

From Education to Consumption Smoothing*

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Abstract

We study consumption and saving behavior by education group in Iceland from 2005-2019, a turbulent period marked by dramatic fluctuations in earnings and capital income. We derive a model in which inherent patience is reflected in the choice of education—a profession with a higher rate of return attracts individuals with a lower rate of subjective time preference. These individuals accumulate more liquid savings, smooth consumption to a greater extent, and have a lower marginal propensity to consume. Using microdata containing the tax returns of all Icelandic taxpayers, we find that higher education is associated with a lower marginal propensity to consume (MPC) due to higher disposable income and more liquidity. Comparing fields by their rate of return on investment, we find lower MPC in higher-rate-of-return fields and greater liquidity. Using survey data, we find supporting evidence that university-educated individuals smooth consumption more than those with shorter education.

Keywords: Education, consumption, inequality, macroeconomic stability.

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1 Introduction

We study consumption smoothing by education during a turbulent period in Iceland, when disposable income fluctuated dramatically due to a financial boom-and-bust and the subsequent economic recovery. The sample period is unique for an advanced economy as the country’s entire banking system collapsed, resulting in a large unforeseen exogenous shock to household income. We use this episode to measure differences in educational groups’ propensities to consume and to assess whether their ability to weather the storm differed across groups.

Education may matter for individuals’ ability to smooth consumption during economic recessions. Not only can a high level of education be associated with relatively high earnings, but it can also increase an individual’s ability to plan for the future, thus improving households’ capacity to smooth consumption throughout the life cycle. There are also substantial differences in the rate of return across university education fields. We hypothesize that individuals who have invested in high-return fields of education smooth consumption more than those who have invested in low-return fields. The mechanism we focus on is inherent patience, a low subjective rate of time preference. High-return fields require giving up income today for higher income tomorrow. More patient individuals value future income more, so they are more willing to make that investment and sort into those fields. According to our thesis, greater patience also makes consumption smoother, implying a lower MPC.

We use a rich administrative panel dataset comprising tax records for all Icelandic taxpayers from 2005 to 2019, combined with various background characteristics, to impute consumption for every household based on after-tax income and net worth at the beginning of each year. We then estimate the marginal propensity to consume for educational groups. We distinguish among people with primary, secondary, and tertiary (university-level) educational attainment, and also between different fields of university education. They differ in the rate of return to education, which we take as a reflection of their inherent patience.¹

¹We avoid aggregation bias ([Attanasio and Weber, 1995](#)) by using individual data for every taxpayer in a

We use the panel dimension of our data, along with information on household characteristics, to estimate households' consumption responses to idiosyncratic transitory income shocks. First, we derive idiosyncratic income and consumption shocks from the within-household relationship between consumption and household characteristics, on the one hand, and between income and household characteristics, on the other. Second, we use 2SLS to estimate the consumption response to idiosyncratic transitory income shocks. Furthermore, we test for heterogeneity in the response of consumption to income shocks across education groups and several other characteristics, including income, wealth, and liquidity.

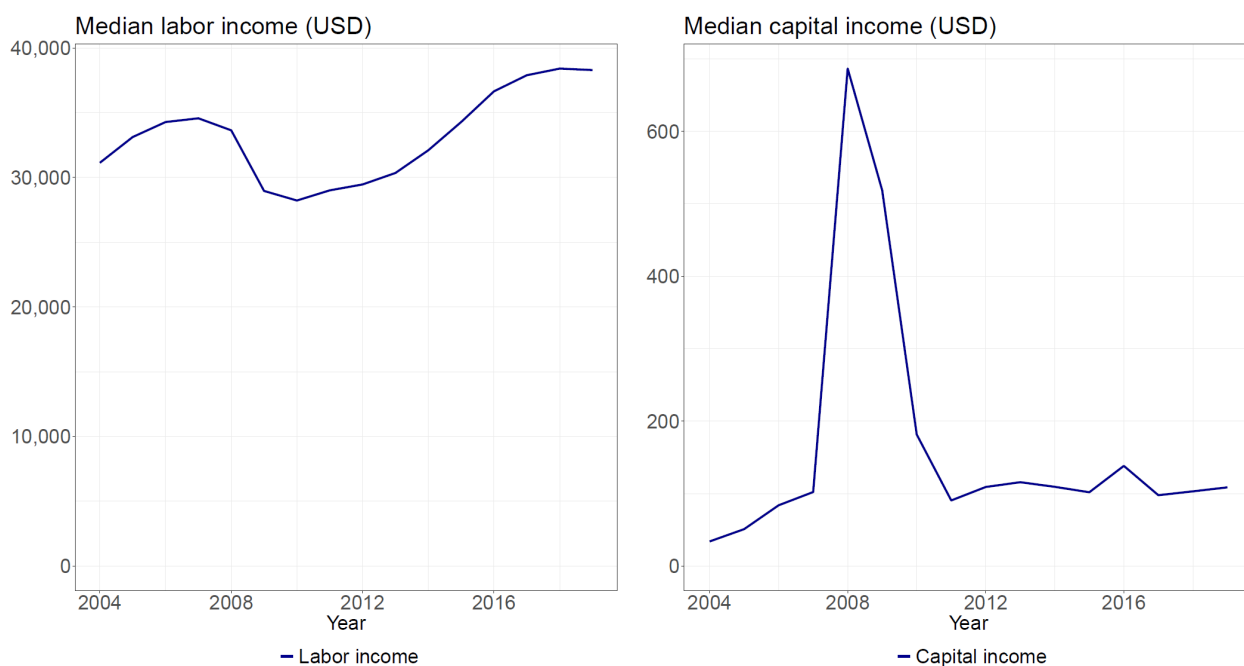
Our sample period, 2005-2019, encompasses major changes in disposable income in Iceland. These changes were unexpected because the collapse of the bubble economy caught most people by surprise, providing a unique opportunity to estimate consumption smoothing by education group and to analyze the time variation in the MPC during this turbulent period. Furthermore, unlike many other studies that estimate MPCs using windfall income, we identify both positive and negative income shocks. Studying the asymmetry in households' consumption responses to income shocks is important for understanding how households respond to different shocks, with implications for the evolution of the MPC over the economic cycle and for the effectiveness of monetary and fiscal policy in influencing demand. Average disposable income at constant prices rose during the financial boom from 2003 to 2008, then fell after the banking collapse in 2008, and finally rose again during the recovery phase prior to the COVID-19 pandemic.

Figure 1 shows the median income from earnings (wages and income of the self-employed) and the median income from capital (before taxes) between 2003 and 2019. Earnings peaked in 2007, the year before the collapse of the country's banking system, declined through 2010, and then increased again. They reached their earlier peak in 2016 and subsequently increased further, reaching a new peak in 2018. The fall from the peak in 2007 to the trough

country, following each taxpayer over time. This enables us to test for heterogeneity in consumption behavior across education groups and several other household characteristics, such as age, wealth, and liquidity, and to examine their consumption responses to transitory income shocks.

in 2010 is 22%. The fluctuations in capital income were even greater. Capital income rose rapidly during the bubble years, increasing approximately 15 times between 2003 and 2007, and then collapsed in 2009 and 2010. These fluctuations in average earnings and income were unanticipated and exogenous to each household’s planned expenditures and savings decisions. Because we have data on each individual’s education, age, marital status, number of children, and wealth, we can estimate the propensity to consume across education groups during this turbulent period while controlling for these variables.

Figure 1: Median annual labor and capital income in US dollars, 2004-2019



Notes: Figure 1 shows median annual labor income (left panel) and median annual capital income (right panel) in 2004-2019 for individuals aged 31-80 in USD at 2019 prices. Both series are converted to 2019 prices using Statistics Iceland’s CPI index and then converted to USD using mid-2019 exchange rates.

We complement our main results with survey evidence on saving motives. The results show that university-educated households are more likely to report consumption smoothing and that financing future consumption is their main motivation for saving. On the other hand, less-educated households are more likely to report behavior consistent with a high propensity to consume from transitory income, such as saving only through mandatory pension contributions.

In summarizing our key results, we find that university-educated households smooth consumption more than other households, as measured by the marginal propensity to consume (MPC) in response to transitory income shocks. Within the university-educated group, there is also a strong negative relationship between the rate of return to education and the share of liquidity constraints and the marginal propensity to consume. We also find an asymmetry in the effects of positive and negative shocks: households' consumption response to negative income shocks is stronger than to positive income shocks. Furthermore, there is heterogeneity in the MPC across income distributions (it varies with income and is lower for high-income individuals) and liquidity (it varies with liquidity and is higher for liquidity-constrained individuals).

Finally, during the global financial crisis and following the collapse of Iceland's banking system, the MPC increased markedly, then normalized once the economic recovery took hold. While this is true across education groups, fluctuations in the MPC are particularly pronounced among university-educated households; the MPC falls more during downturns and rises more during economic recoveries. Studying the time variation in the MPC separately for positive and negative income shocks reveals that the surge during the crisis was largely driven by a particularly strong consumption response to negative income shocks, with households tending to cut their consumption approximately one-to-one. The MPC, in response to positive income shocks, also rose during the crisis, albeit by a smaller amount. Therefore, households increased their consumption slightly more in response to a positive shock during the crisis than during periods closer to equilibrium or during economic expansions. This pattern is consistent with macroeconomic evidence showing that the macroeconomic multiplier increases during economic crises.

From here, the paper proceeds as follows. Section 2 reviews the literature relevant to our study, and Section 3 derives a compact model linking patience to educational choice, saving, and consumption. Section 4 presents our data. Section 5 estimates the effect of education on household consumption behavior, and Section 6 relates the MPC by education to the

share liquidity constrained and the rate of return by field of education. Section 7 presents additional perspectives based on survey evidence. We conclude in Section 8.

2 The context of the paper

Our period of study includes the 2008 financial crisis, which severely affected Iceland. We are not the first to study consumption smoothing during a financial crisis, but our study has the advantage of linking tax return data to each taxpayer's educational level, and of exploring the reasons for our results using survey data on saving motivation.

Our study contributes to the literature on heterogeneity in the MPC in response to unanticipated income shocks. The literature typically finds greater excess sensitivity to transitory income changes than predicted by the permanent income hypothesis, a result attributed to liquidity constraints and uncertainty about income-generating target-saving behavior. [Carroll \(2001\)](#) found that buffer-stock saving generates consumption behavior that resembles the effect of liquidity constraints. We contribute to this literature by measuring the excess sensitivity of income to transitory changes by education during a period when both earnings and capital income fluctuated widely in ways that could not be anticipated.

It is not straightforward to identify which households are liquidity-constrained, but data from tax returns on liquid assets, total assets, net worth, and income enable us to measure liquidity constraints for each taxpayer. [Hayashi \(1985\)](#) uses savings as an indicator of such liquidity constraints, while [Zeldes \(1989\)](#) uses the assets-to-income ratio. [Lusardi \(1996\)](#) uses data from the Consumer Expenditure Survey and the Panel Study of Income Dynamics (PSID) and finds that consumption is excessively sensitive to predictable income growth. [Fagereng et al. \(2021\)](#) study the response of lottery winners in Norway and find that spending peaks in the year of winning and that the MPC for low-liquidity winners is close to one. [Parker et al. \(2013\)](#) use the Consumer Expenditure Survey to calculate the propensity of households in the US to spend out of the economic stimulus payments made in 2008 and

find that households spent 50-90% of the payment on non-durable and durable goods over the three-month period during which they received the payments. Across households, the spending responses were largest for older and low-income households.

The ability and foresight required to accumulate buffer stock savings, having liquid assets to meet unexpected spending needs, and the foresight to take future income into account may be related to education and social status. [Canbary and Grant \(2019\)](#) use the Family Expenditure Survey in the UK to find the relationship between the MPC and socioeconomic status and find that households with higher socioeconomic status have lower MPCs. However, they do not have access to data on household education levels. These findings are consistent with those of [Carroll \(2001\)](#), who found that the MPC declines with income, so that wealthy people spend a smaller proportion of a transitory income shock than poor people, a result consistent with our findings in this paper. From this finding, it follows that the average MPC should increase during a crisis. [Krueger et al. \(2016\)](#) use data from the PSID and document the patterns of household income, consumption, and wealth inequality before and during the Great Recession. They find that wealth inequality can significantly amplify the impact of an aggregate shock when the distribution includes a large fraction of households with little net worth.

Others have examined the relationship between education and financial literacy and its effects on consumption and saving behavior. [Cooper and Zhu \(2016\)](#) discuss how education may matter due to differences in income processes, patience, participation in financial markets, and financial literacy. They find that education affects household finance mainly through increased average income, leaving some role for a lower discount rate. [Lusardi \(2008\)](#) shows that financial illiteracy is widespread among the U.S. population and very acute among those with low education, women, African Americans, and Hispanics.

The degree of consumption smoothing and differences in MPCs across education groups affect the macroeconomic expenditure multiplier and the transmission of monetary and fiscal policy. [Ampudia et al. \(2018\)](#) study the effect of monetary policy on consumption in

the major countries of the euro area. They find that low-income, low-education households demonstrate the largest consumption response to income changes induced by monetary shocks. Therefore, the main effects of monetary policy on consumption are transmitted through low-income households, which have a higher MPC. [Fisher et al. \(2020\)](#) use the PSID from 1999–2013 to examine how the MPC differs across the wealth distribution. They find that the MPC is lower in higher wealth quintiles, indicating that poorer households cannot smooth consumption as much as wealthier households. It follows that increasing wealth inequality reduces aggregate consumption. [Guo et al. \(2023\)](#) employs data from 20 European countries and finds that a higher ratio of hand-to-mouth households increases the value of fiscal multipliers.

We contribute to the literature by using an administrative dataset that includes all taxpayers in Iceland, classified by educational level, to estimate consumption smoothing for education groups over a period that includes very large fluctuations in real disposable income, namely (a) the large increase in disposable income before the financial crisis of 2008, (b) the collapse in 2008-2009, and (c) the subsequent recovery. The choice of the sample period enables us to better identify the propensity of different education groups to consume from disposable income, as well as to distinguish between their propensity to consume in response to unexpected increases and decreases in disposable income. This distinction is crucial, as we find that the MPC in response to negative income shocks is significantly higher than that in response to positive income shocks across all education groups. Furthermore, we document the time variation in the MPC, showing that it increased markedly at the onset of the crisis and the collapse of Iceland’s banking system. Again, this is driven by negative income shocks, as households in all education groups reduced their consumption.

Moreover, we classify university education by field of study, which enables us to link the average MPC by education to the rate of return to studying each field and to the mathematical content of each field. We find a negative relationship between the rate of return to a field of education and the share of individuals liquidity constrained, on the

one hand, and between the rate of return and the MPC, on the other hand. These results suggest a link between the subjective rate of time preference and the MPC, with more patient individuals having more liquidity and a lower MPC.

3 Education and consumption smoothing

Education reflects educational choices that depend on individuals' abilities and interests. We hypothesize that this choice reflects inherent patience (i.e., time preference) and analytical abilities, amongst other factors. Acquiring an education is an investment decision, and some fields of study require longer periods of study and, consequently, yield higher returns than others. Some require more analytical abilities. Patience also affects the propensity to save and build cash buffers, enabling consumers to smooth consumption. In this way, innate patience also affects the propensity to save and consume. We postulate that, as a result, there are differences in the propensity to consume across education groups.

3.1 Patience and choice of field of study

We start with the human capital theory initiated by [Schultz \(1961\)](#), [Becker \(1962, 1964\)](#), and [Mincer \(1962\)](#), followed by [Ben-Porath \(1967\)](#), to mention just a few of the seminal contributions in this field. [Schultz \(1961\)](#) set the ground by making education, health, and training investments rather than consumption, providing the conceptual foundation on which the subsequent human capital theory is built. He offered an explanation for the large residual in growth accounting; much of what appears as unexplained technical progress is, in fact, the accumulation of skills and knowledge. [Becker \(1962\)](#) provided the theoretical foundation by treating education and training as capital formation. In his model, individuals incur costs today in exchange for higher future earnings.² [Mincer \(1962\)](#) modeled on-the-job training as an investment undertaken within the firm. Workers accept lower wages during training

²By distinguishing between general and specific training, Becker clarified when workers or firms pay for investment.

when part of their productivity gains is financed by reduced current pay. As experience accumulates, earnings rise, but at a diminishing rate, reflecting declining investment over the life cycle. The paper provides empirical support for the idea that wage growth mirrors the accumulation of human capital. Together, these papers establish both the logic and the observable implications of human capital investment.

While Becker and Mincer provided the intellectual architecture, [Ben-Porath \(1967\)](#) brought these ideas together in a disciplined life-cycle framework. Individuals allocate time between work and the production of human capital, recognising that the return to investment depends on the number of remaining working years. Because the horizon is long when young, investment is front-loaded; as retirement approaches, it falls. The result is the familiar concave earnings profile.

We use Ben-Porath's human capital framework to link educational choice to consumption behavior. In this framework, educational field choice reflects an intertemporal optimization problem in which individuals trade off current earnings against future returns. Individuals with a lower rate of time preference optimally select into fields with higher lifetime returns and longer training horizons. Let field f determine a return parameter A_f . An individual with a discount factor β_i chooses the intensity of training u_t to maximize lifetime, T , net earnings,

$$V_i(f) = \max_{\{u_t\}} \sum_{t=0}^T \beta_i^t \left[w(1 - u_t)H_t - \psi_f(u_t) \right], \quad (1)$$

where H_t is human capital and $\psi_f(u_t)$ is a convex cost of the training effort, with $\psi'_f(u_t) > 0$ and $\psi''_f(u_t) > 0$. The cost of training consists of the direct cost, $\psi(u_t)$, and the time u_t that would otherwise be spent earning wages. The training only gradually increases human capital, which then raises wage income,

$$H_{t+1} = (1 - \delta)H_t + A_f(u_t H_t)^\alpha, \quad 0 < \alpha < 1. \quad (2)$$

where the parameter α measures the elasticity of human capital generation to the intensity of training and δ is the rate at which human capital depreciates.

This is an intertemporal optimization problem in which additional training, u , reduces current wage income and imposes costs on workers, but gradually augments their human capital and raises their wages. A higher A_f increases the marginal return to human-capital investment, while a higher β_i places greater weight on future returns. This generates increasing differences:

$$\frac{\partial^2 V_i(f)}{\partial \beta_i \partial A_f} > 0. \quad (3)$$

By standard monotone comparative statics, increasing differences between education fields imply positive assortative matching. The effect of increasing returns A_f on the value of a field is larger for more patient individuals (higher β). Intuitively, high-return fields pay later; patient people care more about what comes later, implying that high-return fields become relatively more attractive as patience increases.

Define the value difference between the high-return and low-return fields as

$$\Delta V(\beta) = V(\text{high } A) - V(\text{low } A). \quad (4)$$

Patience (β) increases the weight placed on future earnings. Since the high- A field delivers higher future returns, the relative value $\Delta V(\beta)$ is increasing in β . The figure below shows the relationship between the two. The upward slope reflects complementarity between patience and returns. A higher β increases the relative attractiveness of the high A_f field, implying that more patient individuals are sorted into higher-return educational fields. More patient individuals optimally select higher-return fields.

The sorting result implies that individuals in high-return fields have a higher discount factor on average and vice versa:

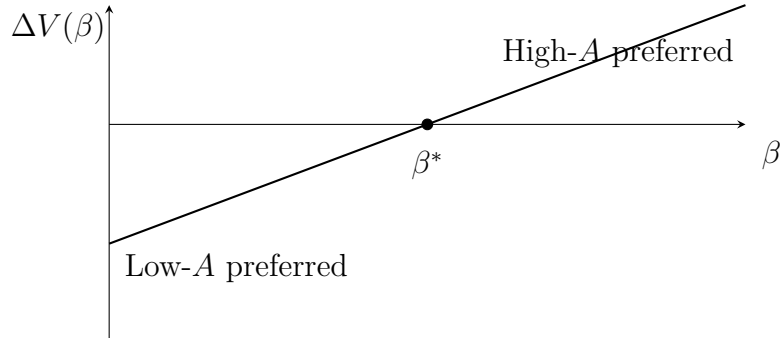


Figure 2: The value difference and patience β .

$$\beta_i \uparrow \Leftrightarrow A_{f(i)} \uparrow.$$

We now turn to the link between patience and consumption smoothing, creating a link between patience, the rate of return to education, and the marginal propensity to consume.

3.2 Patience and consumption

Since the same intertemporal preferences govern consumption smoothing, patient individuals will also exhibit lower marginal propensities to consume in response to transitory income shocks. More patient individuals will accumulate more liquid wealth, such as cash balances, and those with larger cash balances will have a lower marginal propensity to consume out of transitory income. Since these are also the better-educated individuals – those who have studied the highest-return fields – we expect them to have greater liquid wealth and a lower marginal propensity to consume.

There is a substantial literature on the relationship between patience – the rate of time preference – and liquid wealth, and between liquid wealth and the marginal propensity to consume. [Epper et al. \(2020\)](#) find a strong association between individuals’ rate of time preference and their position in the wealth distribution using Danish administrative data for a large sample of middle-aged individuals.³ [Kuchler and Pagel \(2015\)](#) use data from an

³The association remains large after controlling for education, income profile, school grades, initial wealth, parental wealth, credit constraints, demographics, risk preferences, and additional behavioral parameters.

online financial service to show that many consumers fail to stick to their debt paydown plans and attribute this to present bias. [Meier and Sprenger \(2010\)](#) measure individual time preferences in choice experiments, and match them to individual credit reports and tax returns. The results indicate that present-biased individuals are more likely to have credit card debt, controlling for disposable income, other socio-demographics, and credit constraints.

There is also a literature linking liquid assets to the marginal propensity to consume, including [Fagereng et al. \(2021\)](#), [Kaplan et al. \(2014\)](#), and [Johnson et al. \(2006\)](#). [Fagereng et al. \(2021\)](#) use Norwegian administrative data on lottery winnings matched to balance sheets and find strong MPC heterogeneity linked to liquid assets, with MPCs higher for households with low liquid wealth. Liquidity stands out as the household characteristic most strongly related to MPC magnitude. [Kaplan et al. \(2014\)](#) document “hand-to-mouth” households defined by low liquid wealth, and show evidence from eight countries that they have high MPCs, implying that MPC declines with liquid wealth. [Johnson et al. \(2006\)](#) studied the effect of the 2001 tax rebates in the US and found that spending responses were widely larger for households with lower liquidity, consistent with the MPC decreasing in cash balances. [Ganong et al. \(2025\)](#) use data on bank accounts of 50 million American households, identifying exogenous, transitory, and unpredictable shocks to labor income. They find a large marginal propensity to consume in response to labor-income shocks. Furthermore, consumption is most sensitive among households with low liquidity and is almost unchanged among households with high liquidity.

We can capture the essence of the relationship between patience and the propensity to consume with a few equations. In an incomplete-markets environment, optimal consumption can be written as a function, m , of liquid wealth and permanent income,

$$m_{it} = Ra_{i,t-1}^L + y_{it}^P + \varepsilon_{it}, \tag{5}$$

where $R = 1 + r$, a^L is liquid wealth – which includes stocks and bonds – y^P is permanent

income, and ϵ is transitory income. Consumption then becomes a function of m and β :

$$c_{it} = c(m_{it}; \beta_i), \quad (6)$$

It follows that a transitory income shock affects consumption only through its effect on current cash on hand. The marginal propensity to consume out of a transitory shock is hence

$$\frac{\partial c_{it}}{\partial \epsilon_{it}} = \frac{\partial c_{it}}{\partial m_{it}} \frac{\partial m_{it}}{\partial \epsilon_{it}} = \frac{\partial c(m_{it}; \beta_i)}{\partial m_{it}} \equiv c_m(m_{it}; \beta_i), \quad (7)$$

since

$$\frac{\partial m_{it}}{\partial \epsilon_{it}} = 1. \quad (8)$$

with $0 < c_m < 1$, $c_{mm} < 0$ and $c_{m_i\beta_i} < 0$. Thus, the greater the liquid wealth, the lower the marginal propensity to consume out of transitory income.

Greater patience implies larger wealth buffers and hence stronger consumption smoothing, yielding

$$\frac{\partial \text{MPC}_{it}}{\partial \beta_i} = c_{m_i\beta_i}(m_{it}; \beta_i) < 0. \quad (9)$$

We are now ready to combine the effect of patience, β , on educational choice and the relationship between β and consumption smoothing. Combining sorting and smoothing, therefore, implies

$$\beta_i \uparrow \rightarrow \begin{cases} A_f(i) \uparrow \\ m_i \uparrow \rightarrow \text{MPC} \downarrow \end{cases}$$

Hence, individuals in higher-return educational fields save a larger fraction of transitory income shocks, accumulate more liquid wealth, and exhibit lower marginal propensities to consume.

4 Data

We use a dataset of annual administrative tax records from all Icelandic taxpayers from 2005 to 2019. The data are collected by Statistics Iceland and Iceland Revenue and Customs, and include third-party-reported information on multiple sources of income and various assets and liabilities.⁴ The data are linked with other administrative data and therefore include socio-demographic factors as well.⁵

By aggregating information among household members each year using unique household identifiers, we construct household-level measures of income and other characteristics. Each household consists of at most two adults for jointly taxed couples. We address intra-household inequality by assigning each household member an equal share of the household’s income, assets, and liabilities, while allowing background characteristics, such as age, to vary between household members. This approach assumes that financial decisions within a household are made jointly, based on the household’s total income and wealth, rather than individually by each household member, based on their own income and wealth.

We avoid complications arising from young people living with their parents and ensure sufficient observations within each age group by restricting the sample to individuals aged 31 to 80 years, born between 1935 and 1979. We also omit deficient tax records and individuals who have negative income.⁶ Deficient tax records include those who have income from abroad or have failed to file their taxes. Those require tax authorities to either estimate or manually calculate taxes. In some instances, we may lack accurate information on household income and wealth. Therefore, these observations are omitted. Similarly, we discard the top 1

⁴The data include information on income, taxes, assets, and liabilities. Income includes labor income, capital income, income from pension funds, government transfers, and other income such as lottery winnings and grants. Furthermore, we add imputed rent to homeowners’ income. Liabilities include student loans, mortgages, credit card debt, and other forms of debt. Assets include the market value of real estate and cars, stocks and bonds in mutual funds, and money in savings accounts.

⁵These include information on age, gender, education, marital status, occupation, and the number of children.

⁶Although we account for several sources of unrealized capital gains, measured consumption is negative for some households, which can be due to misattributing wealth increases to savings out of income when they are due to unrealized capital gains or to income not observed in the tax records, such as income from inheritances or gifts, or tax evasion (Kolsrud et al., 2020).

percentile of consumption to mitigate bias that may arise from misattributing wealth declines to consumption when they may stem from unrealized capital losses or stock transactions not observed in the data. Finally, we remove from the sample individuals with a saving-to-disposable income ratio lower than -1.⁷

We compute consumption for each household using the accounting identity that a household’s consumption equals its disposable income minus changes in net wealth plus unrealized capital gains (Browning and Leth-Petersen, 2003; Eika et al., 2020);

$$C_{i,t} \equiv Y_{i,t} - \Delta W_{i,t} + \sum_k \Delta p_{k,t} A_{i,k,t-1} \quad (10)$$

where $Y_{i,t}$ is disposable income (annual income in local currency) for individual i at time t . $\Delta W_{i,t}$ is the change in net wealth between periods $t - 1$ and t , and $\Delta p_{k,t} A_{i,k,t-1}$ is unrealized capital gains on asset k . Note that $Y_{i,t}$, $W_{i,t}$, and $A_{i,t}$ are defined as the intra-household averages of disposable income, net wealth, and assets, respectively.

The idea underlying the identity in Equation (10) is that income is either spent, thereby contributing to consumption, or saved, thereby increasing net wealth. However, net wealth is also influenced by factors other than income, namely unrealized capital gains, which arise from changes in the market prices of households’ assets and liabilities and do not affect current consumption. Unrealized capital gains include changes in house prices, investment fund asset prices, the effects of CPI-indexation of household debt, and a 2014-2016 mortgage-relief program, all of which we correct for.

The dataset contains a natural measure of capital gains/losses in real estate, as it includes information on each household’s market value of real estate, as estimated by Register Iceland.⁸ The public institution estimates the market value of all real properties in Iceland

⁷Timing issues occasionally result in income or changes in assets or liabilities which occur in year t being registered in year $t+1$, leading to extreme values for calculated consumption and savings in each year, while still producing a sensible average across the two years. By removing negative consumption values and highly negative saving ratios, we exclude those observations, leaving 1,754,611 observations from 167,838 individuals for our analysis.

⁸Register Iceland is a public institution responsible for maintaining a property register and national register in Iceland.

each year, and its valuations form the basis for property tax and inheritance tax. We have information on the year-end market value of financial assets in investment and savings funds. Following [Eika et al. \(2020\)](#), we assume that there are no intra-year transactions and, therefore, allow for heterogeneous portfolio returns across households in computing the capital gains/losses from such assets. However, direct stock ownership is not recorded at market value. In fact, it does not change from year to year unless households engage in transactions with individual stocks. Therefore, as long as households do not engage in such transactions in a given year, capital gains/losses on individual stocks do not influence our measure of household consumption and savings. Furthermore, a large share of household debt in Iceland is indexed to the CPI, meaning the loan principal is linked to the consumer price index. We have information on the principal, installment amounts, and interest payments for each loan. This allows us to identify indexed loans and compute the indexation, which is effectively an unrealized capital loss. Our dataset also includes information on a 2014-2016 government mortgage-relief program that reduced household debt by an amount equivalent to 3.5% of GDP, thereby constituting a large unrealized capital gain for households that benefited from it.

Finally, we have information on the value of motor vehicles, and we compute homeowners' imputed rent for each household. These two are arguably the most significant components of durable consumption for most households. We assume that annual vehicle consumption equals their depreciation, at 10% under Icelandic tax law, and that consumption of one's own housing equals the imputed rent.⁹

In the absence of unreported income and transactions in individual stocks and given the assumption of no transactions within the year in funds, [Equation 10](#) should give an accurate estimate of consumption. Net wealth encompasses all types of assets, albeit with the caveats discussed above. In addition, we have year-end data on the principal of all

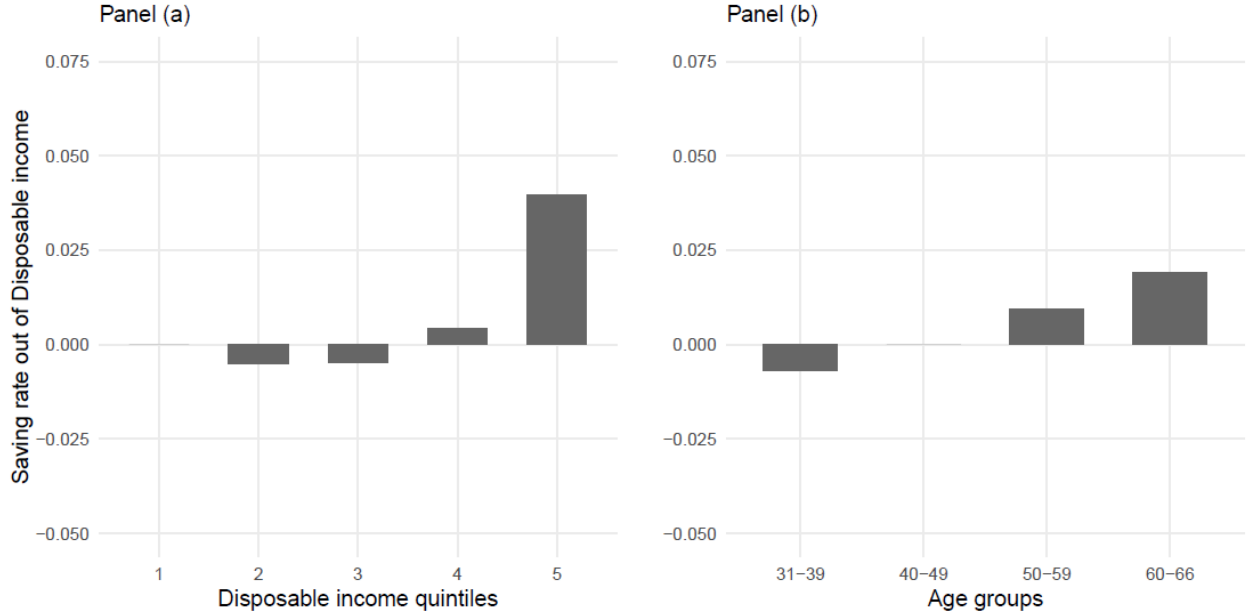
⁹We compute the imputed rent for each household by dividing the value of the real estate of each household by the total value of the real estate and multiplying the result by the aggregate value of the imputed rent from national accounts.

liabilities, including mortgages, consumer loans, auto loans, credit card debt, and student loans. Furthermore, the largest share of unrealized capital gains comes from changes in the valuation of real estate assets, as estimated by third-party reports from Register Iceland. However, there is a risk of measurement errors when households engage in transactions in financial assets or real estate. Also, in the event of separations, we assume that couples divide their assets equally. If this assumption does not hold, it may result in the incorrect attribution of one former spouse's assets to the other. As discussed in [Fagereng and Halvorsen \(2017\)](#), measurement errors and instances of negative consumption can arise from intra-year sales and purchases of houses or financial assets, or if there are changes in a household's composition. For example, a household might pay for a house before the end of a year but only become the registered owner afterward, or vice versa. Such timing issues, discussed in footnote 6, can lead to measurement errors and, in some cases, negative imputed consumption. Following [Fagereng and Halvorsen \(2017\)](#), we exclude households with negative imputed consumption.

Data from consumption surveys are not available to us. Therefore, we cannot validate our consumption imputations by comparing them with survey data. However, we can replicate some stylized facts from the literature. Panel (a) of Figure 3 shows the median saving rate out of after-tax income by income groups in 2019. Income groups are constructed using the distribution of after-tax income within each birth cohort. This ensures that the saving rate in the figure is not driven by households' life-cycle position. As can be seen, the median saving rate in the bottom 50% of the income distribution is smaller than that of the next 40%. We examine the top 10% of the distribution to highlight the group's higher median saving rate than the rest of the sample. In particular, it is approximately three times that of the 50th to 90th percentiles. This is consistent with the literature's findings that rich and higher-income households save more than others (see, for example, [Dynan et al. \(2004\)](#) and [Mian et al. \(2020\)](#)).

Panel (b) of Figure 3 shows the saving rate by age groups for the working age population over the whole sample period of 2005-2019. It shows that, consistent with the predictions of

Figure 3: The saving rate out of disposable income across income and age groups



Notes: The figure shows the median saving rate out of after-tax income. Consumption is computed using Equation (10) and saving is the share of income not consumed. Note that both consumption and after-tax income include imputed values for homeowners' imputed rent, and consumption includes imputed values for vehicle depreciation. Panel (a) shows the saving rate by income groups in 2019. The income groups are formed within each cohort to ensure that saving rates are not influenced by households' life-cycle position. Panel (b) shows the saving rate by age groups for the whole sample period.

a canonical life-cycle model of consumption and saving, the saving rate increases with age among the working-age population. Income is relatively low for workers soon after entering the labor market. As they gain skills and experience, their income increases, as illustrated in Figure 3, and so does their saving rate. The saving rate peaks in the years just before retirement.

Table 1 presents summary statistics for the variables used in the analysis by level of education. It shows that educational attainment has increased across cohorts in recent decades, resulting in the university-educated being, on average, five to six years younger than those without a university education. A larger proportion of those with secondary or tertiary education live with a spouse compared to those with primary education, and a larger proportion live in urban areas. The university-educated have more children under age 18 than other education groups, which may be due to the gap in average ages between groups.

The university-educated have higher income, consumption, and net wealth than those with a secondary school education, who in turn have higher income, consumption, and net wealth than those with a primary school education. University-educated households are more likely to own their place of residence than those with a secondary school education, who are more likely than those with primary school education only. This pattern may reflect the income gap between the groups.

We then come to measures of liquidity constraints. Interestingly, the ratios of net wealth to disposable income, on the one hand, and liquid assets (proxied by bank deposits and financial assets in investment and savings funds) to disposable income, on the other, are lower for university graduates than for secondary school graduates. The latter measure is even lower compared to that of primary school-educated households. The lower average age of those with tertiary education likely explains this finding, as younger households typically have accumulated less wealth relative to their income than older households. Comparing the groups in terms of an absolute liquidity constraint, proxied by liquid assets below USD 8,000 for couples and USD 4,000 for singles, shows more binding constraints for primary-educated households, 53% of whom are liquidity-constrained by this measure, than for university graduates, 37% of whom are liquidity-constrained.

5 Consumption smoothing by education

5.1 Consumption response to transitory income shocks

We estimate the MPC in response to transitory income shocks to assess the extent of consumption smoothing by educational attainment. We follow the methodology proposed by [Blundell et al. \(2008\)](#) and further examined by [Kaplan and Violante \(2010\)](#). First, we regress log income and log consumption on individual fixed effects, dummies for age, year, gender, education, marital status, number of children, the interaction between marital status and the number of children, residence, net wealth deciles, and the log of real estate assets. We

Table 1: Summary statistics

	Primary (390,776 obs.)	Secondary (742,003 obs.)	Tertiary (628,123 obs.)
Age	55.38 (12.61)	54.20 (11.71)	49.16 (10.66)
Spouse	0.44 (0.50)	0.74 (0.44)	0.81 (0.39)
No. of children	0.35 (0.79)	0.53 (0.92)	1.03 (1.14)
Urban	0.50 (0.50)	0.60 (0.49)	0.75 (0.43)
Disposable income	40,005 (26,406)	48,347 (39,659)	63,278 (46,332)
Consumption	39,539 (22,069)	47,470 (26,000)	61,205 (33,209)
Net wealth	93,472 (171,543)	137,018 (201,777)	160,838 (266,825)
Real estate	114,781 (120,560)	167,134 (126,790)	213,279 (143,104)
Net wealth-to-income	1.67 (2.78)	1.63 (2.30)	1.34 (2.23)
Liquid asset-to-income	0.55 (1.42)	0.56 (1.40)	0.54 (1.57)
Liquidity-constrained	0.53 (0.50)	0.44 (0.50)	0.37 (0.48)

Notes: This table reports variable means for the full sample period 2005-2019. Standard deviations are shown in parentheses. Disposable income, consumption, net wealth, and real estate values are reported in USD. Nominal variables are converted to 2019 prices using Statistics Iceland's CPI index and then converted to USD using mid-2019 exchange rates. For married households, disposable income and consumption are divided by two to obtain individual-level values. A household is considered liquidity-constrained if liquid assets are less than USD 8,000 for couples and USD 4,000 for singles. Urban is 1 for those living in urban areas and zero for those living in rural areas.

proceed by obtaining the first differenced residuals of log consumption, $\Delta\tilde{c}_{i,t}$, and log income, $\Delta\tilde{y}_{i,t}$. As in [Blundell et al. \(2008\)](#), the income process for each household is decomposed into a permanent component P and a mean-reverting transitory component ν . Hence, income growth is given by:

$$\Delta\tilde{y}_{i,t} = P_{i,t} + \Delta v_{i,t} \tag{11}$$

Finally, we obtain the MPC out of transitory income shocks using a 2SLS regression of $\Delta\tilde{c}_{i,t}$ on $\Delta\tilde{y}_{i,t}$, which is instrumented by $\Delta\tilde{y}_{i,t+1}$ as it is correlated with the transitory shock at time t , but not with the permanent one. Specifically, we estimate

$$\begin{aligned} \Delta\tilde{y}_{i,t} &= \alpha_0 + \beta_{0,E}\Delta\tilde{y}_{i,t+1} \times E_{i,t} + \epsilon_{0,i,t} \\ \Delta\tilde{c}_{i,t} &= \alpha_1 + \beta_{1,E}\Delta\hat{y}_{i,t} \times E_{i,t} + \epsilon_{1,i,t} \end{aligned} \tag{12}$$

where $E_{i,t}$ again is an indicator for the education groups, with primary education serving as a benchmark. Thus, the above specification is estimated for the full sample rather than separately for each group, as in the previous section.

The β_1 estimates are reported in [Table 2](#). The first column contains the full sample of individuals aged 31-66. Columns (2) and (3) report estimates for positive and negative shocks, which we discuss in [Section 5.2](#).

We find that the MPC out of transitory income shocks is lower for university-educated households than for the other two groups. The difference between the MPC of university-educated households and secondary-educated households is statistically significant at the 1% significance level, while the difference between university-educated households and primary-educated households is statistically significant at the 5% level. We conclude that university-educated working-age households smooth consumption in response to transitory income shocks to a greater extent than households in the other two education groups.¹⁰

¹⁰Tables [A1](#) and [A2](#) demonstrate the robustness of the above results. In [A1](#), we drop the top 5 percentiles of consumption instead of the top 1 percentile, on the one hand, and assign households to an education group if and only if all members within the household belong to that education group, on the other hand. In [A2](#),

Table 2: MPC by education for working-age individuals

	(1) Overall	(2) Negative shocks	(3) Positive shocks
$\hat{y}_{i,t} \times \textit{primary}$	0.514 ^{***} (0.020)	0.729 ^{***} (0.052)	0.433 ^{***} (0.022)
$\hat{y}_{i,t} \times \textit{secondary}$	0.602 ^{***} (0.013)	0.754 ^{***} (0.036)	0.543 ^{***} (0.015)
$\hat{y}_{i,t} \times \textit{university}$	0.502 ^{***} (0.014)	0.677 ^{***} (0.034)	0.425 ^{***} (0.017)
R^2	0.032	0.032	0.032

Notes: This table presents 2SLS estimates from Equation (12). Column (1) pools positive and negative transitory income shocks. Columns (2) and (3) report MPC estimates separately for negative and positive transitory income shocks, respectively. The estimates are based on 951,384 households aged 31 to 66 in 2005-2019. Standard errors clustered at the individual level are in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level and * denotes significance at the 10% level.

There is more than one channel through which education may affect consumption smoothing. On average, university-educated households have higher incomes (see Table 1), which may be associated with a lower MPC in response to transitory income shocks as in the buffer-stock model Carroll (2001). As a result, wealthy households optimally spend a smaller proportion of their transitory income shocks than poor households. This is also consistent with empirical estimates showing that higher-income households save a greater share of their income than lower-income households (Dynan et al., 2004; Mian et al., 2021). Thus, it may be the level of income, rather than the educational attainment itself, that explains the relatively lower average MPC for transitory income shocks among university-educated households. The university-educated may also be less liquidity-constrained, as is shown in Table 1. This brings us to our proposed explanation that higher-return university degrees attract more patient individuals, who are then more likely to accumulate buffer-stock savings

alternative standard-error clustering methods are used (standard errors at the individual and year levels, cohort and year levels, and urbanization and year levels). All results are robust to alternative clustering methods.

and smooth consumption.¹¹

We study this by examining heterogeneity in the MPC from transitory income across the income and liquidity distributions, the latter proxied by net wealth-to-disposable income, liquid wealth-to-disposable income, and a direct measure of liquidity constraints. For the first three variables, we estimate the MPC for each subgroup, constructed using quintiles of the distributions. Regarding the direct measure of liquidity constraints, a household is considered liquidity-constrained if liquid wealth, defined as the sum of bank deposits and assets in investment funds, is below USD 8,000 for couples and USD 4,000 for singles, as in Section 4.¹² Figure 4 shows the coefficient estimate of the MPC for each education group and each subgroup and the shares of the former in the latter.¹³

The MPC is declining in income, net wealth-to-income, and liquid wealth-to-income, and is lower for those who are not liquidity constrained, as in Gelman (2021).¹⁴ There is no clear difference between educational groups controlling for these factors. Therefore, the relatively lower MPC reported for university-educated households in Table 2 is partly explained by the fact that many less-educated households are in lower-income quintiles and therefore have a high MPC, whereas relatively few are in higher quintiles. The opposite is true for higher-educated households. This is evident in the columns of Figure 4, and the pattern is clearest for the income quintiles. The share of the primary-educated is highest in the lowest-income quintile and then declines monotonically across the higher quintiles. The share of the university-educated is lowest for the lowest quintile and then rises monotonically to the highest quintile. There is also a clear pattern in the bottom-left figure: a larger share of the secondary-educated than the university-educated are liquidity-constrained, whereas a

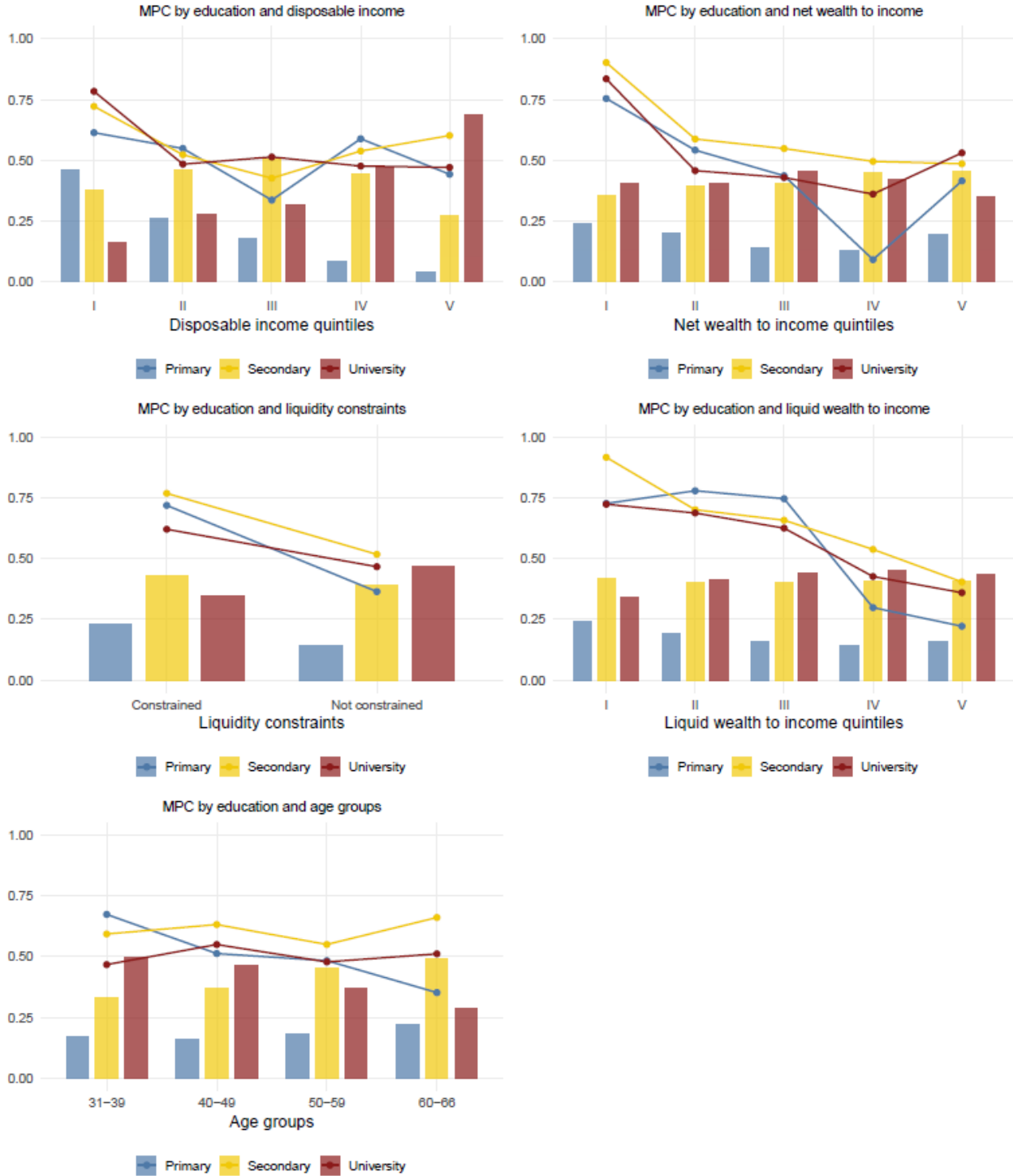
¹¹Our data do not allow us to test for a relationship between education and financial literacy and its effects on consumption behavior, see Lusardi (2008).

¹²Now we have more endogenous variables – namely, the transitory income shock for each education group interacted with the relevant subgroup. Hence, we need additional instruments. As before, these are $\Delta \tilde{y}_{i,t+1}$, interacted with education groups and now also with the relevant subgroup.

¹³See also Tables A3 to A7 in the Appendix for more detailed regression results.

¹⁴However, the MPC is slightly higher for the university-educated in the highest net wealth-to-income quintile than in the second, fourth, and fifth quintiles, indicating the presence of wealthy consumers who live hand-to-mouth due to liquidity shortages, as suggested by Kaplan et al. (2014).

Figure 4: MPC by income, wealth and liquidity



Notes: The shows the MPC estimates for the working-age population (aged 31-66) from Equation (12) with additional interactions with disposable income quintiles (upper left panel), net wealth-to-income quintiles (upper right panel), absolute liquidity constraint (lower left panel), and liquid wealth-to-income quintiles (lower right panel). Liquid wealth is defined as the sum of bank deposits and assets in investment and savings funds. A household is considered liquidity-constrained in the lower left panel if liquid wealth is below USD 4,000 for singles and USD 8,000 for couples. The estimates are based on 1,423,797 households in 2005-2019.

larger share of the university-educated are not liquidity-constrained than of secondary- and primary-educated.

5.2 Asymmetry in the MPC out of transitory income shocks

Next, we allow for asymmetry in the MPC, depending on whether households face a positive or negative income shock. Our motivation is that responding to a negative transitory income shock might be more challenging from a practical standpoint than responding to a positive shock; for example, due to liquidity constraints or imperfections in the capital markets. The specification is the same as before, except that we separate those with positive transitory income shocks from those with negative shocks using indicator variables. Specifically, we estimate the following modification of Equation (12):

$$\begin{aligned}\Delta y_{i,t} &= \alpha_0 + \beta_{0,E,-} \Delta y_{i,t+1} \times E_{i,t} \times I^- + \beta_{0,E,+} \Delta y_{i,t+1} \times E_{i,t} \times I^+ + \epsilon_{0,i,t} \\ \Delta c_{i,t} &= \alpha_1 + \beta_{1,E,-} \Delta \widehat{y}_{i,t} \times E_{i,t} \times I^- + \beta_{1,E,+} \Delta \widehat{y}_{i,t} \times E_{i,t} \times I^+ + \epsilon_{1,i,t}\end{aligned}\tag{13}$$

where I^- and I^+ are indicator variables for negative transitory income shocks and positive transitory income shocks, respectively. The results are reported in and Table 2.

Two lessons emerge from this. First, all education groups smooth positive income shocks to a much larger extent than negative income shocks, as the MPC for positive shocks is significantly lower than that for negative shocks.¹⁵ Second, university-educated households smooth consumption out of positive income shocks to a significantly larger extent than other households. They also smooth negative income shocks more than other households with secondary education.¹⁶

¹⁵This is consistent with the findings of [Christelis et al. \(2019\)](#) who studies responses of a representative sample of Dutch households to survey questions.

¹⁶Appendix Figures [A1](#) to [A5](#) explore heterogeneities in the MPC out of the positive and negative transitory income shocks defined in Equation (13) interacted with income, wealth and liquidity. As in [Figure 4](#), we find limited evidence of systematic differences between educational groups. In general, MPCs in response to negative shocks are higher and less precisely estimated than those in response to positive shocks.

5.3 Time variation in the marginal propensity to consume

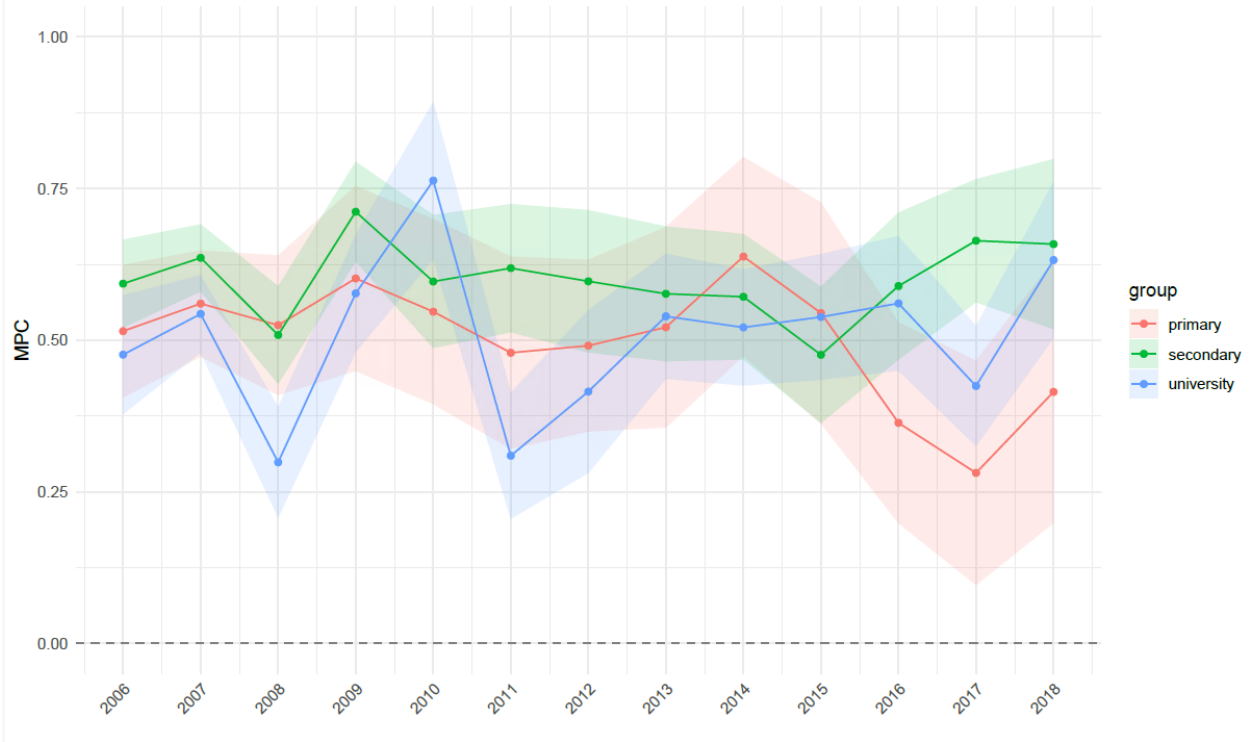
In this section, we illustrate the time variation in the MPC estimated in Section 5.1. The analysis is motivated by the previous section, in which we found that the MPC is significantly lower for positive transitory income shocks than for negative transitory income shocks. This holds for all education groups. The findings suggest that the MPC may be higher during economic downturns and crises than during periods of near-equilibrium or expansion.

The empirical strategy is the same as that in Figure 4; however, it replaces the interaction term for the relevant subgroup with fixed effects for the year. As such, fixed effects for the year are added to the interaction between the instrument and the education group in Equation (12). Figure 5 presents the results, highlighting the significant decrease in the MPC at the onset of the financial crisis in 2008 and a subsequent increase in 2009 and 2010.

The fall in the MPC in 2008 and the subsequent increase in 2009 and 2010 are most pronounced among university-educated households. As the economy began to recover in 2011, the MPC increased across all groups; however, the increase was smaller for households with primary or secondary education than for those with university education. Therefore, although all education groups experienced a notable decrease in MPC during the crisis and a subsequent increase once recovery took hold, the fluctuations were most pronounced for university-educated households. The greater fall in 2008 implies greater consumption smoothing for the university-educated.¹⁷

¹⁷Appendix Figure A6 shows the time variation of the MPC separately for negative and positive income shocks. It shows that the increase in the MPC during the crisis, as reported in Figure 5, is driven by strong consumption in response to negative income shocks. In fact, during the crisis, households appear to have reduced consumption by approximately one-to-one in response to a negative income shock. Once the economic recovery took hold in 2011, the MPC declined after adjusting for negative income shocks, suggesting that households increased consumption smoothing. The MPC in response to positive income shocks also rose during the crisis, but to a lesser extent. Households increased their consumption slightly more in response to a positive shock during the crisis than when the economy was closer to equilibrium or during economic expansions. As such, households also appear to smooth consumption to a lesser extent during the crisis than outside the crisis.

Figure 5: MPC by year



Notes: Figure 5 shows how the estimated MPCs vary over our sample period. It is estimated with a slight variation of Equation 13. In particular, year fixed effects are added to the interactions in the 2SLS specification in Equation 13. The regression includes controls for individual and year fixed effects and dummy variables for gender, marital status, number of children, the interaction between marital status and number of children, education, sector of work and the degree of urbanisation. Furthermore, we control for the log of real estate assets.

6 MPC by rate of return

So far, we have compared households by their educational attainment level (primary, secondary, and tertiary). However, individuals with tertiary education may differ substantially in the type of human capital they acquire. University education in particular encompasses fields with very different training requirements, earnings profiles, and lifetime returns. The monetary rate of return differs across fields due to differences in future earnings and the required length of studies. Here, we compare individuals by the rate of return to their fields of education.

Fields of education are based on ISCED codes, and we use two-digit codes for university graduates. For secondary school, we group individuals into three groups, while the primary

remains a single group, see table 3. When estimating MPCs by field, we classify fields by household, as we do for educational levels. For households with two adult members, the household is classified by the higher educational attainment. If both partners have university degrees in different fields, the household is assigned to both fields.

Table 3: Internal Rate of Return to University Education by Field of Study

Field	IRR	Field	IRR	Field	IRR
Teaching	0.021	Law	0.129	Health care	0.104
Arts	0.000	Life sciences	0.055	Social services	0.038
Humanities	0.008	Physical sciences	0.044	Personal services	0.000
Social sciences	0.070	Computer science	0.147	Other fields	0.040
Business and economics	0.118	Engineering	0.150	Architecture	0.101
Reference group: upper secondary vocational					

Notes: The internal rate of return (IRR) is estimated by comparing the lifetime income profile of university graduates in each field to that of upper secondary graduates. The IRR is the discount rate r that solves: $\sum_{t=20}^{70} \frac{y_t^{\text{uni}} - y_t^{\text{hs}}}{(1+r)^{t-20}} = 0$, where y_t^{uni} is mean post-tax earnings at age t for university graduates in the given field and y_t^{hs} is mean post-tax earnings at age t for upper secondary graduates. We only include those with positive earnings. During study years (ages 20–23), university students are assumed to earn no income. Fields with IRR = 0 have lifetime university earnings that do not exceed upper secondary earnings. Income data are from 2019. Fields with fewer than 100 individuals are grouped into Other fields.

To measure the economic returns associated with different fields, we estimate the internal rate of return (IRR) to university education for each field of study. The IRR is the discount rate that equates the present value of the lifetime income profile of university graduates in a given field to that of upper secondary graduates, accounting for the opportunity cost of studying. During their study years, university students are assumed to earn only a fraction of the median upper-secondary income during the summer breaks from university. Our objective is not to identify a causal effect of education on income, but to proxy for the lifetime rate-of-return differential between each university field and upper secondary education. See Table 3 for further details. Estimates range from zero, where the net present value of an upper secondary vocational degree exceeds that of a university degree, to IRRs of 0.13 for law and 0.15 for engineering.

Table 4 reports the MPC by field of education. Focusing on statistically significant estimates, MPC ranges from 0.24 to 0.63. It is high for primary and secondary education, vocational degrees, and low-return university degrees, such as the arts, humanities and social services. It is much lower for higher-return degrees, such as engineering, health care, law, and business.

Table 4: Marginal Propensity to Consume by Field of Study

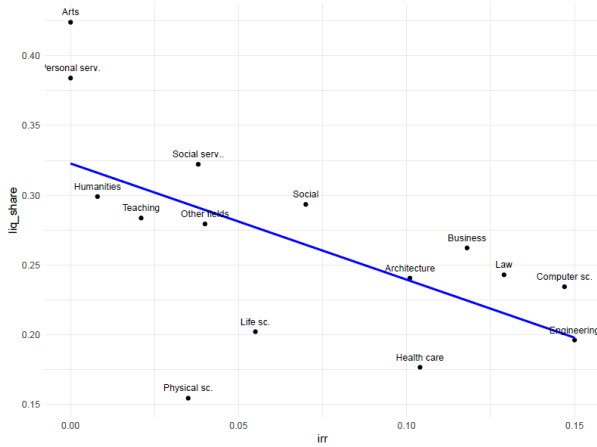
Field	Est.	Field	Est.	Field	Est.
Primary	0.514*** (0.020)	Media	0.449*** (0.112)	Engineering	0.245*** (0.045)
Academic upper secondary	0.486*** (0.026)	Business	0.358*** (0.028)	Manufacturing	0.373 (0.229)
Vocational trades	0.462*** (0.025)	Law	0.297*** (0.058)	Architecture	0.377*** (0.066)
Vocational services	0.521*** (0.044)	Life sc.	0.123 (0.081)	Agricultural	0.109 (0.142)
Post-secondary	0.377*** (0.092)	Physical sc.	-0.012 (0.119)	Health care	0.366*** (0.035)
Teaching	0.409*** (0.029)	Math/stat.	0.109 (0.266)	Social serv.	0.365*** (0.092)
Arts	0.629*** (0.074)	Computer sc.	0.236** (0.072)	Personal serv.	0.568** (0.216)
Humanities	0.392*** (0.055)	Social sc.	0.472*** (0.056)	Other fields	0.399** (0.149)
Controls: year fixed effects					

Notes: Dependent variable is household consumption. Each coefficient is the estimated marginal propensity to consume for households where the head holds the given field of study, estimated via interaction with income residuals. Fields with fewer than 100 individuals in 2019 are grouped into Other fields. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

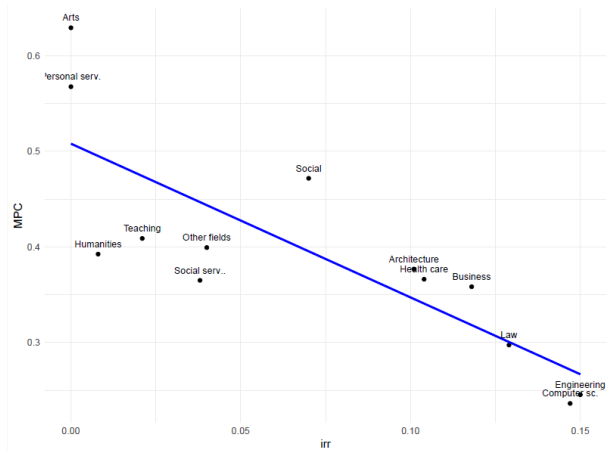
Figures 6a plots the share of liquidity-constrained households against the IRR estimates by field, and 6b plots the MPC against the IRR. We present only estimates for university degrees and those that are statistically significant. A negative relationship is observed in both panels, suggesting that fields with higher rates of return are associated with lower MPC and lower shares of liquidity-constrained individuals.

Figure 6: MPC, Liquidity Constraint Share, and Internal Rate of Return by Field

(a) Liquidity Constraint Share and Internal Rate of Return by Field



(b) MPC and Internal Rate of Return by Field



Notes: Panel A shows the share of liquidity-constrained individuals by educational field plotted against the internal rate of return from table 3. Panel B shows the MPC estimates from table 4 plotted against the internal rate of return to education.

Households in the high-income fields are substantially less likely to be liquidity-constrained. This applies to fields such as engineering, law, and health care. These fields then also exhibit low MPC values. In contrast, the proportion of individuals in low-return fields, such as the arts and personal services, who are liquidity constrained is higher, and so is the MPC. These findings are consistent with the model of Section 3.

7 Further perspectives based on survey evidence

We conducted a survey to better understand households’ motivations and behavior regarding saving, and to gather information on these results. The survey covered 946 individuals. Of these, 33.6% work in the private sector, 27.3% work in the public sector, 22.9% are not employed, 11.5% are self-employed, and the rest work for private institutions and voluntary associations.¹⁸ The first question is:

Which of the following choices best describes your main motivation to save? (multiple answers not

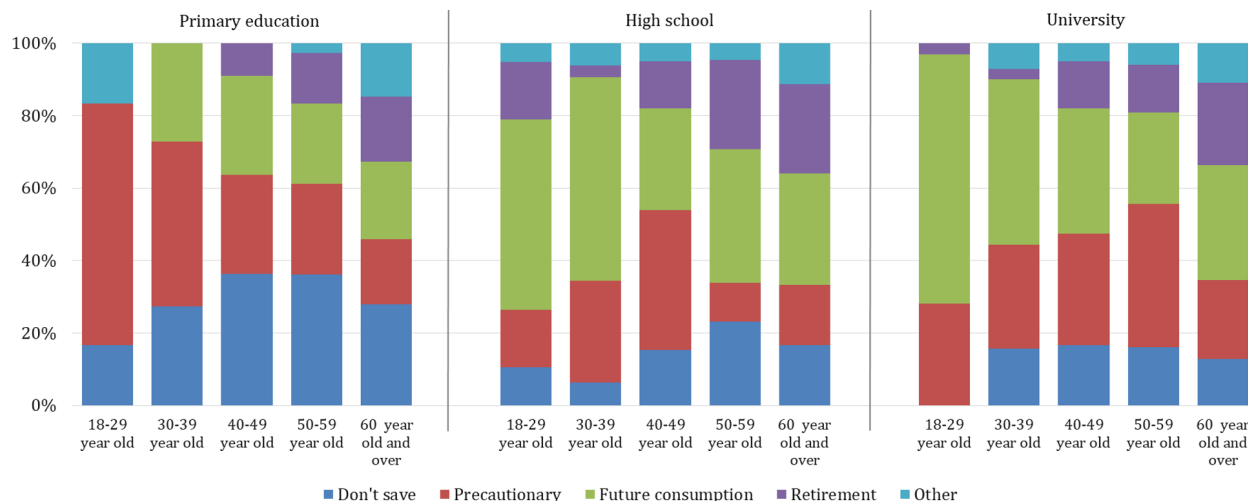
¹⁸The survey was conducted by the firm Maskina for the purpose of this study between 27 September and 7 October 2021.

allowed).

(1) I don't save; (2) I save for retirement; (3) I save to be able to react to unanticipated expenditures or drop in income; (4) I save for specific future expenditures such as housing and vehicles; (5) I save for future expenditures such as hobbies or vacations; (6) I save to finance future consumption; (7) I save out of habit; (8) I save to provide bequests; or (9) Other.

Responses are presented in Figure 7 below. Primary-educated households are more motivated by buffer savings, labeled precautionary, when young, whereas the buffer savings motivation seems to peak later in life for university-educated households. The university-educated are more motivated to save for future consumption in their youth than their less educated counterparts.

Figure 7: Main motivation for saving, by education and age



Notes: Figure 7 shows results from question 1, by education and age. Choices (4), (5), and (6) are grouped together and labelled as future consumption while choices (7), (8), and (9) are grouped together and labelled as other. Based on 785 observations, including 136 individuals whose highest educational attainment is primary education, 269 whose highest educational attainment is secondary school education, and 380 who are university-educated.

Retirement seems to play a less important role in motivating saving behavior among the university-educated. A larger proportion of non-university-educated individuals report not saving, consistent with the declining MPC with income.

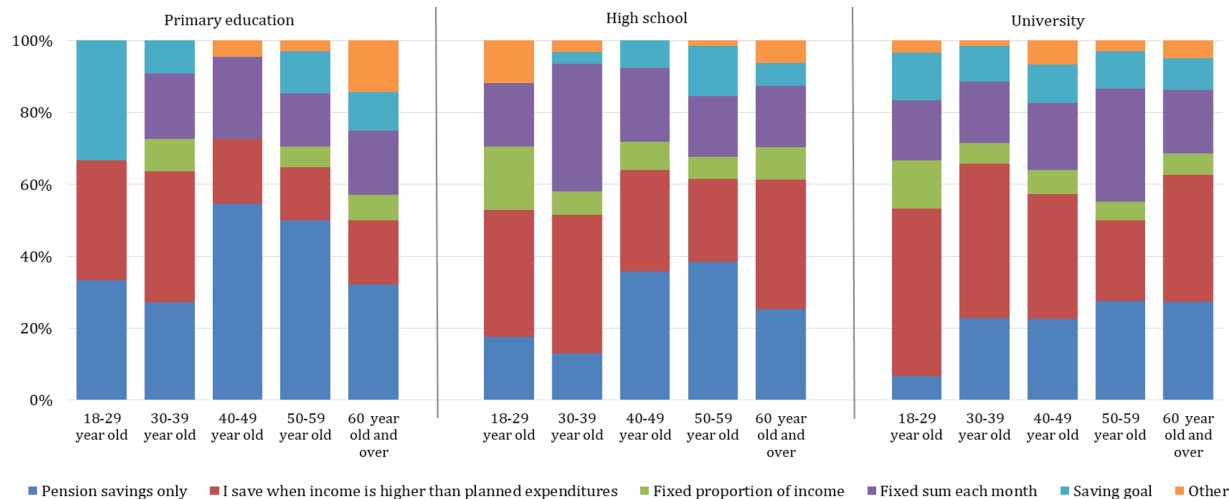
The second question is:

Which of the following options best describes how you save, apart from pension savings?

(1) I don't save apart from pension savings; (2) I have specific expenditures each month, and I save if my income is higher, (3) I save a fixed proportion of my income each month, (4) I save a fixed sum each month, (5) I set myself a specific goal for savings over a period and organize my saving accordingly, (6) Other. Again, multiple answers are not permitted.

Figure 8 decomposes saving behavior by education and age. It turns out that people without a university degree are more likely to rely solely on pension savings. This implies that any changes in disposable income would directly affect current consumption. However, consumption smoothing behavior, captured by saving when income exceeds planned expenditures, increases with education. This corresponds to our findings that those with a higher level of education have a lower propensity to consume out of current income, which is somewhat consistent with the estimation results in Table 2 suggesting that university-educated households have the lowest MPC out of transitory income shocks.

Figure 8: Saving behavior, by education and age



Notes: Figure 8 shows results from question 2, by education and age. Based on 767 observations, including 129 individuals whose highest educational attainment is primary education, 263 whose highest educational attainment is secondary school education, and 375 who are university-educated.

To assess whether individuals with different levels of education exhibit different saving behaviors, we conducted a series of logistic regressions; see Table 5. The dependent variables represent different saving motives or methods, while the explanatory variables include education level, alongside controls for income, age, gender, saving capacity, and whether the individual reported active saving behavior.¹⁹

¹⁹The dummy variable *saving capacity* is derived from a survey question asking, “Which of the following

Table 5: Survey Data, Logit Regression Results

	Dependent Variables		
	Saving Motive: Future Consumption (1)	Saving Motive: No saving (2)	Saving Method: Passive (3)
Constant	-0.876* (0.471)	-2.731*** (0.772)	-1.562*** (0.472)
High School	0.483* (0.271)	-0.583* (0.311)	0.746*** (0.283)
University	0.284 (0.275)	-0.323 (0.319)	0.719** (0.288)
N	732	732	732
Controls	Yes	Yes	Yes

Notes: Table 5 presents the results of a logistic regression analysis conducted on the survey data. The dependent variable in column (1) is a dummy variable equal to 1 for individuals who selected options (4)-(6) in response to question 1. For column (2), the dependent variable is a dummy variable equal to 1 for individuals who reported not saving in question 1. In column (3), the dependent variable is a dummy variable equal to 1 for those who reported saving only when their income exceeds their expenditures (option 2 in question 2). Control variables include gender, age, income brackets, and saving capacity (equal to 1 for individuals reporting that their income typically exceeds their expenditures). An additional control for whether an individual reports being an active saver (options (3)-(5) in question 2) is included only in columns (1) and (2). *** denotes significance at the 1% level, ** denotes significance at the 5% level and * denotes significance at the 10% level. N is the number of observations.

In general, we find that people with different levels of education exhibit notable differences in saving motives and methods, even after accounting for income. In particular, our findings indicate that individuals with only primary education are less likely to save for future consumption and more likely to report not saving at all than those with higher levels of education. In addition, people with university education are more likely to exhibit passive saving behavior—that is, saving only when income exceeds expenditures—rather than establishing systematic saving rules or saving at all, suggesting that passive-saver consumption choices are relatively independent of income and indicative of a low MPC. This aligns with our earlier findings that for the working-age population, best describes your or your family’s overall financial situation?” The response options were: (1) Expenditures are approximately equal to income, (2) Expenditures are usually higher than income, and (3) Expenditures are usually lower than income. *Saving capacity* is coded as 1 if respondents selected option (3), and 0 otherwise. Similarly, the dummy variable *active saver* is coded as 1 for individuals who reported following a saving rule, corresponding to options (3)-(5) in question 2, and 0 otherwise.

the MPC is lowest among university-educated individuals.

8 Concluding remarks

Differences in time preferences, reflected in educational choices, generate systematic heterogeneity in consumption behavior. We propose a model in which individuals with differing inherent patience, or discount rates, self-select into education, with more patient individuals choosing fields that offer higher rates of return. To test this hypothesis, we use administrative tax records from Iceland for 2005–2019—a period marked by large fluctuations in real disposable income following the 2008 financial crisis—to compare consumption behavior across households with different levels of educational attainment—primary, secondary, and tertiary—as well as across fields of university education.

Our results suggest that consumption smoothing increases with education. University-educated households respond less to unexpected changes in transitory income than lower-educated households. Allowing for heterogeneity, we find that this partly reflects their overrepresentation in the upper part of the income distribution, where the marginal propensity to consume is lower, as well as their lower likelihood of being liquidity constrained. Within university education, fields with higher monetary rates of return—those more likely to attract patient individuals—are associated with greater liquidity and lower marginal propensities to consume.

We also find a clear asymmetry in consumption responses. Households smooth positive transitory income shocks to a much greater extent than negative shocks, an effect driven by non-liquidity-constrained households. While constrained households exhibit high marginal propensities to consume—close to 0.75—following both positive and negative shocks, the response of unconstrained households to positive shocks is considerably more muted, with a marginal propensity to consume of around 0.4. Examining time variation, we find that the marginal propensity to consume increased markedly following the global financial crisis and the collapse of Iceland’s banking system. This increase is driven by a sharp rise in the response to negative transitory income shocks across all education groups, with households adjusting primarily by reducing consumption.

These results are complemented by survey evidence suggesting that university-educated house-

holds are more likely to report consumption smoothing, even after controlling for income, and that financing future consumption is their main motive for saving. In contrast, less-educated households are more likely to exhibit behavior consistent with a high propensity to consume out of transitory income, such as relying mainly on mandatory pension saving.

Our results suggest that differences in time preferences, reflected in educational choices, are a central source of heterogeneity in consumption behavior. Individuals who select into higher-return fields accumulate greater liquidity and exhibit lower marginal propensities to consume. This heterogeneity shapes the distribution of liquidity and the response of consumption to income shocks over the business cycle. In our framework, education mainly operates as a sorting mechanism rather than a causal determinant, revealing underlying differences in patience that drive both human capital investment and consumption behavior.

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Appendix A

A1. Robustness checks

A1.1 Robustness to sample restrictions

In our main estimation, we omit the top 1 percentile in imputed consumption to alleviate biases from potentially misattributing wealth declines to consumption when they might stem from unrealized capital losses or stock transactions not observed in the data. Here, we test the robustness to this by omitting the top 5 percentiles instead. Table A1 column (2) reports the MPCs for this sample. The MPCs are somewhat lower than those of the baseline model in column (1). This is to be expected given the omission of more observations at the top of the consumption distribution. However, in both cases, university-educated households have a significantly lower MPC in response to transitory income shocks than primary- or secondary-school-educated households. The difference is statistically significant at the 1% significance level, whereas in the main text, the difference between the MPCs of university-educated and primary school-educated households was significant at the 5% significance level.

A1.2 Alternative education classification

In our main specification, we define the household's level of education as the educational attainment of the more educated member of the household. However, some households with mixed educational attainment might have more in common with households whose education matches the lower-educated spouse. To ensure that our main results are robust to our education classification, we redo our analysis for three alternative education groups: households in which all members have a primary education (this is the same sample as in our main specification), households in which all members have a secondary school education, and households in which all members have a university degree. Households with mixed educational attainment are, thus, omitted. Table A1 column (3) shows the resulting MPC estimates. They are broadly similar to the baseline estimation in column (1).

A1.3 Robustness to alternative standard error clustering

Table A2 presents robustness of our MPC estimates with alternative standard error clustering.

A2. Supplementary figures and tables

Figures A1 to A5 show the MPC in response to positive and negative transitory income shocks across education groups, by wealth, income, and liquidity.

Figure A6 shows the time variation in the MPC out of negative income shocks in panel (a) and positive income shocks in panel (b).

Figure A7 shows the share of observations with negative consumption across age, disposable income, and permanent income groups. Overall, approximately 12% of observations have negative imputed consumption values. Those observations are omitted in the main analysis. The figures show little evidence of particularly high rates of negative imputed consumption among certain types of households, apart from those with very low incomes, mostly in the lowest 5%. The frequency of negative consumption is approximately constant over the life cycle.

Tables A3 to A7 reports the estimates and standard errors underlying Figure 4.

Table A1: Sample selection

	(1) Baseline	(2) Drop top 5%	(3) Drop mixed couples
$\hat{y}_{i,t} \times primary$	0.514 ^{***} (0.020)	0.426 ^{***} (0.023)	0.515 ^{***} (0.020)
$\hat{y}_{i,t} \times secondary$	0.602 ^{***} (0.013)	0.442 ^{***} (0.016)	0.572 ^{***} (0.018)
$\hat{y}_{i,t} \times university$	0.502 ^{***} (0.014)	0.319 ^{***} (0.017)	0.538 ^{***} (0.020)
R^2	0.032	0.024	0.034

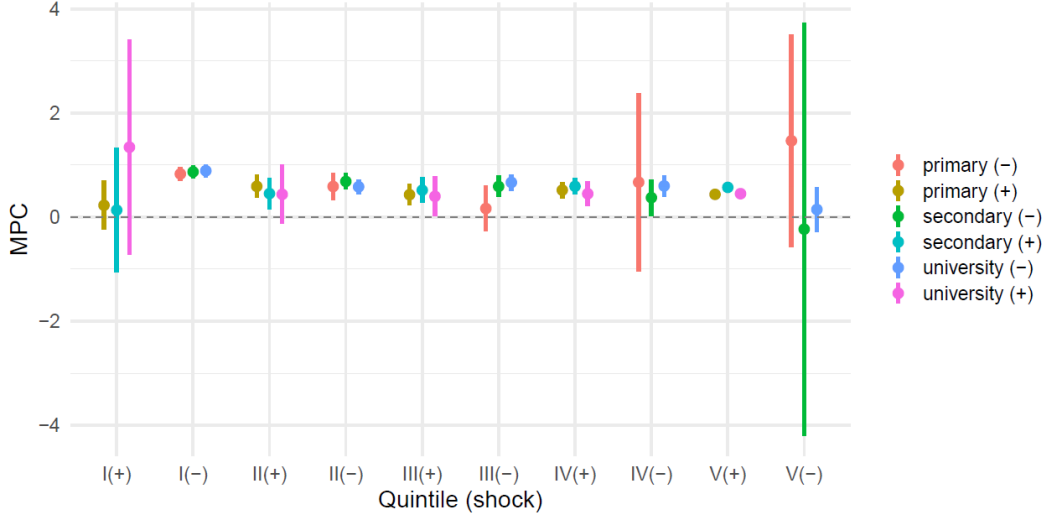
Notes: This table presents 2SLS estimates from Equation (12). Column (1) presents baseline estimates. Column (2) drops the top 5 percentiles in consumption omitted, instead of the top 1 percentile in the main analysis. In column (3) households are assigned to an education group if, and only if, all members within the household belong to that education group. The estimates are based on 951,384 households aged 31 to 66 in 2005-2019. Standard errors clustered at the individual level are in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level and * denotes significance at the 10% level.

Table A2: Clustered standard errors

	(1) Baseline	(2) id + year	(3) Cohort + year	(4) Urbanization + year
$\hat{y}_{i,t} \times primary$	0.514 ^{***} (0.020)	0.514 ^{***} (0.023)	0.514 ^{***} (0.027)	0.512 ^{***} (0.020)
$\hat{y}_{i,t} \times secondary$	0.602 ^{***} (0.013)	0.602 ^{***} (0.020)	0.602 ^{***} (0.021)	0.601 ^{***} (0.013)
$\hat{y}_{i,t} \times university$	0.502 ^{***} (0.014)	0.502 ^{***} (0.032)	0.502 ^{***} (0.032)	0.503 ^{***} (0.014)
R^2	0.032	0.032	0.032	0.032

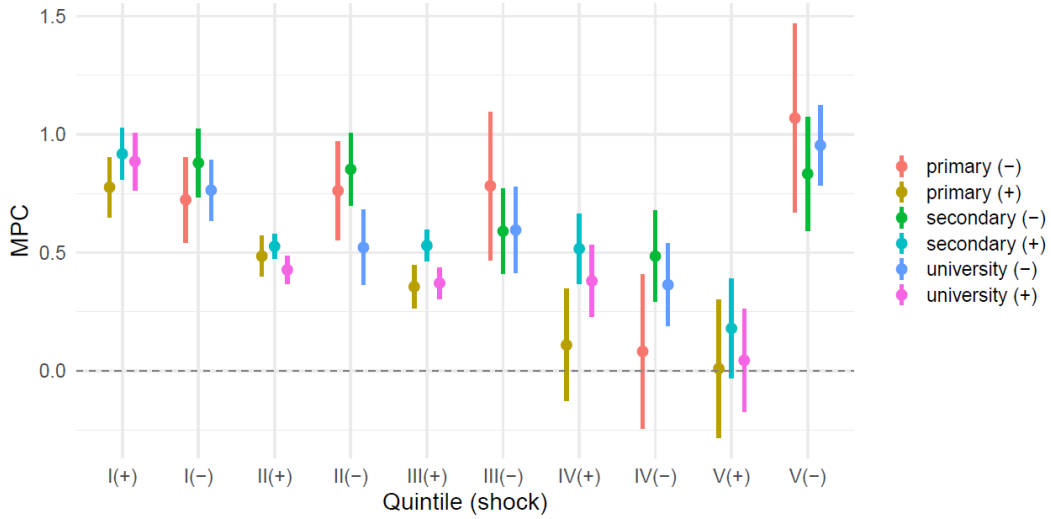
Notes: This table presents 2SLS estimates from Equation (12). All columns report the same point estimates; only the clustering of standard errors differs. Column (1) clusters standard errors at the individual level (baseline). Column (2) applies two-way clustering at the individual and year level. Column (3) applies two-way clustering at the cohort and year level. Column (4) applies two-way clustering at the urbanization and year level. The estimates are based on 951,384 households aged 31 to 66 in 2005-2019. *** denotes significance at the 1% level, ** denotes significance at the 5% level and * denotes significance at the 10% level.

Figure A1: MPC by education and disposable income



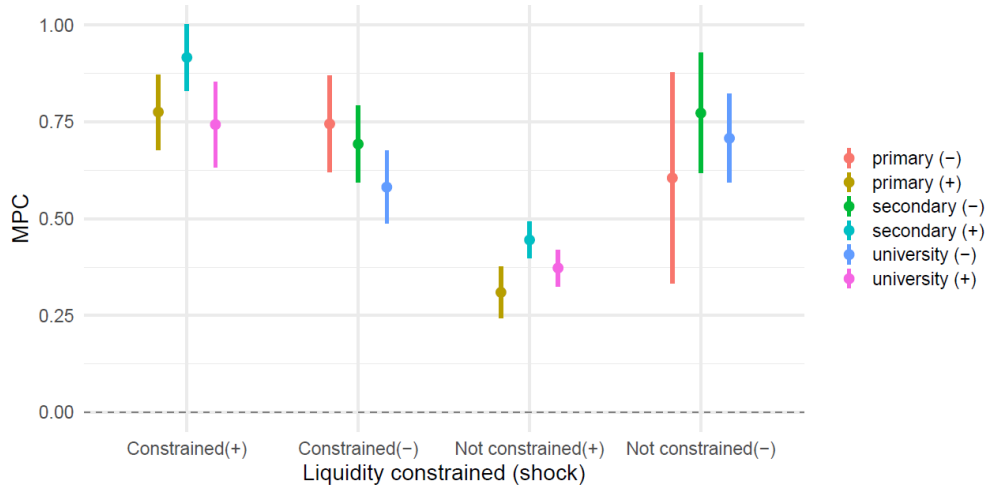
Notes: The figure shows the MPC estimates from Equation (13) with added interactions for disposable income quintiles.

Figure A2: MPC by education and net wealth to income



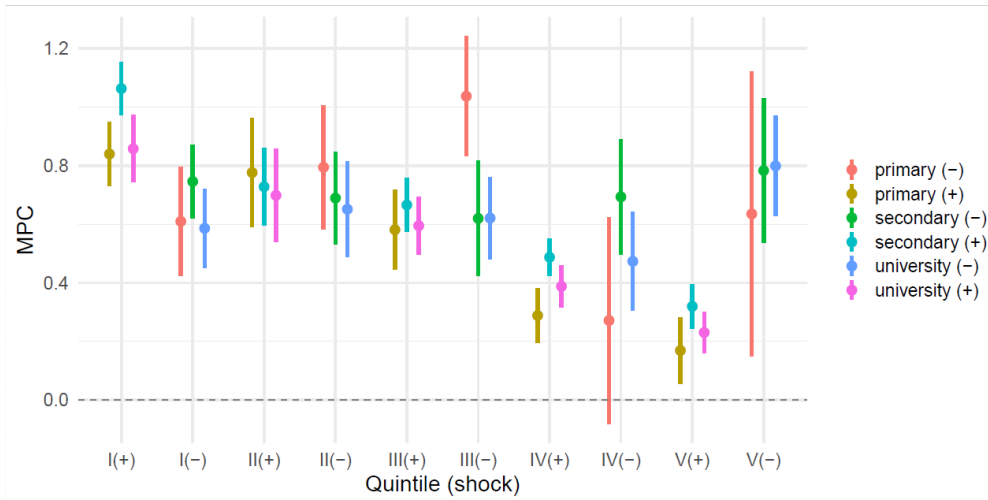
Notes: The figure shows the MPC estimates from Equation (13) with added interactions for net-wealth-to-disposable-income quintiles. The points refer to the MPC coefficient estimates, and 95% confidence intervals based on standard errors clustered at the individual level are represented by the vertical lines. I(-) on the x-axis refers to the first quintile of the distribution and a negative transitory income shock. I(+) refers to the first quintile of the distribution and a positive transitory income shock. The other quintiles are represented analogously.

Figure A3: MPC by education and liquid wealth to income, age 31–66



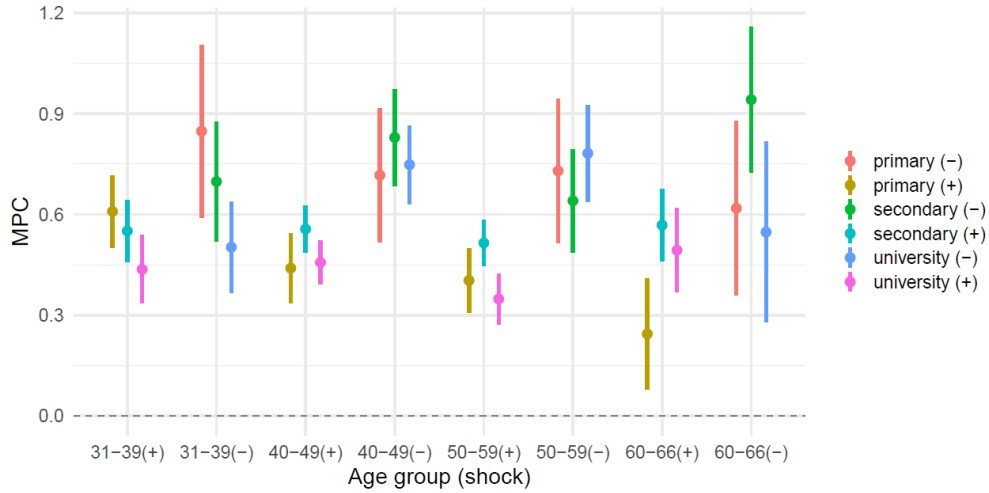
Notes: The figure shows the MPC estimates from Equation (13) with added interactions for liquid asset-to-disposable-income quintiles. The points refer to the MPC coefficient estimates, and 95% confidence intervals based on standard errors clustered at the individual level are represented by the vertical lines. Primary-educated households are shown in blue, secondary-educated households in yellow, and university-educated households in red. I(-) on the x-axis refers to the first quintile of the distribution and a negative transitory income shock. I(+) refers to the first quintile of the distribution and a positive transitory income shock. The other quintiles are represented analogously.

Figure A4: MPC by education and liquidity constraints, age 31-66



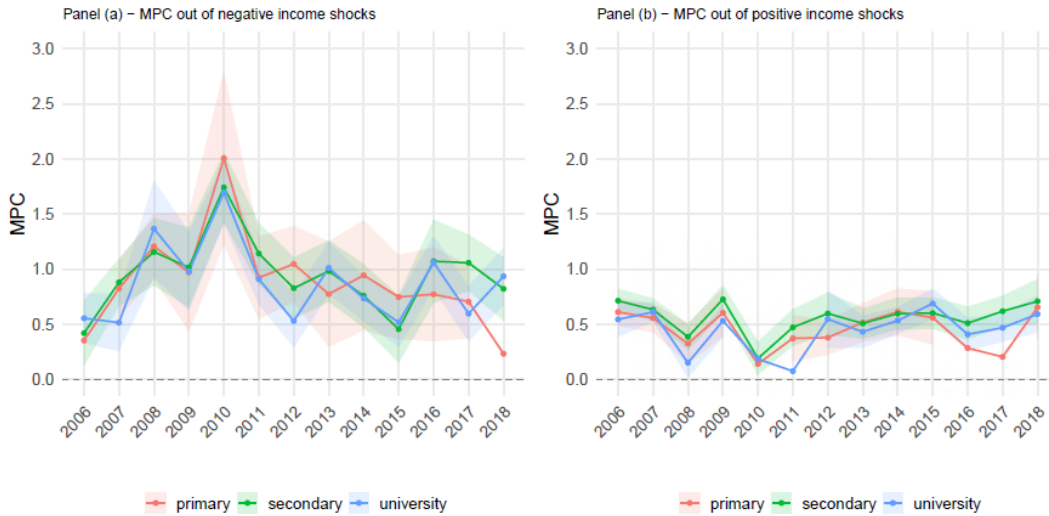
Notes: The figure shows the MPC estimates from Equation (13) with added interactions for liquidity constraints. A household is considered liquidity-constrained if the sum of bank deposits and assets in investment and savings funds is below USD 4,000 for singles and USD 8,000 for couples. The points refer to the MPC coefficient estimates, and 95% confidence intervals based on standard errors clustered at the individual level are represented by the vertical lines. Constrained (-) on the x-axis refers to liquidity-constrained households and a negative transitory income shock. Constrained (+) refers to liquidity-constrained households and a positive transitory income shock. Non-constrained households are represented analogously.

Figure A5: MPC by education and age group



Notes: The figure shows the MPC estimates from Equation (13) with added interactions for age groups. The points refer to the MPC coefficient estimates, and 95% confidence intervals based on standard errors clustered at the individual level are represented by the vertical lines. 31-39(-) on the x-axis refers to the age group 31 to 39 and a negative transitory income shock. 31-39(+) refers to the age group 31 to 39 and a positive transitory income shock. The other age groups are represented analogously.

Figure A6: MPC out of positive and negative income shocks by year



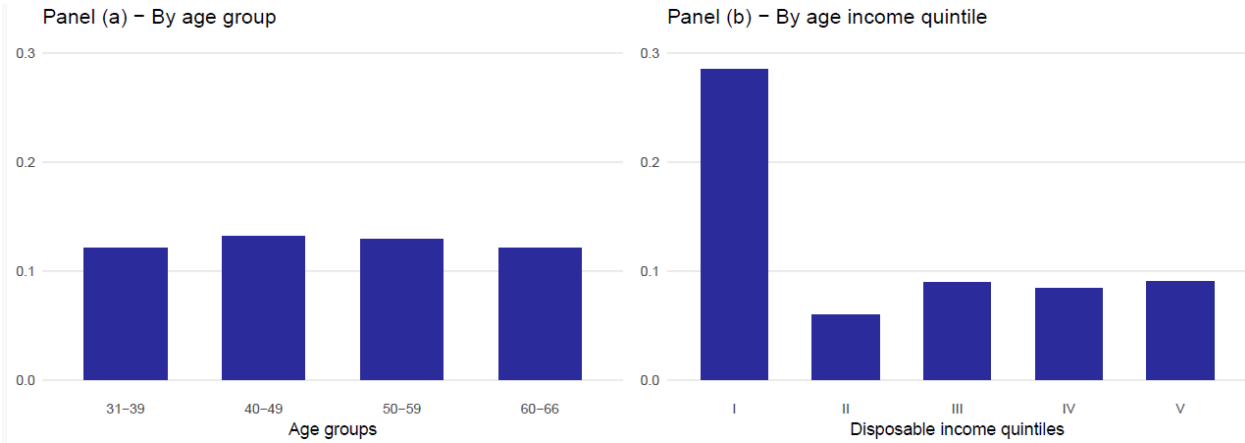
Notes: The figure plots the time variation in the MPC separately for positive and negative income shocks. It is estimated with a slight variation of Equation 13. Age effects are omitted to allow for the inclusion of traditional year fixed effects in the regression of log income and consumption on various household characteristics to identify the consumption and income shocks. The regression includes controls for individual and year fixed effects and dummy variables for gender, marital status, number of children, the interaction between marital status and number of children, education, sector of work and the degree of urbanisation. Furthermore, we control for the log of real estate assets.

Table A3: MPC by disposable income quintiles

	Primary	Secondary	University
$\Delta \hat{y}_{i,t} \times Q1$	0.614 ^{***} (0.052)	0.722 ^{***} (0.044)	0.784 ^{***} (0.054)
$\Delta \hat{y}_{i,t} \times Q2$	0.549 ^{***} (0.069)	0.523 ^{***} (0.047)	0.484 ^{***} (0.052)
$\Delta \hat{y}_{i,t} \times Q3$	0.336 ^{***} (0.079)	0.426 ^{***} (0.056)	0.514 ^{***} (0.054)
$\Delta \hat{y}_{i,t} \times Q4$	0.589 ^{***} (0.071)	0.538 ^{***} (0.053)	0.476 ^{***} (0.058)
$\Delta \hat{y}_{i,t} \times Q5$	0.442 ^{***} (0.021)	0.602 ^{***} (0.014)	0.471 ^{***} (0.016)
<hr/>			
$N = 951,384 \quad R^2 = 0.033$			

Notes: MPC estimates obtained from Equation (12) with additional interactions with disposable income quintiles. The estimates are based on households aged 31 to 66 in 2005-2019. Standard errors clustered at the individual level are in parentheses. Q1 is the lowest quintile and Q5 is the highest. *** denotes significance at the 1% level, and ** denotes significance at the 5% level. N is the number of observations.

Figure A7: Share of observations with negative consumption by age and income



Notes: The figure plots the share of observations with negative consumption by age groups.

Table A4: MPC by net-wealth-to-income quintiles

	Primary	Secondary	University
$\Delta \hat{y}_{i,t} \times Q1$	0.754 ^{***} (0.047)	0.902 ^{***} (0.037)	0.835 ^{***} (0.039)
$\Delta \hat{y}_{i,t} \times Q2$	0.542 ^{***} (0.030)	0.588 ^{***} (0.020)	0.457 ^{***} (0.023)
$\Delta \hat{y}_{i,t} \times Q3$	0.436 ^{***} (0.038)	0.548 ^{***} (0.023)	0.429 ^{***} (0.025)
$\Delta \hat{y}_{i,t} \times Q4$	0.091 (0.075)	0.496 ^{***} (0.041)	0.361 ^{***} (0.044)
$\Delta \hat{y}_{i,t} \times Q5$	0.415 ^{***} (0.077)	0.486 ^{***} (0.044)	0.530 ^{***} (0.043)
<hr/> $N = 951,384 \quad R^2 = 0.034$ <hr/>			

Notes: Presents the MPC estimates obtained from Equation (12) with additional interactions with net-wealth-to-income quintiles. The estimates are based on households aged 31 to 66 in 2005-2019. Standard errors clustered at the individual level are in parentheses. Q1 is the lowest quintile and Q5 is the highest. *** denotes significance at the 1% level, and ** denotes significance at the 5% level. N is the number of observations.

Table A5: MPC by liquidity constraint

	Primary	Secondary	University
$\Delta \hat{y}_{i,t} \times NC$	0.364 ^{***} (0.023)	0.517 ^{***} (0.015)	0.466 ^{***} (0.016)
$\Delta \hat{y}_{i,t} \times LC$	0.719 ^{***} (0.036)	0.768 ^{***} (0.026)	0.620 ^{***} (0.031)
<hr/> $N = 951,384 \quad R^2 = 0.034$ <hr/>			

Notes: Table presents the MPC estimates obtained from Equation (12) with additional interactions with a liquidity constraint. A household is considered liquidity constrained if liquid assets are less than USD 8,000 for couples and USD 4,000 for singles. The estimates are based on households aged 31 to 66 in 2005-2019. Standard errors clustered at the individual level are in parentheses. NC denotes not constrained and LC denotes liquidity constrained. *** denotes significance at the 1% level, and ** denotes significance at the 5% level. N is the number of observations.

Table A6: MPC by bank deposit quintiles

	Primary	Secondary	University
$\Delta \hat{y}_{i,t} \times Q1$	0.727 ^{***} (0.045)	0.917 ^{***} (0.034)	0.723 ^{***} (0.039)
$\Delta \hat{y}_{i,t} \times Q2$	0.779 ^{***} (0.065)	0.701 ^{***} (0.047)	0.689 ^{***} (0.051)
$\Delta \hat{y}_{i,t} \times Q3$	0.746 ^{***} (0.056)	0.657 ^{***} (0.037)	0.625 ^{***} (0.038)
$\Delta \hat{y}_{i,t} \times Q4$	0.298 ^{***} (0.038)	0.537 ^{***} (0.025)	0.426 ^{***} (0.027)
$\Delta \hat{y}_{i,t} \times Q5$	0.221 ^{***} (0.033)	0.404 ^{***} (0.021)	0.359 ^{***} (0.022)
<hr/>			
$N = 951,384 \quad R^2 = 0.035$			

Notes: MPC estimates obtained from Equation (12) with additional interactions with bank deposit quintiles. The estimates are based on households aged 31 to 66 in 2005-2019. Standard errors clustered at the individual level are in parentheses. Q1 is the lowest quintile and Q5 is the highest. *** denotes significance at the 1% level, and ** denotes significance at the 5% level. N is the number of observations.

Table A7: MPC by age group

	Primary	Secondary	University
$\Delta \hat{y}_{i,t} \times 31-39$	0.674 ^{***} (0.046)	0.593 ^{***} (0.034)	0.467 ^{***} (0.031)
$\Delta \hat{y}_{i,t} \times 40-49$	0.513 ^{***} (0.036)	0.632 ^{***} (0.023)	0.550 ^{***} (0.022)
$\Delta \hat{y}_{i,t} \times 50-59$	0.484 ^{***} (0.034)	0.550 ^{***} (0.022)	0.479 ^{***} (0.026)
$\Delta \hat{y}_{i,t} \times 60-66$	0.352 ^{***} (0.052)	0.661 ^{***} (0.033)	0.512 ^{***} (0.045)
<hr/>			
$N = 951,384 \quad R^2 = 0.032$			

Notes: MPC estimates obtained from Equation (12) with additional interactions with age groups. The estimates are based on households aged 31 to 66 in 2005-2019. Standard errors clustered at the individual level are in parentheses. *** denotes significance at the 1% level, and ** denotes significance at the 5% level. N is the number of observations.