, sample selection bias may still exist and the regression analysis may over-estimate the magnitude of the effects of income volatility changes on leverage ratio changes unless purely exogenous

borrowing constraint criteria are used. Therefore, we should be aware of the biases when interpreting the analysis results.

We also checked the possibility that changes in income volatility may have asymmetric effects on households' leverage choices. In this regard, we divided households into several groups, one with increased income volatility and the other with decreased income volatility. However, the statistically significant relationship became insignificant if we divide the sample. Though it is premature to conclude there is no asymmetric effects of income volatility changes on households' leverage, our data and income volatility measures do not show the asymmetric relations.

### 2.6. Heterogeneity across groups

We now examine the response of leverage ratio to income volatility changes across different groups.

#### 2.6.1. Age: young vs. old

A variety of literatures studied households' behavior in the aspects of the life-cycle theory. For example, [Blundell et al. \(2008\)](#) and [Kaplan and Violante \(2010\)](#) showed that household savings and consumptions are more affected if the present value of human wealth divided by total



**Table 13**  
Leverage ratio change by groups: age.

		Total	Young	Middle	Old
Income Volatility	Dec.	0.21 → 0.22 (+0.017)	<b>0.24 → 0.23 (-0.005)*</b>	0.29 → 0.33 (+0.039)	0.14 → 0.13 (-0.011)
	Mid.	0.20 → 0.21 (+0.004)	<b>0.23 → 0.22 (-0.008)*</b>	<b>0.25 → 0.24 (-0.008)*</b>	<b>0.14 → 0.13 (-0.009)*</b>
	Inc.	<b>0.21 → 0.21 (-0.008)*</b>	<b>0.25 → 0.21 (-0.037)*</b>	<b>0.28 → 0.27 (-0.011)*</b>	<b>0.15 → 0.15 (-0.009)*</b>
	Total	0.21 → 0.21 (+0.004)	<b>0.24 → 0.22 (-0.014)*</b>	0.26 → 0.27 (+0.002)	<b>0.14 → 0.13 (-0.009)*</b>

Note: The first number in the table is the average leverage ratio for the first 3 years, the second number is the average for the second 3 years, and the numbers in parentheses are the difference between the two periods. “Young” is age ≤ 40, “Middle” is between 40~55 and “Old” is age > 55 at 2015.

wealth, which is the sum of human wealth and financial wealth, are high and vice-versa. For people far from the end of the life cycle, increased income volatility makes it harder to forecast future earnings, so they would have more precautionary savings motives. For older households, uncertainties in earning are less substantial, since their future earnings are smaller than younger households. This makes old households less responsive to income volatility changes (Table 13).

A simple comparison of leverage ratio changes during our sample period with different volatility change groups shows that young households with increased income volatility decreased their leverage ratio most quickly, while middle aged households with decreased income volatility increased their leverage ratio the most.

Table 14 shows a regression analysis of the relationship between income volatility changes and leverage ratio. Young household did not exhibit a sensitive reaction to income volatility changes. This may be due to the possibility that young households perceive their future income to be very uncertain, thus, current volatile income may be perceived as not a big change. As Guvenen (2007) and Chang et al. (2018) noted, because of high unemployment rates, frequent job turnovers and unknown career paths, young workers have less knowledge about their true earning ability. On the other hand, middle aged households had very sensitive leverage responses to income volatility changes. For them, a one-unit increase in income volatility change was associated with a 9.8 percentage points decrease in leverage ratio. For old households, it was estimated that income volatility changes and household leverage choice did not have a statistically significant relation. This can be attributed to their remaining future earnings being small, volatility changes of their income did not affect their asset and liability choices.

### 2.6.2. Home ownership: renters vs homeowners

If a household is planning to purchase a house, enlarged income volatility will lead them to save more in order to buy a house, which can be interpreted as precautionary saving motive. On the contrary, if a household already owns a house and does not plan to enlarge the house space or buy an additional house, increased income volatility will lead to more debt in order to temporarily smooth their consumption, since such households can pay back the liability later by sell off the house. In sum, net short of house would lower their leverage ratio in response of enlarged income volatility, while net long of house position would raise their leverage ratio

Using the questions regarding real estate assets in SFLC, we divide households into three groups. The first group is households with no house. By definition, they are renters and do not own any house. The second group is households owning one house. The house may be either

**Table 14**  
Response of leverage ratio: age.

	Total	Young	Middle	Old
$\Delta SD_t$	-0.034**	-0.038	-0.098***	0.001
$\Delta y_t$	-0.020*	-0.021	-0.111***	0.028**
Obs.	6,064	1,015	2,267	2,782

Note: Young are age ≤ 40, the Middle is between 40~55, and old are age > 55.

**Table 15**  
Basic statistics of house holdings (as of 2014).

	Number of house holdings (NHH)			Total
	0	At least more than 1	At least more than 2	
Renters	38.1 %	0.8 %	–	38.9 %
Homeowners	0.0 %	36.0 %	25.1 %	61.1 %
Total	38.1 %	36.8 %	25.1 %	100.0 %

Note: “Renters” and “Homeowners” refers to the contract type for a households’ current residence. By definition, the proportion of homeowners with holding no house is zero. For renters, distinguishing a household with holding one house and more than two houses is technically not possible, since the survey question is about the market value, not the number of real estate assets. However, for simplicity, we categorized renters with more than one house into renters, holding just one house, and we did not count the down payment as an independent real estate asset.

the current residence or another house with currently residence under a ‘rental-contract’. The third group is households with holding more than two houses. The first group is obviously ‘net-short’ of house. The second group can be classified as ‘net-long’ of house, but if the household age is young, one should consider the possibility that the household will move to a larger house, meaning they are effectively ‘net-short’ of house. In our data, households enlarged their house space until around age sixty, peaking at house space of 86.9 square meters. Finally, the third group is obviously considered ‘net-long’ position of real estate assets (Table 15).

We briefly looked at the leverage ratio changes over 6 years. On average, households owning at least 2 houses seemed to have a very sensitive response to income volatility changes. Households with ‘increased income volatility’ and ‘holding at least 2 houses’ (NHH 2) lowered their leverage ratio by 2.3 percentage points, while households with ‘increased income volatility’ and ‘owning no house at all’ (NHH 0) increased their leverage ratio by 1.2 percentage points. This seems the opposite to our previous hypothesis that ‘short-position’ of households, which indicates ‘holding no house’ (NHH 0) would lower leverage ratio in response to increased income volatility. We will further check the hypothesis in regression analysis. Households with holding at least 1 house (NHH 1) increased their leverage ratio in response of income volatility increase. On average, the leverage ratio decreased as the number of house holding increases. For the later 3 years average, the average leverage ratio for NHH 0 (holding no house) was 0.29, for NHH 1 (holding at least 1 house) was 0.17, and for NHH 2 (at least 2 houses) was 0.14 (Table 16).

Table 17 reports the regression analysis results. For houses holding no house at all, a one-unit increase in income volatility was associated with a 6.7 percentage points decrease in the leverage ratio, which is a more sensitive response compared to the average households. This indicates the possibility that our previous hypothesis would be valid. Households with ‘net-short’ position in real estate assets would save more if they face increased income volatility, in order to prepare for future purchases of a house. However, for owners of one house, the relationship between income volatility changes and leverage seemed to be weak. For owners of more than two houses, increased income volatility was associated with deleveraging. This seems odd, since they

**Table 16**  
Leverage ratio change by groups: number of house.

		Total	NHH 0	NHH 1	NHH 2
Income Volatility	Dec.	0.21 → 0.22 (+0.017)	0.27 → 0.32 (+0.042)	0.17 → 0.16 (-0.012)	0.14 → 0.16 (+0.021)
	Mid.	0.20 → 0.21 (+0.004)	0.26 → 0.28 (+0.027)	0.17 → 0.18 (+0.002)	0.14 → 0.14 (-0.003)
	Inc.	<b>0.21 → 0.21 (-0.008)*</b>	0.26 → 0.27 (+0.012)	0.18 → 0.18 (+0.008)	0.16 → 0.14 (-0.023)
	Total	0.21 → 0.21 (+0.004)	0.26 → 0.29 (+0.027)	0.17 → 0.17 (+0.000)	0.15 → 0.14 (-0.002)

Note: The first number in the table is the average leverage ratio for the first 3 years, the second number is the average for the last 3 years, and numbers in parentheses are the difference between the two periods. NHH 0 refers to households holding no house at all. NHH 1 is holding at least 1 house, NHH 2 is holding at least 2 houses.

**Table 17**  
Response of leverage ratio: number of house holding.

	Total	NHH 0	NHH 1	NHH 2
$\Delta SD_i$	-0.034**	-0.067*	0.015	-0.040***
$\Delta y_i$	-0.020*	-0.056*	0.013	-0.010
Obs.	6,064	2,198	2,210	1,656

already own abundant assets, and can raise more debt or sell off assets to respond to increased income volatility, and easily smooth their consumption. However, according to the regression analysis result, they de-leveraged in response to increased income volatility.

### 2.6.3. Job industry: safe vs. risky

It is crucial to consider how households perceive the income volatility changes. If they perceive it as a temporary shock, they will not make many adjustments. However, the way in which households perceive income volatility shock is not directly observable. One way of overcoming this problem is to consider job industry changes. If a person changes his (her) job from a safe to a risky industry, it is reasonable to say that he (she) will perceive income volatility change as permanent.

SFLC micro data classifies job industries into 21 groups. We restricted households to those who did not change their job industry during our sample periods, and calculated the average of standard deviation of income volatility in each job industry. We defined a safe industry as one with the lowest volatility top 7 industries, and risky industry as the highest volatility top 7 industries. The safest 7 industries were ‘international organization’ (standard deviation of income 0.079), ‘electricity supply’ (0.143), ‘public administration’ (0.180), ‘finance’ (0.190), ‘scientific research’ (0.196), ‘social welfare’ (0.207) and ‘telecommunication’ (0.208). The riskiest 7 industries were ‘others’ (0.532), ‘agriculture’ (0.367), ‘lodging’ (0.329), ‘retail’ (0.282), ‘real estate’ (0.279), ‘water supply’ (0.277) and ‘mining’ (0.271). Then, we defined households who changed from a safe to a risky, and from a risky to a safe industry as follow:

- *Safe to risky (STR): Changed their job from a safe to a risky industry between the first 3 years and the last 3 years*
- *Risky to Safe (RTS): changed from a risky to a safe industry*
- *No change (NC): households who did not change their job industry*

Table 18 reports the average leverage ratio changes across different groups. Households who changed their job from a safe to a risky

**Table 18**  
Leverage ratio change by groups: job industry.

		Total	Safe to risky	Risky to safe	No change
Income Volatility	Dec.	0.21 → 0.22 (+0.017)	0.42 → 0.27 (-0.147)	0.17 → 0.19 (+0.019)	0.21 → 0.22 (+0.009)
	Mid.	0.20 → 0.21 (+0.004)	0.27 → 0.32 (+0.051)	0.23 → 0.21 (-0.016)	0.19 → 0.20 (+0.007)
	Inc.	<b>0.21 → 0.21 (-0.008)*</b>	0.20 → 0.20 (-0.001)	0.23 → 0.24 (+0.006)	0.23 → 0.21 (-0.015)
	Total	0.21 → 0.21 (+0.004)	0.27 → 0.26 (-0.007)	0.21 → 0.21 (-0.002)	0.20 → 0.21 (+0.003)

Note: The first number in the table is the average leverage ratio for the first 3 years, the second number is the average for the last 3 years, and numbers in parentheses are the difference between the two periods.

industry lowered their leverage ratio by 0.7 percentage points, while those who changed their job from a risky to a safe industry lowered their leverage ratio by only 0.2 percentage points. On the other hand, those who did not change their job industry at all increased their leverage ratio by 0.3 percentage points. This may indicate that households who changed their job industry, no matter whether from risky to safe, or safe to risky, saved more money in response to their changed future income process. Even RTS (from risky to safe) households deleveraged, and this can be thought that job industry change itself is a very major change for a household, so they would feel more need for precautionary savings. However, we could not observe a clear relationship between income volatility changes and leverage ratio changes in those who changed their job industry, either from safe to risky or risky to safe.

We also estimated the relationship between  $\Delta SD_i$  and leverage ratio, but the estimated coefficients were insignificant for those who changed their job from ‘safe to risky’ and ‘risky to safe’ (Table 19). Thus, we further narrowed down the targets to those who changed their job from safe to risky industries and their income volatility ‘actually’ increased. The sample size shows that about half of households faced ‘real’ increased income volatility when they changed their job from a safe to a risky industry. Those who actually faced increased income volatility had a significant relationship between income volatility changes and leverage ratio. For them, a one-unit increase in income volatility was associated with an 18.4 percentage points decrease of leverage ratio, which seems consistent with our hypothesis. We also considered workers’ job status changes, such as from temporary to permanent job. However, the results were statistically insignificant.

## 3. Household leverage and consumption

### 3.1. Data and stylized consumption patterns

In this section, we turn our attention to household consumption, and analyze the relationship between consumption and income volatility changes. We use the Survey of Financial and Living Conditions (SFLC) micro household data, which is the same with the previous section. The only difference is that since the half of SFLC, Household Financial Survey does not contain households’ consumption data, we use the other half, Household Welfare Survey only. Therefore, our sample decreases from 6064 households to 2989 households with complete consumption data. We analyze the links between households’ consumption behavior and changes in income volatility with a balanced panel of  $N = 2989$  and  $T = 6$  years.

**Table 19**  
Response of leverage ratio: job industry change.

	Total	STR	STR & Inc	RTS	No change
$\Delta SD_i$	-0.034**	-0.008	-0.184***	-0.028	-0.042**
$\Delta y_i$	-0.020*	0.013	-0.110**	-0.004	-0.037**
Obs.	6,064	287	124	105	2,586

Note: 'STR & Inc' refers to households who changed job from a safe to a risky industry and faced increased income volatility.

Before estimating the consumption function of Korean households with an econometric model, we search if there is any stylized consumption pattern across different household groups. We divide households into several groups by age, income, job status, and home ownership. Here, we compare households' consumption, debt-financing, earning and debt-servicing behaviors between 2014 and 2017. The reason why we start from 2014 is that the Household Welfare Survey began to provide households' debt repayments record since 2014.

First, we divided households into age segments. Following the threshold in previous sections, young households are those with age less than 40, middles are between 40 and 55, and old households are age older than 55. Old households showed the lowest consumption growth. Over 3 years, their consumption increased only 3.0 percent, which is much lower than the total average of 12.1 percent. Furthermore, the old households reported the highest growth rate in income level, and biggest increase in debt level, and the lowest increases in income level. This indicates that old households' low growth rate of consumption were related with low income growth rate. Households with highest debt level growth rate were young households. Their debt level increased 53.6 percent during 3 years. This resulted highest increase in DSR, which is measured as  $\frac{\text{principal payments} + \text{interest payments}}{\text{disposable income}}$ . As before, the disposable income is before interest payments (Table 20).

Table 21 reports the consumption and leverage changes by income segment, but it's hard to find any stylized patterns among groups. The consumption growth was weakest in the top 20 percentiles, which recorded 5.9 percent growth rate, only half of the total average of 12.1 percent. Debt growth was highest in 40~60 percentiles, at 41.5 percent. But the debt-growth rate of low income households was very low. The lowest 20 percentile households' debt growth rate was 15.2 percent, and low 20~40 percent group's debt growth rate was only 3.1 percent. This may reflect that low income households were excluded in debt-financing activities as the authority adopted new loan regulation such as DSR. Lowest income growth and highest DSR change were in the top 20 percentile.

In Table 22, we divided households by job status criteria in 2014. Consumption growth of own business was weakest. Households with permanent job showed biggest increase in debt-level. This indicates that relatively stable income was helpful in raising more debts. Own business households' income growth rates were lowest and DSR changes were highest. This seems closely related to the lowest consumption growth of own business households. In overall, their income changes were most adverse, and considering the relatively high debt level

**Table 20**  
Consumption and debt changes by age.

Age Segments	Consumption growth	Debt Level growth	Income growth	DSR changes
Young	20.5 %	53.6 %	14.7 %	12.1 % <b>p</b>
Middle	12.1 %	21.9 %	16.6 %	8.7 % <b>p</b>
Old	3.0 %	27.2 %	12.2 %	2.2 % <b>p</b>
Total	12.1 %	27.2 %	12.2 %	7.0 % <b>p</b>

Note: Age groups are as of 2014. Growth rates are a comparison between 2014 and 2017. Bold numbers refers to the groups with the most adverse changes, which are the lowest in consumption growth, the highest in debt level growth, the lowest in income growth, and the highest in DSR changes.

**Table 21**  
Consumption and debt changes by income.

Income Segments	Consumption growth	Debt Level growth	Income growth	DSR changes
Low 20 percentile	15.4 %	15.2 %	55.3 %	-14.7% <b>p</b>
20~40 percentile	16.0 %	3.1 %	33.1 %	6.3 % <b>p</b>
40~60 percentile	13.7 %	41.5 %	21.5 %	8.3 % <b>p</b>
60~80 percentile	10.5 %	32.2 %	9.0 %	16.7 % <b>p</b>
Top 20 percentile	5.9 %	22.0 %	-1.6%	18.1 % <b>p</b>
Total	12.1 %	27.2 %	12.2 %	7.0 % <b>p</b>

Note: Income segments are as of 2014. Growth rates are comparisons between 2014 and 2017. Bold numbers refers to the groups with the most adverse changes, which are lowest in consumption growth, highest in debt level growth, lowest in income growth, and highest in DSR changes.

**Table 22**  
Consumption and debt changes by job status.

Job status	Consumption growth	Debt Level growth	Income growth	DSR changes
Permanent	13.0 %	41.5 %	12.2 %	6.5 % <b>p</b>
Temporary	10.2 %	24.3 %	13.3 %	3.0 % <b>p</b>
Own business	8.3 %	13.4 %	8.2 %	16.6 % <b>p</b>
Others	12.5 %	12.5 %	15.6 %	-1.2% <b>p</b>
Total	12.1 %	27.2 %	12.2 %	7.0 % <b>p</b>

Note: Job status is as of 2014. Growth rates are comparisons between 2014 and 2017. Bold numbers refers to the groups with most adverse changes, which are lowest in consumption growth, highest in debt level growth, lowest in income growth, and highest in DSR changes.

growth and DSR changes, own business households' overall financial soundness has been weakened. It is interesting that permanent job households' debt level growth was highest, but their DSR changes were relatively moderate. This seems to indicate that their loans were mainly 'straight' loans, which do not involve principal payments before the maturity.

Table 23 shows consumption and leverage changes in home ownership criteria. Consumption growth was lowest in households with holding at least two houses. Their income growth rates were also lowest, and DSR changes were highest. This indicates that their low consumption growth was closely related to low income growth and increased debt-service burdens. On the other hand, households with holding no house at all showed the highest debt level growth, but debt-servicing burdens for them showed no big changes. This may be due to the possibility that households with no house needed additional debts in order to pay increased prices for Jeonse, and that Jeonse-collateral loans are almost straight loans with a 2-year maturity. The jeonse price index rose 9.9 percent from March 2014 to March 2017, according to KB Kookmin Bank. Note that SFLC assets and liabilities are as of the end of March each year. Therefore, even though "Jeonse" households' debt growth was highest, their debt-servicing burden did not increase much.

We also divided households with income volatility change criteria

**Table 23**  
Consumption and debt changes by home-ownership.

Number of house holding	Consumption growth	Debt Level growth	Income growth	DSR changes
0	17.3 %	39.9 %	17.0 %	6.5 % <b>p</b>
At least 1	12.4 %	30.9 %	12.3 %	4.2 % <b>p</b>
At least 2	6.1 %	17.7 %	7.7 %	12.1 % <b>p</b>
Total	12.1 %	27.2 %	12.2 %	7.0 % <b>p</b>

Note: Home ownership criterion is as of 2014 base. Growth rates are comparisons between 2014 and 2017. Bold numbers refers to the groups with most adverse changes, which are lowest in consumption growth, highest in debt level growth, lowest in income growth, and highest in DSR changes.

**Table 24**  
Consumption and debt changes by income volatility.

Income volatility	Consumption growth	Debt Level growth	Income growth	DSR changes
Volatility decreased	13.6 %	35.5 %	10.0 %	-3.0%p
No big change	12.8 %	26.2 %	12.3 %	4.3 %p
Volatility increased	8.6 %	21.7 %	13.8 %	22.8 %p
Total	12.1 %	27.2 %	12.2 %	7.0 %p

Note: Growth rates are comparisons between 2014 and 2017. Bold numbers refers to the groups with most adverse changes, which are lowest in consumption growth, highest in debt level growth, lowest in income growth, and highest in DSR changes.

we used in previous chapter. Consumption growth was lowest in 'income volatility increased'. Considering their rapidly increased debt-service burden, their low consumption growth seems to be related to their debt-servicing burdens. We saw that households with increased income volatility lowered their leverage ratio. This implies they paid back (redeemed) some of their debts and this is shown in increased DSR, which includes principal payments for debts.

On the other hand, households with decreased income volatility showed high consumption growth rate and debt level growth rate. This can be attributed to the fact that such households can raise more debt with stable income, which may be helpful in the loan approval process. Notably, their income growth was lowest. Coinciding with rapidly increased debt levels and low income growth, one can conjecture that high consumption growth may be a result of debt-financing for consumption (Table 24).

We found some stylized patterns in consumption growth. In the standard criteria for household socioeconomic variables, such as age, income, job status and home ownership, household groups that showed the lowest consumption growth also had the lowest income growth. This indicates a close relationship between consumption and income. The main findings in this patterns are as follow:

However, in income volatility change criterion, the relationship between consumption growth and income growth breaks. Households with increased income volatility had the lowest consumption growth, even though their income growth rates were highest among groups. This seems to be due to the increased income volatility, as they lowered their leverage ratio, redeemed some of their debts and reduced their spendable money.

### 3.2. Baseline regression

In this section, we estimate household's consumption equation in order to identify the effects of income, wealth and debt level changes on consumption with the consideration of changes of income volatility. Following Campbell and Cocco (2007); Yoo and Byun (2012); Choi et al. (2015) and Park (2019), we estimate consumption equation using following specification. We use GMM dynamic panel estimation method proposed by Arellano and Bond (1998). The estimation method is known to be designed for dynamic "small-T, large-N" panels. The basic model is as follows:

$$\ln c_{i,t} = \alpha + \beta_0 \ln c_{i,t-1} + \beta_1 \ln y_{i,t} + \beta_2 Z_{i,t} + u_i + e_{i,t} \quad (5)$$

where the subscript  $i$  denotes each household,  $t$  is the year,  $c$  is the logged value of consumption,  $y$  is logged household income, and  $Z$  is a vector of household characteristics. We include number of family members as a demographic variable and the value of households' real estate asset values in order to capture the wealth effects. To evaluate the relationship between debt changes and consumption, we include debt levels. Finally, interest rates households face in loan market are included. All variables, except the number of family members, are deflated by consumer price index (CPI) and log-transformed, so that all variables are in real terms.  $u_i$  is household  $i$ 's idiosyncratic effect which is invariant with time.  $e$  is an error term. Since dynamic panel estimation includes lagged value of dependent variable in explanatory variables, controlling the endogeneity is needed. We follow the method

Arellano and Bond (1991) suggested. Difference equation form of Eq. (5) can be expressed as follows:

$$\ln c_{i,t} - \ln c_{i,t-1} = \beta_0 (\ln c_{i,t-1} - \ln c_{i,t-2}) + \beta_1 (\ln y_{i,t} - \ln y_{i,t-1}) + \beta_2 (Z_{i,t} - Z_{i,t-1}) + (e_{i,t} - e_{i,t-1}) \quad (6)$$

The lagged variables in level terms are used when estimating the difference equation, such as Eq. (6). But in many cases, household income, house price and debt level are variables with a unit root with random walk. Therefore, we use two-stage system GMM estimation suggested by Arellano and Bover (1995) and Windmeijer (2005) that use both equation, the level Eq. (5) and difference Eq. (6). We also report the Arellano-Bond test statistic that affirms the adequacy of the use of instrumental variables. Rejecting the AR(1) hypothesis while not rejecting the AR(2) hypothesis implies the use of instrumental variables was proper.

Standard consumption theory tells that when permanent income hypothesis (PIH) holds and credit market is perfect, coefficient of households' income is near zero, if income shock is temporary. Income coefficient would be positive if households are borrowing-constrained or the income shock is perceived as a permanent one, in particular, for young households whose the net present value of future earnings (human wealth) is large. If the borrowing constraint is binding, consumers must forcedly defer consumption, meaning that consumption grows more over time than it would with perfect credit markets. There is another important reason why consumers may want to postpone consumption, which is the desire to protect against income risk, the precautionary saving motives. If households face live just two periods, the second period's income uncertainty makes household to save more in first period. Yoo and Byun (2012) and Choi et al. (2015) reported positive coefficient of income, ranging from 0.09 to 0.15 with Korean household micro panel data. Campbell and Cocco (2007) reported income coefficient around 0.3. with UK household micro repeated cross sectional data. Park (2019) reported a negative coefficient of income with Korean household micro panel data, but their coefficients were statistically insignificant.

Wealth effects are known to have two kinds of effects on consumption. The first is that increasing households' perceived wealth increases life-time budget constraints. The second is through relaxation of borrowing constraints. Households can raise more debt with increased wealth, allowing them to consume more. Choi et al. (2015) reported that wealth effects increase with age, though the absolute value of wealth effects were smaller than income effects. Park (2019) reported that old households had about 9 times greater wealth effects than the average, and young households had 'negative' wealth effects, meaning house price increases were related to decreases in consumption.

Finally, if the purpose of households' debt-raising is for consumption expenditures, the relationship between debt and consumption will be positive. The second channel of wealth effects (relaxation of borrowing constraints) implicitly assumes that more debt-raising will be related to more consumption. On the contrary, households' deleveraging, which is essentially equivalent to saving, will be associated with less consumption. All these relations suggest a positive relationship between debt and consumption. However, for highly indebted households, leverage and consumption will be negatively related if high debt



**Table 25**  
Summary Statistics of regression variables.

	Mean	S.D.	Percentiles		
			25 %	50 %	75 %
Consumption	2.915	0.738	2.443	3.026	3.449
Income	3.478	0.952	2.935	3.637	4.139
Interest rate	0.017	0.018	0.021	0.025	0.026
Family size	2.894	1.301	2.000	3.000	4.000
House price	3.777	2.577	0.000	4.874	5.703
Debt	2.233	2.199	0.000	2.335	4.233

Note: All variables except interest rate and family size, are deflated by CPI and log transformed. Before log-transformation, we replaced with 1 if the value is zero.

levels induce increased debt servicing burdens. Therefore, it is difficult to postulate a single-direction relationship between household leverage and consumption, and such conjectures are needed to be checked with empirical data.

Before estimating the regression equation, we report descriptive statistics of variables. We changed all nominal values to real ones and log-transformed. In order to help understand the overall values in Korean won terms, we also report nominal values before log-transformation in parentheses in Table 25. Table 26 reports correlations among variables. It seems that there are no major correlations other than 'consumption-income' and 'consumption-family size'. But those relations seemed to be natural.

Table 27 reports the estimation results for Eq. (5). On average, the lagged value of consumption exerted the biggest influence on current consumption, reflecting the high persistency of consumption. Coefficients of income were estimated at about 0.16, implying a one percent increase of income was associated with 0.16 percent increase in consumption. This result is similar to the estimation by Choi et al. (2015). They reported the income coefficient was around 0.14.

Interest rate, which is defined as the rate of newly extended loans by depository institutions, had negative sign, which is consistent with the conventional intertemporal consumption model, but this was estimated to be insignificant. We also tried other versions of estimation with different setting of interest rates. We adopted the deposit rates as interest rates, and we dropped the interest rate variable in explanatory variable, but the results were similar to Table 27.

A one person increase in family member was estimated to be associated with 10 percent increase in consumption. House price was estimated to be insignificant in our baseline model. This indicates that the wealth effects for average households are small.

Finally, the coefficient of debt was positive and it was statistically significant. A one percent increase in debt was associated with 0.008 percent increase in consumption.

Arellano-Bond test statistics that are reported in the bottom row of Table 29 affirms the adequacy of the use of instrumental variables. Rejecting the AR(1) hypothesis while not rejecting the AR(2) hypothesis implies that the use of instrumental variables was proper. We also tried other versions of estimation with different variables. For example, we included age squared to capture the standard hump-shaped consumption pattern over life-cycle, but the coefficient of age squared was

**Table 26**  
Correlations of variables.

	(a)	(b)	(c)	(d)	(e)	(f)
Consumption (a)	1.000					
Income (b)	0.813	1.000				
Interest rate (c)	0.007	0.021	1.000			
Family size (d)	0.671	0.586	0.001	1.000		
House price (e)	0.336	0.365	0.030	0.228	1.000	
Debt (f)	0.440	0.426	0.019	0.352	0.422	1.000

positive, which implies a convex pattern over life-cycle. We thought the hump-shaped consumption pattern could be captured by income changes over time, since income level exhibits a hump-shaped over life-cycle.

### 3.3. Income volatility changes and consumption

In order to consider the effects of changes in income volatility on consumption, we estimated the same consumption equation with different household groups divided by the income volatility changes. Households who faced big changes, either increases or decreases, had a lower coefficient of income. This indicates households did not alter their consumption much in response to income volatility changes. Households with no big changes in income volatility had bigger coefficient of income. Households with decreased income volatility had relatively big coefficient of debt, indicating their consumption was more related to debt level changes. For other groups, the coefficients of debt were estimated to be insignificant (Table 28).

In order to double-check households' consumption behavior changes in response to increased income volatility, we use the interaction term between  $I\{Volatility\ Increase\}_i$  and each variable. We also considered interaction terms using  $\Delta SD_i$ , but the estimation results were similar. Only the 'Income  $\times I\{Volatility\ Increase\}_i$ ' term was statistically significant. Households with increased volatility did not adjust their consumption on income changes. The coefficient even indicates if income rises, consumption would be lowered, since their income responses are  $0.476(\text{income}) - 0.549(\text{income} \times I_{Vol\_Inc}) = -0.073$ . This implies that when faced with a substantial increase in income volatility, households maintained their consumption expenditure level even under more volatile income changes. Other interaction terms were estimated to be statistically insignificant, implying that there are no clear effects of income volatility changes on households' wealth effects and debt-raising effects.

### 3.4. Borrowing constraints and consumption

In this section, we search changes of consumption behaviors among (potentially) borrowing constrained households.

#### 3.4.1. By LTV

According to standard consumption theory, borrowing-constrained households would have bigger income coefficient, while coefficient of income for households without borrowing constraint would be near zero. In Table 30, the coefficient of income for potentially borrowing constrained households was bigger in  $LTV_i^N$ , while potentially borrowing constrained households' coefficient was smaller in  $LTV_i^B$  criteria. Thus, it is difficult to conclude borrowing constrained households had bigger income coefficient.

In LTV ratio criteria, 'potentially' borrowing constrained households had bigger coefficient of debt levels. Compared to the average households' debt coefficient 0.008, households with LTV ratio higher than 0.6 had debt coefficients of 0.026 ~ 0.031. This indicate their consumptions were more affected by their debt-financing activities. This also implies if they deleverage their debt level, their consumption would be lowered further. A one percent increase (decrease) in debt was associated with 0.026 ~ 0.031 percent increase (decrease) in consumption.

Other coefficients, such as income and family size and house prices, were similar to that of average households, and the coefficient of interest rates were estimated to be statistically insignificant, as it was in the estimation for the average households.

#### 3.4.2. By net wealth

The income coefficient for households with net wealth of less than 5000 10k Korean won was 0.270, which is bigger than the average households and households with net wealth larger than 5000 10k Korean won. Households with net wealth less than zero had smaller

**Table 27**  
Estimation results for basic model.

	(i)	(ii)	(iii)	(iv)
Consumption (lag1)	0.189*** (0.032)	0.185*** (0.032)	0.183*** (0.032)	0.183*** (0.032)
Income	0.164*** (0.024)	0.163*** (0.026)	0.163*** (0.026)	0.162*** (0.026)
Interest rate	-0.157 (0.134)	-0.093 (0.135)	-0.089 (0.136)	-0.087 (0.136)
Family size		0.104*** (0.013)	0.105*** (0.013)	0.104*** (0.013)
House price			-0.002 (0.004)	-0.005 (0.004)
Debt level				0.008** (0.003)
Observations	11,956	11,956	11,956	11,956
A-B test p-value				
AR(1)	0.000	0.000	0.000	0.000
AR(2)	0.965	0.741	0.727	0.833

Note: This model was estimated by the two-stage system GMM method. \*\*\*, \*\*, \* denote statistical significance at 1 %, 5 %, 10 % levels, respectively.

**Table 28**  
Estimation results for different volatility groups.

Dep. Variable:	Income volatility decreased	No big change	Income volatility increased
Consumption (lag1)	0.181*** (0.053)	0.221*** (0.042)	0.218*** (0.077)
Income	0.154*** (0.048)	0.282*** (0.021)	0.118*** (0.029)
Interest rate	0.434 (0.299)	-0.268 (0.183)	-0.352 (0.262)
Family size	0.120*** (0.025)	0.075*** (0.018)	0.109*** (0.022)
House price	-0.015* (0.008)	-0.000 (0.006)	-0.001 (0.007)
Debt level	0.021*** (0.007)	0.003 (0.004)	0.010 (0.007)
Observations	2,924	6,064	2,968

Note: This model is estimated by the two-stage system GMM method. \*\*\*, \*\*, \* denote statistical significance at 1 %, 5 %, 10 % levels, respectively.

**Table 29**  
Estimation with interaction term.

Dep. Variable: Consumption	(A)	(B)	(C)
Income	0.476*** (0.103)	0.154*** (0.031)	0.166*** (0.026)
Interest rate	-0.378** (0.166)	-0.213 (0.169)	-0.166 (0.156)
Family size	0.090*** (0.016)	0.108*** (0.015)	0.111*** (0.008)
House price	-0.007* (0.004)	0.044 (0.036)	-0.007 (0.005)
Debt level	0.008** (0.003)	0.005 (0.005)	0.045 (0.034)
Income × <i>I<sub>VOL_INC</sub></i>	-0.549*** (0.154)		
House price × <i>I<sub>VOL_INC</sub></i>		-0.163 (0.125)	
Debt × <i>I<sub>VOL_INC</sub></i>			-0.140 (0.127)
Observations	11,956	11,956	11,956

Note: This model is estimated by the two-stage system GMM method. \*\*\*, \*\*, \* denote statistical significance at 1 %, 5 %, 10 % levels, respectively.

income coefficient, but it was statistically insignificant (Table 31).

Coefficient of debt for potentially borrowing-constrained households was estimated to be higher than the average households, and this seems to be consistent to the results we obtained in LTV criteria. Coefficient of house price was estimated to be negative and statistically significant, implying they are ‘net-short’ of real estate assets. Other variables were estimated to be roughly not very different from those of LTV criteria.

**Table 30**  
Estimation results: LTV.

Dep. Variable:	<i>LTV<sub>i</sub><sup>N</sup> ≤ 0.6</i>	<i>LTV<sub>i</sub><sup>N</sup> &gt; 0.6</i>	<i>LTV<sub>i</sub><sup>B</sup> ≤ 0.6</i>	<i>LTV<sub>i</sub><sup>B</sup> &gt; 0.6</i>
Consumption				
Income	0.153*** (0.025)	0.198*** (0.047)	0.160*** (0.026)	0.107* (0.059)
Interest rate	-0.066 (0.138)	-1.501** (0.645)	-0.138 (0.141)	-0.363 (0.482)
Family size	0.109*** (0.013)	0.053 (0.071)	0.107*** (0.013)	0.105** (0.045)
House price	-0.001 (0.004)	-0.032*** (0.011)	-0.002 (0.004)	-0.015 (0.010)
Debt level	0.007* (0.003)	0.026** (0.010)	0.005 (0.003)	0.031*** (0.010)
Observations	11,434	522	10,862	1,094

Note: This model is estimated by the two-stage system GMM method. \*\*\*, \*\*, \* denote statistical significance at 1 %, 5 %, 10 % levels, respectively.

**Table 31**  
Estimation results: net wealth.

Dep. Variable: Consumption	<i>NW<sub>i</sub> &lt; 0</i>	<i>NW<sub>i</sub> &lt; 5,000</i>	<i>NW<sub>i</sub> ≥ 5,000</i>
Income	0.104 (0.075)	0.270*** (0.078)	0.131*** (0.023)
Interest rate	1.077 (0.907)	0.002 (0.269)	-0.148 (0.155)
Family size	0.190*** (0.053)	0.124*** (0.030)	0.100*** (0.014)
House price	-0.033 (0.023)	-0.032*** (0.008)	0.000 (0.004)
Debt level	0.041* (0.021)	0.018** (0.008)	0.005 (0.004)
Observations	218	2,721	9,235

Note: *NW<sub>i</sub> < 5,000* refers to households with net wealth less than 5,000 10k Korean won. This model is estimated by the two-stage system GMM method. \*\*\*, \*\*, \* denote statistical significance at 1 %, 5 %, 10 % levels, respectively.

### 3.4.3. By HDRI

The estimation results of income coefficients seem to reject the standard consumption theory that borrowing constrained households would have higher income coefficient on consumption. ‘Potentially not’ borrowing constrained households, whose HDRI were less than 100, had highest value of income coefficient.

On the other hand, as we found in LTV and net wealth criteria, borrowing constrained households had a higher coefficient of debt, implying their consumptions were more related to debt. Households with HDRI higher than 100 had a debt coefficient 0.038, which is six times bigger than households with HDRI less than 100. However, households with DSR higher than 0.4 had relatively small coefficient of debt and it was statistically insignificant. This seems to be consistent to the result we found in Chapter 2.5 that households’ leverage response was more related to DTA measure, and DSR measure seemed to have

**Table 32**  
Estimation results: HDRI.

Dep. Variable: Consumption	$HDRI_i \leq 100$	$HDRI_i > 100$	$DSR_i > 0.4$	$DTA_i > 1.0$
Income	0.173*** (0.025)	0.071*** (0.022)	0.071*** (0.015)	0.170** (0.081)
Interest rate	-0.147 (0.141)	-0.337 (0.635)	0.064 (0.391)	-0.105 (0.692)
Family size	0.098*** (0.014)	0.147*** (0.035)	0.146*** (0.032)	0.160*** (0.042)
House price	-0.005 (0.004)	-0.013 (0.019)	-0.010 (0.008)	-0.022 (0.016)
Debt level	0.006** (0.003)	0.038* (0.020)	0.004 (0.006)	0.034** (0.013)
Observations	11,369	587	1,819	414

Note: This model is estimated by the two-stage system GMM method. \*\*\*, \*\*, \* denote statistical significance at 1 %, 5 %, 10 % levels, respectively.

little power in explaining households' leverage choices (Table 32).

### 3.4.4. By borrowing rate

Here, we use households' effective borrowing rates as a criterion for borrowing constraints. The regression results in Table 33 are different from the results we obtained in other criteria. Income coefficients were estimated to be statistically insignificant, and more importantly, coefficients of debt were small and insignificant for 'potentially' borrowing constrained households. We think it is not appropriate to apply borrowing rate related criteria in the analysis of households' consumption. The only statistically significant coefficient for this criterion was the number of family members.

### 3.4.5. Borrowing constraints and income volatility changes

Here, we analyze the effects of increased income volatility on households' consumption behavior. As we estimated in Table 29, we use the interaction term of  $I\{Volatility\ Increase\}_i$  and other key variables, including income, house price and debt. We estimated all separate equations, but for simplicity, we report the coefficient of interaction term variables only, in order to ascertain whether households' changes in income volatility had effects on each key variable. Since our primary concern in this section is whether borrowing constrained households changed their consumption behavior in response to income volatility changes, we restrict our sample to households with potentially borrowing-constrained in terms of each criterion we used in this section.

Table 29 reports that an increase in income volatility lowers borrowing constrained households' income coefficient. The coefficients were statistically significant in LTV and HDRI criteria, and not significant in net wealth and borrowing rates criteria. But all coefficients

**Table 33**  
Estimation results: borrowing rate.

Dep. Variable: Consumption	$r_i^L \leq 1.5 \times r^B$	$r_i^L > 1.5 \times r^B$	$r_i^L > 2.0 \times r^B$
Income	0.141*** (0.040)	0.092** (0.038)	0.055 (0.034)
Interest rate	-0.123 (0.254)	-0.274 (0.377)	-0.338 (0.539)
Family size	0.070*** (0.024)	0.150*** (0.029)	0.152*** (0.037)
House price	-0.006 (0.006)	0.006 (0.012)	0.027 (0.020)
Debt level	0.009 (0.007)	0.000 (0.009)	0.001 (0.011)
Observations	3,483	1,650	871

Note:  $r_i^L$  refers to household  $i$ 's effective borrowing rate and  $r^B$  refers to the average newly extended loans interest rate charged by depository institutions. This model is estimated by the two-stage system GMM method. \*\*\*, \*\*, \* denote statistical significance at 1 %, 5 %, 10 % levels, respectively.

**Table 34**  
Estimation results with interaction term.

Dep. Variable: Consumption	$LTV_i^B > 0.6$	$NW_i < 5000$	$HDRI_i > 100$	$r_i^L > 1.5 \times r^B$
Income $\times I_{Vol\_Inc}$	-1.231*** (0.428)	-0.142 (0.232)	-0.286** (0.120)	-0.081 (0.275)
House price $\times I_{Vol\_Inc}$	-0.411 (0.437)	-0.239 (0.311)	0.000 (0.257)	-0.108 (0.298)
Debt level $\times I_{Vol\_Inc}$	-0.118 (0.343)	-0.549* (0.310)	0.423*** (0.151)	-0.035 (0.370)
Observations	1,094	2,721	587	1,650

Note: Coefficient in each cell are estimated with every different specification. This model is estimated by the two-stage system GMM method. \*\*\*, \*\*, \* denote statistical significance at 1 %, 5 %, 10 % levels, respectively. Numbers in parenthesis are robust standard errors.

were estimated to be negative. This implies that faced with income volatility, borrowing constrained households smoothed their consumption, even under more volatile income changes. However, previous analysis showed that the average households also had smaller income coefficient if they face increased income volatility. Thus, it is still not clear whether borrowing-constrained households 'more' lowered their income coefficient than the average households, in response of income volatility changes. But one thing that seems clear is that income coefficients tend to be lower if income volatility increases.

Next, it is not clear that enlarged income uncertainty increase affects households' wealth effects. One of our prior hypothesis was that increased human wealth uncertainty would lower wealth effects by precautionary saving motives. However, the regression results say the relationship is unclear. The effects of income volatility changes on debt level changes were also estimated to be not significant (Table 34).

## 3.5. Heterogeneity across groups and consumption

In this section, we search for changes in consumption behaviors with the consideration of household heterogeneity

### 3.5.1. By age

The coefficient of income was highest in the middle aged group, while old households had the lowest income coefficient. A one percent increase in income was associated with 0.189 percent increase in current consumption for middle aged households, but old households' consumption only increased 0.144 percent with the same rate of income growth. This is consistent with the life-cycle theory of consumption where old aged households have shorter periods for their income earning years, so their consumption is less affected by income changes. On the other hand, young households' income coefficient was estimated to be lower than that for middle aged households. This implies that young workers face substantial uncertainty about their future earnings, making their consumption less responsive than that of middle aged households (Table 35).

Young households' coefficient of debt levels was highest, while middle aged households had a smaller and insignificant coefficient. This indicates that young households' consumption is more related to their debt level changes. Old households also had a relatively large coefficient of debt levels, since their consumption is more affected by asset and liability conditions than their income.

### 3.5.2. By home ownership

Income coefficient for households with at least one house was highest, while the coefficient for households with at least two houses were lowest. Income coefficient for households with no house was between households with at least one and two houses.

Note that this criterion is different from 'renters vs. owner-occupied.' Households with no house would be considered as 'net-short' of

**Table 35**  
Estimation results: different age group.

Dep. Variable: Consumption	Young ( $age_i \leq 40$ )	Middle ( $40 < age_i \leq 55$ )	Old ( $age_i > 55$ )
Income	0.171** (0.069)	0.189*** (0.071)	0.144*** (0.031)
Interest rate	0.065 (0.313)	-0.300 (0.212)	-0.083 (0.235)
Family size	0.131*** (0.033)	0.071*** (0.023)	0.144*** (0.019)
House price	-0.000 (0.007)	0.004 (0.006)	-0.014* (0.008)
Debt level	0.014* (0.008)	0.004 (0.005)	0.012** (0.005)
Observations	1,879	4,351	5,726

Note: This model is estimated by the two-stage system GMM method. \*\*\*, \*\*, \* denote statistical significance at 1 %, 5 %, 10 % levels, respectively.

**Table 36**  
Estimation results: number of house holding.

Dep. Variable: Consumption	Number of house holding		
	No house	At least one	At least two
Income	0.176*** (0.045)	0.200*** (0.054)	0.096*** (0.022)
Interest rate	-0.048 (0.228)	-0.195 (0.218)	-0.461* (0.270)
Family size	0.100*** (0.021)	0.097*** (0.021)	0.123*** (0.023)
House price	-0.014*** (0.005)	-0.003 (0.005)	0.085*** (0.021)
Debt level	0.008 (0.005)	0.003 (0.005)	0.009 (0.006)
Observations	4,143	4,424	3,389

Note: This model is estimated by the two-stage system GMM method. \*\*\*, \*\*, \* denote statistical significance at 1 %, 5 %, 10 % levels, respectively.

real estate assets, and households with more than two houses would be classified as 'net-long.' The coefficient of house price was estimated to be significantly positive for households with at least two houses. This indicates that as they are 'net-long' in real estate assets, increases in their real assets were strongly related with their current consumption. This is consistent with the results of Park (2019). For households with no house, the coefficient was negative. We also further divided households into different age groups, but we could not find any significant difference (Table 36).

3.5.3. By job industry change

Table 37 reports households who changed their job industry from

**Table 37**  
Estimation results: job industry change.

Dep. Variable: Consumption	Safe to risky industry	Risky to safe industry	No change
Income	0.170*** (0.056)	0.520*** (0.138)	0.132*** (0.045)
Interest rate	-1.575** (0.680)	-0.451 (0.865)	-0.170 (0.200)
Family size	0.069 (0.045)	0.100 (0.076)	0.058*** (0.021)
House price	0.007 (0.021)	-0.009 (0.021)	-0.004 (0.005)
Debt level	-0.007 (0.022)	0.009 (0.018)	0.014*** (0.005)
Observations	508	208	5,108

Note: This model is estimated by the two-stage system GMM method. \*\*\*, \*\*, \* denote statistical significance at 1 %, 5 %, 10 % levels, respectively.

**Table 38**  
Estimation results with household heterogeneity.

Dep. Variable: Consumption	Age young	Age middle	Age old	House Net short	House Net long
Income $\times I_{Vol\_Inc}$	-1.021*** (0.279)	-0.665*** (0.252)	-0.049 (0.256)	-0.486*** (0.155)	0.140 (0.419)
House price $\times I_{Vol\_Inc}$	0.255 (0.249)	-0.212 (0.149)	0.548 (0.450)	-0.033 (0.238)	-0.027 (0.417)
Debt level $\times I_{Vol\_Inc}$	-0.100 (0.134)	-0.178 (0.115)	0.202 (0.272)	-0.356*** (0.120)	0.118 (0.396)
Observations	1,879	4,351	5,726	4,143	3,389

Note: Coefficient in each cell are estimated with every different specification. This model is estimated by the two-stage system GMM method. \*\*\*, \*\*, \* denote statistical significance at 1 %, 5 %, 10 % levels, respectively. Numbers in parenthesis are robust standard errors.

risky to safe had the highest income coefficient. This result is intuitive, since as households perceive their income uncertainty decreased permanently, precautionary saving motive would be lowered, so their current income exerted more effects on current consumption. However, due to the small sample size, the results are not free from robustness issue.

3.5.4. Household heterogeneity and income volatility changes

It is found that faced with increased income volatility, income coefficients were lowered, which is similar to the result we saw in borrowing-constrained households. Income coefficient of young and net short in real estate assets were more affected by income volatility increases. However, it is difficult to say wealth effects and the effects of debt on consumption had significant changes when households face increased income volatility (Table 38).

4. Concluding remarks

In this paper, we have used Korean households' micro level data to estimate the response of household leverage and consumption to income volatility changes. The main findings were as follows:

First, an increase in households' income uncertainty was associated with households' deleveraging. In the aspect of risk management incentives of human wealth and 'tangible' wealth, this can be considered as risk-averse households adjusting their risk exposure stemming from 'tangible' wealth if they face increases in human wealth uncertainty. In particular, potentially borrowing-constrained households lowered their leverage ratio more rapidly in response to income volatility increases. As income volatility increases, borrowing-constrained households might face a 'forced' deleveraging needs, indicating they were no longer able to roll-over the existing debts or cannot raise additional debt. In terms of households' socio-economic variables, middle-aged households and household with 'net-short' of real estate assets had lowered leverage ratio more quickly in response to income volatility changes. This is consistent with the standard life-cycle theory that old households are less affected by income shock, since they have shorter periods of earning time, while young and middle aged households are more affected by human wealth uncertainty. And as poor households are more risk-averse, households with few real assets were more responsive to income uncertainty changes.

Second, faced with increased income volatility, households' income coefficients on consumption were lowered. This reflects households' consumption smoothing behaviors. In particular, consumption among households that were borrowing-constrained in terms of asset-related measures, middle aged households, and 'net-short' in real estate assets were more affected by an increase in income volatility. Coinciding with households' leverage choice change, highly indebted households' consumption would be more affected by income volatility changes.

However, since our analysis heavily depends on SFLC, which is



survey-based soft data, our results are not free from survey biases. And the length of the time series we used in panel analysis was only six years. This makes it hard to identify the structural changes in income volatility, which was the primary measure in our analysis. We did not consider households' liquidity conditions, which incorporates important factors in households' financial decision making. Finally, constructing a structural model would be needed to find more implications of the effects of income volatility changes on households' behavior.

## References

- Abe, N., Yamada, T., 2009. Nonlinear income variance profiles and consumption inequality over the life cycle. *J. Int. Econ.* 23 (3), 344–366.
- Arellano, M., Bond, S., 1991. Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *Rev. Econ. Stud.* 58, 277–297.
- Arellano, M., Bond, S., 1998. Dynamic Panel Data Estimation Using DPD98 for Gauss: A Guide for Users.
- Arellano, M., Bover, O., 1995. Another look at the instrumental variable estimation of error-components models. *J. Econom.* 68, 29–51.
- Attanasio, O.P., 1995. The Intertemporal Allocation of Consumption: Theory and Evidence. *Carnegie-Rochester Conference Series on Public Policy*, vol. 42. Elsevier, pp. 39–56 (1).
- Blundell, R., Pistaferri, L., Preston, I., 2008. Consumption inequality and partial insurance. *Am. Econ. Rev.* 98, 1887–1921.
- Brunnermeier, M.K., Nagel, S., 2008. Do wealth fluctuations generate time-varying risk aversion? Micro-evidence on individuals. *Am. Econ. Rev.* 98 (3), 713–736.
- Campbell, J.Y., Cocco, J.F., 2007. How do house prices affect consumption? Evidence from micro data. *J. Monet. Econ.* 54 (3), 591–621.
- Chang, Y., Hong, J., Karabarbounis, M., 2018. Labor market uncertainty and portfolio choice puzzles. *Am. Econ. J. Macroecon.* 10 (2), 222–262.
- Chang, Y., Hong, J., Karabarbounis, M., Wang, Y., 2019. Income Volatility and Portfolio Choices. Working Paper.
- Choi, S., Song, S., Kim, Y., 2015. The effects of house prices on consumption: evidence from micro panel data on mortgage borrowers. *Econ. Anal.* 21, 2 the Bank of Korea.
- Crook, J., 2003. The Demand and Supply for Household Debt: A Cross Country Comparison. Working Paper. Credit Research Centre, University of Edinburgh.
- Deaton, A.S., 1992. *Understanding Consumption*. Oxford University Press, Oxford.
- Gu, B., 2007. Structural changes and prospect of bank financing in Korea. *J. Money Financ.* 21, 29–52 the Korea Money and Finance Association.
- Guvenen, F., 2007. Learning your earning: are labor income shocks really very persistent? *Am. Econ. Rev.* 97 (3), 687–712.
- Jappelli, T., Pistaferri, L., 2017. *The Economics of Consumption, Theory and Evidence*. Oxford University Press, Oxford.
- Kaplan, G., Violante, G.L., 2010. How much consumption insurance beyond self-insurance? *Am. Econ. J. Macroecon.* 2 (4), 53–87.
- Ogawa, K., Wan, J., 2007. Household debt and consumption: a quantitative analysis based on household micro data for Japan. *J. Hous. Econ.* 16, 127–142.
- Park, C., 2019. Through which channel do house price changes affect consumption? Evidence from panel data in South Korea. *Anal. Korean Econ.* 25 (1) 2019, 4, Korea Institute of Finance.
- Song, S., 2018. Leverage, Hand-to-Mouth Households, and MPC Heterogeneity: Evidence from South Korea. BOK Working Paper No. 2018-21.
- the Bank of Korea, 2015. Financial Stability Report 2015. June. .
- the Bank of Korea, 2017. Financial Stability Report 2017. June. .
- Windmeijer, F., 2005. A finite sample correction for the variance of linear efficient two-step GMM estimators. *J. Econom.* 126 (1), 25–51.
- Yoo, K., Byun, Hae Won, 2012. The increase in household debt and borrowing constraints. The bank of Korea, economic research institute. 2011. *Econ. Anal.* 18 (1), 3.
- Zhou, Y., 2003. Precautionary saving and earnings uncertainty in Japan: a household-level analysis. *J. Jpn. Int. Econ.* 17 (2), 192–212.

## Further reading

- [dataset] Bank for International Settlements., 2019. Credit to the non-financial sector statistics. <https://www.bis.org/statistics/totcredit.htm?m=6%7C380%7C669>.
- [dataset] Korea Labor Institute., 2019. Korean Labor and Income Panel Study, micro raw data from year 2012 to year 2017. [https://www.kli.re.kr/klips\\_eng/index.do](https://www.kli.re.kr/klips_eng/index.do).
- [dataset] Statistics Korea., 2019. Survey of Household Finances and Living Conditions, micro raw data from year 2012 to year 2017. <https://mdis.kostat.go.kr/index.do>.
- [dataset] the Bank of Korea., 2019. Economic Statistics System. <http://ecos.bok.or.kr/>.