Education and Consumption Smoothing*

Svend E. Hougaard Jensen † Arnaldur S. Kristjansson ‡

Sigurdur P. Olafsson § Thorsteinn S. Sveinsson ¶ Gylfi Zoega ‖

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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 that had a heterogeneous effect on individual taxpayers. We develop 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. In the model, these individuals accumulate more liquid savings, smooth consumption to a greater extent, and have a lower marginal propensity to consume. Using register data containing the tax returns of all taxpayers in Iceland, we find that higher education is associated with a lower marginal propensity to consume (MPC) largely due to higher disposable income and more liquidity. Comparing university fields by their rate of return, we find lower MPCs in higher-rate-of-return fields as well as greater liquidity. Finally, using survey data, we find supporting evidence that university-educated individuals smooth consumption more than those with shorter education.

Keywords: Education, patience, consumption smoothing.

JEL Codes: E21, E24

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†Department of Economics, Copenhagen Business School; shj.eco@cbs.dk

‡Department of Economics, University of Iceland; askristjansson@hi.is

§Department of Economics, Copenhagen Business School; sigurdur.pall.olafsson@fjr.is

¶Economics and Monetary Policy, Central Bank of Iceland; thorsteinn.sigurdur.sveinsson@sedlabanki.is

‖Department of Economics, University of Iceland, and Birkbeck Business School, University of London; gz@hi.is

1 Introduction

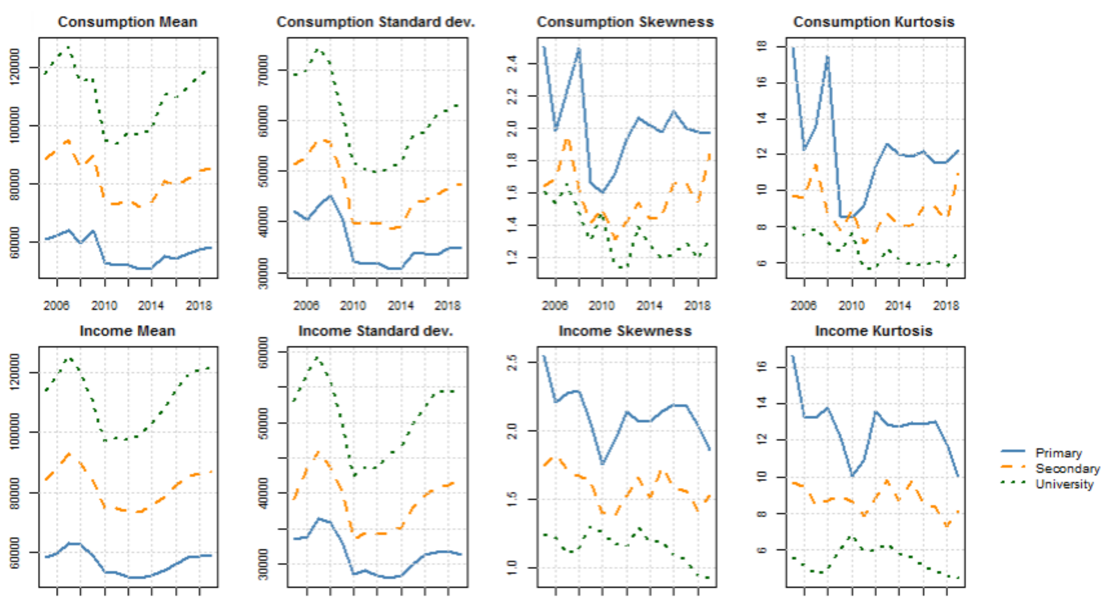
We study consumption smoothing by education during a turbulent period in Iceland, when disposable income fluctuated dramatically owing to a financial boom, the subsequent banking collapse, and the economic recovery. These events generated substantial differences in household income shocks. We exploit this heterogeneity to estimate the marginal propensity to consume (MPC) for individuals with primary, secondary, and tertiary (university-level) education and across different fields of study. The MPC is our measure of consumption smoothing.

Education may matter for individuals' ability to smooth consumption in the face of income shocks. We hypothesize that educational choices reflect underlying patience, which affects saving behavior and consumption smoothing. Alternatively, it has been proposed in the literature that education may lower the rate of subjective time preference. Patience is not directly observed in our administrative data. Instead, educational attainment—and, within university education, the choice among fields with different expected rates of return—provides information about underlying time preference and reflects differences in ability, interests, and other individual characteristics. In our model, individuals with a lower rate of time preference are more willing to sacrifice current earnings for higher future earnings by choosing high-return educational fields. Their patience is also reflected in consumption behavior, as they accumulate liquid savings and smooth consumption more effectively.

We use a rich administrative panel dataset comprising tax records for all taxpayers in Iceland from 2005 to 2019, combined with various background characteristics. We compute consumption for each household using the accounting identity: household consumption equals disposable income minus changes in net wealth plus unrealized capital gains. We exploit the panel dimension of the data to derive idiosyncratic income and consumption shocks and estimate households' consumption responses using 2SLS. We then examine heterogeneity across education groups and other household characteristics, including income, wealth, liquidity and the rate of return to education.

Our sample period (2005–2019) encompasses the financial boom, the banking collapse, and the subsequent recovery, generating major changes in household disposable income that had a heterogeneous effect on individual taxpayers. Because these developments were largely unexpected, they provide a unique opportunity to estimate consumption smoothing across education groups. Unlike most studies based on windfall income, we identify both positive and negative transitory income shocks, allowing us to examine asymmetries in households' consumption responses. Figure 1 shows that the financial crisis and its aftermath was associated with substantial changes in the cross-sectional distributions of disposable income and consumption.

Figure 1: Moments of disposable income and consumption, 2004-2019



Note: Per capita household disposable income and consumption in US dollars at 2019 prices.

The first four moments of both distributions changed markedly during the crisis and the subsequent recovery, indicating that the crisis altered the distribution of consumption and income rather than simply shifting their means. This is consistent with households being affected differently by the crisis and its aftermath, generating the cross-sectional variation in income that underlies our identification of households' consumption responses to transitory income shocks.

Our main findings are as follows. 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. University-educated households exhibit lower MPCs than other households. Moreover, within this group, higher-return fields are associated with lower MPCs and more liquidity. We also find stronger consumption responses to negative than to positive income shocks, and substantial heterogeneity by income and liquidity. The MPC also rose sharply during the crisis, especially following negative income shocks, before returning to pre-crisis levels during the recovery.

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. More broadly, the paper links the literatures on human capital, household finance, and consumption smoothing by showing how educational choices are associated with differences in intertemporal household behavior.

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 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. In a similar vein, Carroll (2001) found that buffer-stock saving generates consumption behavior that resembles the effect of liquidity constraints.

A growing literature links education to household financial behavior. Campbell (2006) reviews evidence that more-educated households participate more actively in financial markets, hold more diversified portfolios, and make better financial decisions. Cooper and Zhu (2016) estimate a structural life-cycle model in which differences in lifetime earnings explain much of the education gap in wealth accumulation, although differences in discount factors also contribute.Jappelli and Padula (2013) derive a model that implies that the stock of financial literacy early in life is positively correlated with the stocks of literacy and wealth later in life and find empirical support for these predictions. Jappelli and Padula (2015) extend this framework to portfolio choice and retirement saving. Canbary and Grant (2019) find, using UK data, that households with higher socioeconomic status have lower MPCs. 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.

Another strand of the literature studies the relationship between education and time preference. Sunde et al. (2022) find a positive relationship between measured patience and human capital across countries, measured by educational attainment and average years of schooling. They also find that patience is strongly correlated with the stock of physical capital at the country level and national saving rates. Falk et al. (2018) find that patience is positively associated with both saving and education. An alternative view is that education itself affects time preference.Becker and Mulligan (1997) argue that people can affect their time-preference rate through schooling, which focuses attention on the future and increases the weight placed on future outcomes. Bishai (2004) estimates time preference from the National Longitudinal Survey of Youth and finds that older, more educated individuals value future utility more highly.

We contribute to the literature by developing a simple theoretical model in which higher discount factors influence educational choices by increasing the length of education and the attractiveness of high-return fields, which in turn are associated with greater liquidity and consumption smoothing. We then use administrative panel data covering all taxpayers in Iceland, classified by educational level, to estimate consumption smoothing across education groups during a period of unusually large idiosyncratic income fluctuations. We find that university-educated individuals smooth consumption more than those who did not complete university, and that the rate of return to a field of study is negatively related to the MPC.

The stylized theoretical model developed in the next section formalizes the hypothesis that differences in time preference influence educational choices. Our empirical analysis is consistent with this mechanism, but it does not rule out the alternative view that education itself affects time preference.

3 Education and consumption smoothing

We think of education as an observable outcome of an intertemporal choice problem. We do not observe, nor do we try to measure, individuals' subjective rates of time preference directly. Throughout the paper, we use "patience" as shorthand for a low subjective rate of time preference, or equivalently a high discount factor β. Our hypothesis is that educational choices—particularly the choice among university fields with different expected returns—provide information about underlying patience in addition to ability, interests, and other factors.

In our model, more demanding fields of study yield higher returns in terms of future earnings and attract more patient students willing to sacrifice more in the short run for future returns. Patience also affects the propensity to save and build cash buffers, enabling consumers to smooth consumption. This provides a link between educational choice and consumption smoothing.

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. 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. By distinguishing between general and specific training, Becker clarified when workers or firms pay for investment. Mincer (1962) modeled on-the-job training as an investment undertaken within the firm. Workers accept lower wages during training 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.

Ben-Porath (1967) brought these ideas together in a life-cycle framework. Individuals allocate time between work and investing in human capital, recognizing that the return to investment depends on the number of remaining working years. Because the horizon is long when young, investment is greater in the early part of the working life and falls as the worker approaches retirement. 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, the choice of education 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 discounted lifetime, T, net earnings,

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

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. Training gradually increases human capital, which then raises wage income,

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

where the parameter α measures the elasticity of human capital generation with respect 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 future marginal return to human-capital investment, while a higher β_i places greater weight on future returns. This generates increasing differences:

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

By standard monotone comparative statics, increasing differences between education fields imply positive associations between patience and returns. In other words, the effect of increasing returns A_f on the value of a field is larger for more patient individuals. Intuitively, high-return fields give higher returns later, and patient people care more about what comes later, implying that high-return fields become relatively more attractive as patience increases.

Our theoretical framework assumes that patience affects educational choice. Becker and

Mulligan (1997) instead argue that schooling itself increases patience. They argue that people become more patient by attending school because schooling focuses students' attention on the future through problem solving, deadlines, and examinations. Thus, repeated problem solving and examinations give students the ability to see into the future. Both mechanisms predict a positive association between education and consumption smoothing.

Our empirical results in Section 5 do not discriminate between education as a sorting device and education as a causal factor. Instead, we will link educational choices to liquid assets and the estimated marginal propensity to consume.

3.2 Patience and consumption

Intertemporal preferences affect consumption smoothing. 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 shocks. 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 and liquid wealth. 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. Kuchler and Pagel (2015) use data from an online financial service in the U.S. 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. 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, whereas it 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, current cash-on-hand can be written as

$$m_{it} = (1+r)a^L_{i,t-1} + y^P_{it} + \varepsilon_{it}, \tag{4}$$

where r is the rate of return, a^L denotes liquid wealth, including stocks and bonds, y^P is permanent income, and ε is transitory income and $a_{it} \equiv m_{it} - c_{it}$. Consumption is then a function of cash-on-hand and patience:

$$c_{it} = c(m_{it}; \beta_i) \tag{5}$$

A transitory income shock affects consumption only through its effect on current cash on hand. The marginal propensity to consume (MPC) out of a transitory income shock is therefore

$$MPC_{it} \equiv \frac{\partial c_{it}}{\partial \varepsilon_{it}} = c_m(m_{it}; \beta_i)\,.$$

Assuming $0 < c_m < 1$, $c_{mm} < 0$, and $c_{m\beta} < 0$, the MPC is decreasing in both cash-on-hand and patience. Individuals with greater liquid wealth exhibit lower marginal propensities to consume in response to transitory income shocks.

Holding cash on hand fixed, the direct effect of patience on the MPC is $c_{m\beta}(m_{it}; \beta_i) < 0$. Patience also affects the MPC indirectly through its effect on wealth accumulation. The total effect of patience on the MPC is therefore

$$\frac{d\,\mathrm{MPC}_{it}}{d\beta_i} = c_{m\beta}(m_{it}; \beta_i) + c_{mm}(m_{it}; \beta_i)\,\frac{\partial m_{it}}{\partial \beta_i} < 0. \tag{6}$$

Since $c_{m\beta} < 0$, $c_{mm} < 0$, and more patient individuals accumulate greater liquid wealth, $\partial m_{it}/\partial \beta_i > 0$, both terms are negative. Patience therefore lowers the MPC directly through greater consumption smoothing and indirectly through the accumulation of larger wealth buffers.

4 Data

We use a dataset of annual administrative tax records from all taxpayers in Iceland 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.[1] The data are linked with other administrative data and therefore include socio-demographic factors as well.[2]

By aggregating information among household members each year using unique household identifiers, we construct household-level measures of income and other characteristics. Households are either single-person households or jointly taxed couples. For households with

[1]The 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.

[2]These include information on age, gender, education, marital status, industry, and the number of children.

two adult members, the household is classified by the higher partner's educational attainment. Our educational variables are binary for each of three educational degrees, which does not allow us to take averages for couples. Instead, we assume that both partners benefit from the partner with the higher level of education.[3] Industry and age are measured at the individual level, whereas consumption and saving are household decisions. We therefore assign each adult an equal share of household income, consumption, assets, and liabilities, while allowing individual characteristics, such as age and industry, to vary between partners. This reflects our assumption that financial decisions are made jointly within the household, based on the household's total income and wealth. The resulting data allow us to compare consumption smoothing across individuals with different educational attainment.

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 66 years, born between 1935 and 1979. We also omit deficient tax records and individuals who have negative consumption.[4] Deficient tax records include those who have income from abroad or have failed to file their taxes. This requires 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 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.[5]

[3]Table A1 shows results excluding mixed couples with different educational attainment.The results remain similar.

[4]Although 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 inter-generational transfers or gifts (Kolsrud et al., 2020). The share of individuals with negative consumption is relatively stable across the age and income distributions, except in the first disposable income quintile, as shown in Figure A1.

[5]Timing 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

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);

$$C_{i,t} \equiv Y_{i,t} - \Delta W_{i,t} + \sum_{k} \Delta p_{k,t} A_{i,k,t-1} \tag{7}$$

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 for couples as the average of their disposable income, net wealth, and assets, respectively.

The idea underlying the identity in Equation (7) 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.[6] The public institution estimates the market value of all real properties 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

individuals for our analysis.

[6] Register Iceland is a public institution responsible for maintaining a property register and national register in Iceland.

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 motor vehicle values, 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.[7]

In the absence of unreported income and transactions in individual stocks and given the assumption of no transactions within the year in funds, Equation 7 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 liabilities, including mortgages, consumer loans, auto loans, credit card debt, and student loans.These liabilities are included in the calculation of household net wealth used to construct consumption. 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

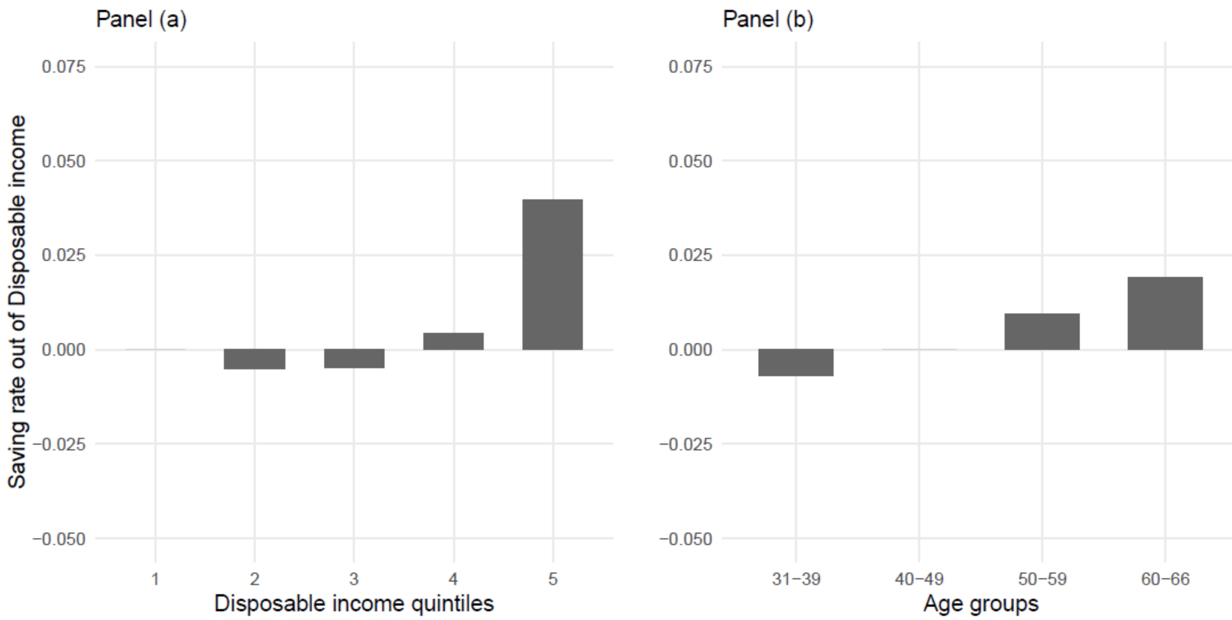
[7]We compute the imputed rent for each household by dividing the value of the real estate of each household by the total value of the real estate in the country and multiplying the result by the aggregate value of the imputed rent from national accounts.

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 4, 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 2 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 2 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 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 2, and so does their saving rate. The saving rate peaks in the years just before

Figure 2: 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 (7) and saving is the share of income not consumed. Note that both consumption and after-tax income include 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.

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 and year fixed effects,[8] dummies for age, gender, 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 proceed by obtaining the first-differenced residuals of log consumption and log income, denoted by $\Delta\tilde{c}_{i,t}$ and $\Delta\tilde{y}_{i,t}$ for individual i at time t. As in Blundell et al. (2008), the income pro-

[8] Year fixed effects are represented by year dummies that are orthogonal to a time trend and normalized to sum to zero (Deaton and Paxson, 1994).

Table 1: Summary statistics

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

cess for each household is decomposed into a permanent component P and a mean-reverting transitory component ν. Hence, residual income growth for individual i is given by

$$\Delta\tilde{y}_{i,t} = P_{i,t} + \Delta v_{i,t}. \tag{8}$$

We assume that permanent innovations are serially uncorrelated and are orthogonal to the transitory component. Because the transitory component is mean reverting, future income growth is correlated with the current transitory innovation but orthogonal to the current permanent innovation. Consequently, $\Delta\tilde{y}_{i,t+1}$ serves as an instrument for identifying the consumption response to transitory income shocks.

The 2SLS regressions are estimated using the first-differenced residuals of log income and log consumption, $\Delta\tilde{y}_{i,t}$ and $\Delta\tilde{c}_{i,t}$, obtained from the first-stage residualisation. We obtain the MPC out of transitory income shocks by first instrumenting $\Delta\tilde{y}_{i,t}$ by $\Delta\tilde{y}_{i,t+1}$ as future income growth is correlated with the current transitory income shock through the mean reversion of the transitory component, while remaining orthogonal to the current permanent income innovation. Specifically, we estimate

$$\begin{aligned}\Delta\tilde{y}_{i,t} &= \alpha_0 + \beta_{0,E}\Delta\tilde{y}_{i,t+1} \times E_{i,t} + \epsilon_{0,i,t}\\ \Delta\tilde{c}_{i,t} &= \alpha_1 + \beta_{1,E}\Delta\hat{\tilde{y}}_{i,t} \times E_{i,t} + \epsilon_{1,i,t}\end{aligned} \tag{9}$$

where $E_{i,t}$ again is a vector of indicator variables for the education groups, with primary education serving as a benchmark, and $\hat{\tilde{y}}$ is the fitted value from the first stage of the regression. Thus, the above specification is estimated for the full sample rather than separately for each group, as in the previous section.

To see the intuition behind the identifying assumption, note that $\Delta v_{i,t} = v_{i,t} - v_{i,t-1}$, so that Equation (8) can be written as

$$\Delta\tilde{y}_{i,t} = P_{i,t} + v_{i,t} - v_{i,t-1}, \tag{10}$$

while

$$\Delta\tilde{y}_{i,t+1} = P_{i,t+1} + v_{i,t+1} - v_{i,t}. \tag{11}$$

Hence,

$$\begin{aligned}\operatorname{Cov}\left(\Delta\tilde{y}_{i,t+1}, \Delta\tilde{y}_{i,t}\right) &= \operatorname{Cov}\left(P_{i,t+1} + v_{i,t+1} - v_{i,t},\ P_{i,t} + v_{i,t} - v_{i,t-1}\right) \\ &= -\sigma_v^2,\end{aligned} \tag{12}$$

because all cross-covariances vanish except $\operatorname{Cov}(-v_{i,t}, v_{i,t}) = -\sigma_v^2$. Thus, adjacent income growth rates are correlated only through the transitory component. Since permanent innovations are serially uncorrelated and orthogonal to the transitory component, lagged income growth contains information about transitory income shocks but is orthogonal to the current permanent innovation. This property underlies our instrumental-variable estimator of the marginal propensity to consume out of transitory income shocks. The descriptive evidence in Figure 1 is consistent with this interpretation, showing that the financial crisis generated substantial changes in the cross-sectional distribution of income and consumption that extend beyond movements in their means.

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.

Table 2: MPC by educational attainment

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

Notes: This table presents 2SLS estimates from Equation (9). 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 individuals 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.

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 that of 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% significance 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.[9]

There is more than one channel through which education may affect consumption smooth-

[9]Tables A1 and A2 demonstrate the robustness of the above results. In A1, we drop the top 5 percentiles of consumption rather than the top 1 percentile and also assign households to an education group if and only if all members of the household belong to that education group. In A2, 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.

ing. 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 of 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 and smooth consumption.[10]

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.[11] Figure 3 shows the coefficient estimate of the MPC for each education group and each subgroup and the shares of the former in the latter.[12]

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).[13] There

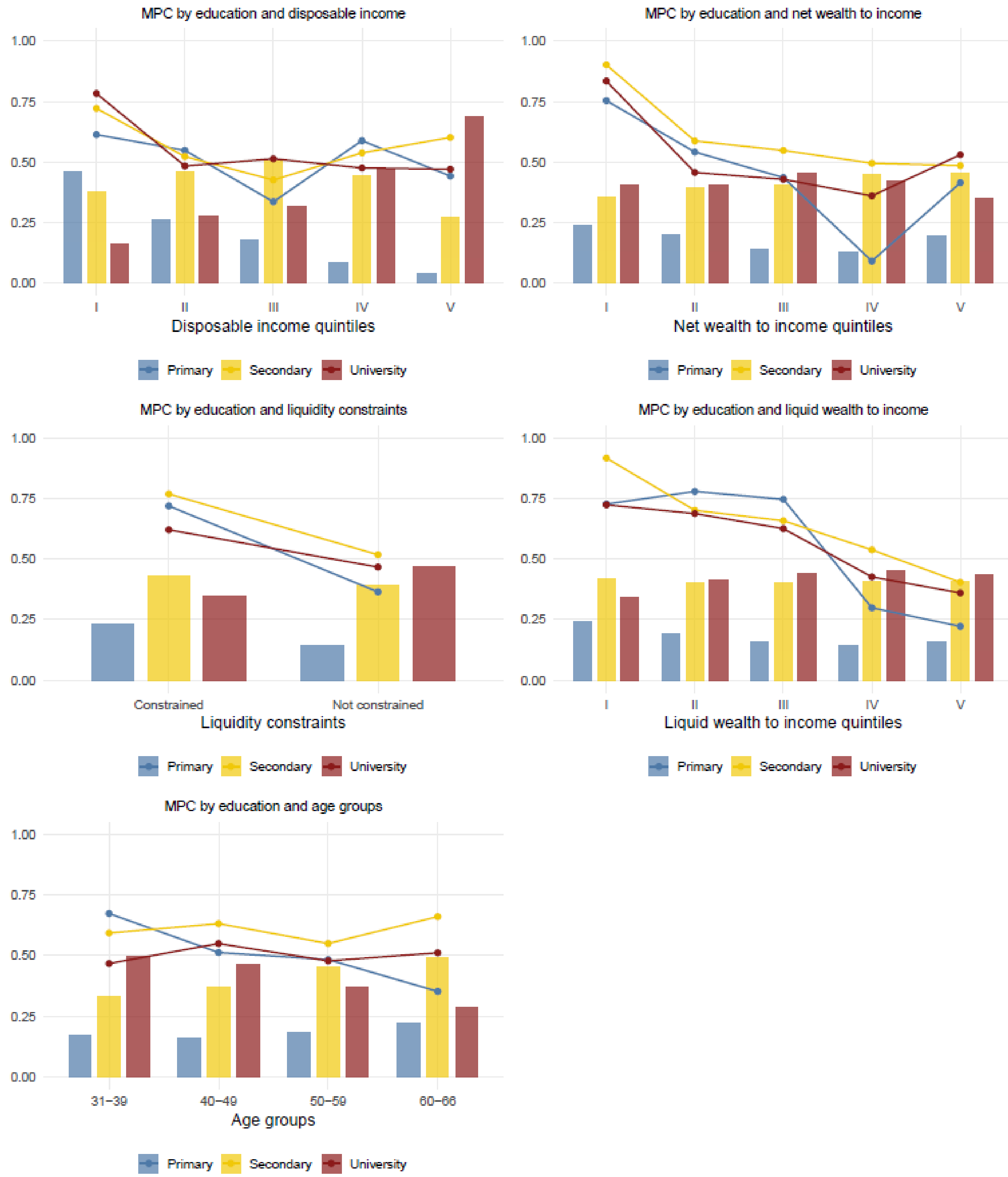
[10]Our data do not allow us to test for a relationship between education and financial literacy and its effects on consumption behavior, see Lusardi (2008).

[11]Now 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.

[12]See also Tables A3 to A7 in the Appendix for more detailed regression results.

[13]However, 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

Figure 3: MPC by income, wealth and liquidity



Notes: The lines show the MPC estimates for the population (aged 31-66) from Equation (9) 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). The bars show the distribution of the education groups where couples are allocated to their higher group. 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 951,384 individuals in 2005-2019.

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

This leaves us with our proposed explanation that higher-return university degrees attract more patient individuals, who are then more likely to accumulate buffer-stock savings and smooth consumption. We will address it in Section 6 below.

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 (9):

live hand-to-mouth due to liquidity shortages, as suggested by Kaplan et al. (2014).

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

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

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.[14] 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 households with secondary education.[15]

5.3 Aggregate shocks and the time variation in the MPC

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 ones. 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.

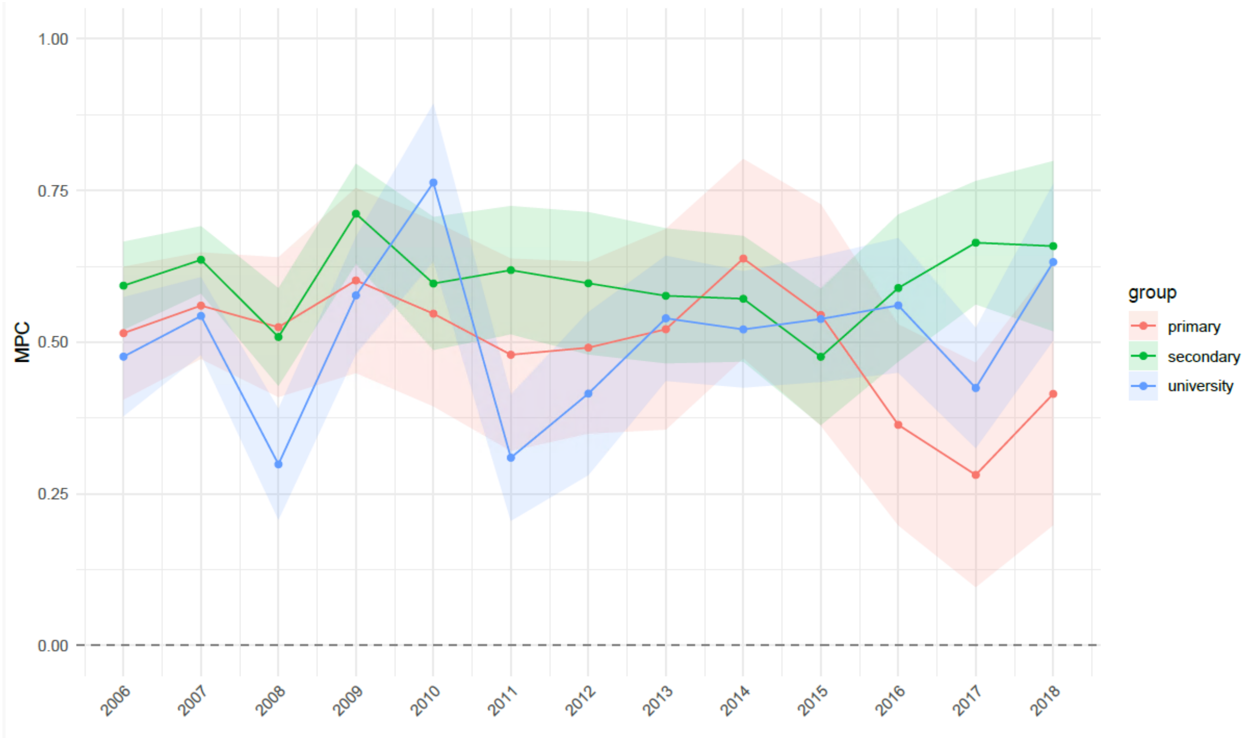
The empirical strategy is the same as in Figure 3; however, it replaces the interaction term for the relevant subgroup with year fixed effects. As such, fixed effects for the year are added to the interaction between the instrument and the education group in Equation (9). Figure 4 presents the results, highlighting the significant decrease in the MPC in the runup to the financial crisis in 2008 and a subsequent increase in 2009 and 2010 when both real

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

[15] Appendix Figures A2 to A6 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 3, 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.

earnings and capital income fell abruptly.

Figure 4: MPC by year



Notes: Figure 4 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 the value of real estate assets.

The fall in the MPC in 2008 and the subsequent increase in 2009 and 2010 are most pronounced among university-educated households. Then, as the economy began to recover in 2011, the decrease was greater for households with university education than for those without. Therefore, although all education groups experienced a fall in the MPC in the runup to the crisis, followed by an increase in 2009 and 2010 and a subsequent fall once income started to recover, the fluctuations were most pronounced for university-educated households. We note from Figure 1 that fluctuations in mean disposable income were greater among the university-educated during the crisis, which hit the banking sector disproportionally. The greater fall in 2008 indicates greater consumption smoothing for the university-educated.

We also derived the time variation of the MPC separately for negative and positive income shocks (see Appendix, Figure A7). The fall in the MPC in 2008 is a response to positive income shocks. The rise in the MPC in 2010, in contrast, is due to a rise in the MPC out of negative income shocks, as is the fall in the post-crisis years. 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. This shows that the increase in the MPC during the crisis, as reported in Figure 4, is driven by a strong response of consumption to response to negative income shocks.

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-educated member. If both partners have university degrees in different fields, the household is assigned to both fields.[16]

[16] For example, we can take a couple where the wife is an economist and the husband has completed secondary school. In this case, and consistent with the previous classification, they would both be classified as economists. If the husband was a lawyer, they would both be classified as lawyers and economists.

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. 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 the results and the methodology description in Table 3. 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, the 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***	Media	0.449***	Engineering	0.245***
	(0.020)		(0.112)		(0.045)
Academic upper secondary	0.486***	Business	0.358***	Manufacturing	0.373
	(0.026)		(0.028)		(0.229)
Vocational trades	0.462***	Law	0.297***	Architecture	0.377***
	(0.025)		(0.058)		(0.066)
Vocational services	0.521***	Life sc.	0.123	Agricultural	0.109
	(0.044)		(0.081)		(0.142)
Post-secondary	0.377***	Physical sc.	−0.012	Health care	0.366***
	(0.092)		(0.119)		(0.035)
Teaching	0.409***	Math/stat.	0.109	Social serv.	0.365***
	(0.029)		(0.266)		(0.092)
Arts	0.629***	Computer sc.	0.236**	Personal serv.	0.568**
	(0.074)		(0.072)		(0.216)
Humanities	0.392***	Social sc.	0.472***	Other fields	0.399**
	(0.055)		(0.056)		(0.149)
Controls: year fixed effects					

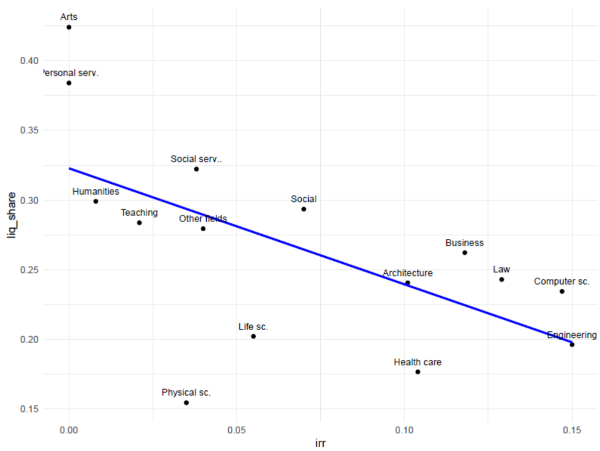
Notes: Each coefficient is the estimated marginal propensity to consume for households where the head holds the given field of study, estimated via interaction with income residuals. Fields with fewer than 100 individuals in 2019 are grouped into Other fields. Standard errors in parentheses. $^{***}p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

Figures 5a plots the share of liquidity-constrained households against the IRR estimates by field, and 5b plots the MPC against the IRR. We present only statistically significant estimates for university degrees. 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.

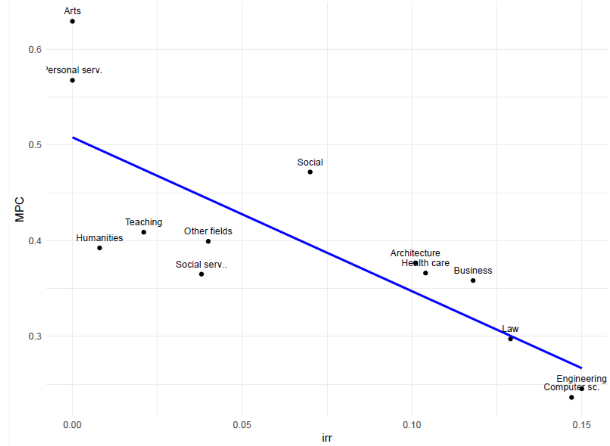
Households in high-rate-of-return fields are substantially less likely to be liquidity-constrained. This applies to fields such as engineering, law, and health care. These fields then also exhibit low MPC values. In contrast, the proportion of individuals in low-return fields, such as the arts and personal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

Figure 5: 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 taken from table 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.[17] The first question is:

Which of the following choices best describes your main motivation to save? (Multiple answers not allowed.)

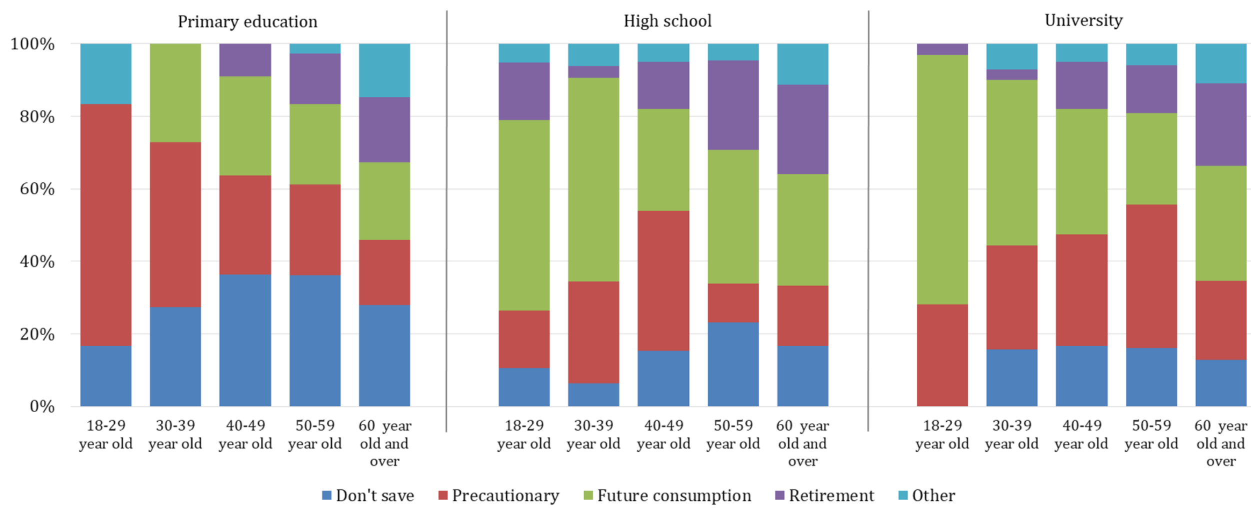
(1) I don't save; (2) I save for retirement; (3) I save to be able to react to unanticipated expenditures or drop in income; (4) I save for specific future expenditures such as housing and vehicles; (5) I save for future expenditures such as hobbies or vacations; (6) I save to finance future consumption;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

Responses are presented in Figure 6 below. Primary-educated households are more motivated by buffer savings, labeled precautionary, when young, whereas the buffer savings motivation

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

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

Figure 6: Main motivation for saving, by education and age



Notes: Figure 6 shows results from question 1, by education and age. Choices (4), (5), and (6) are grouped together and labeled as Future consumption, while choices (7), (8), and (9) are grouped together and labeled as Other. Based on 785 observations, including 136 individuals with primary education, 269 with secondary education, and 380 with university education.

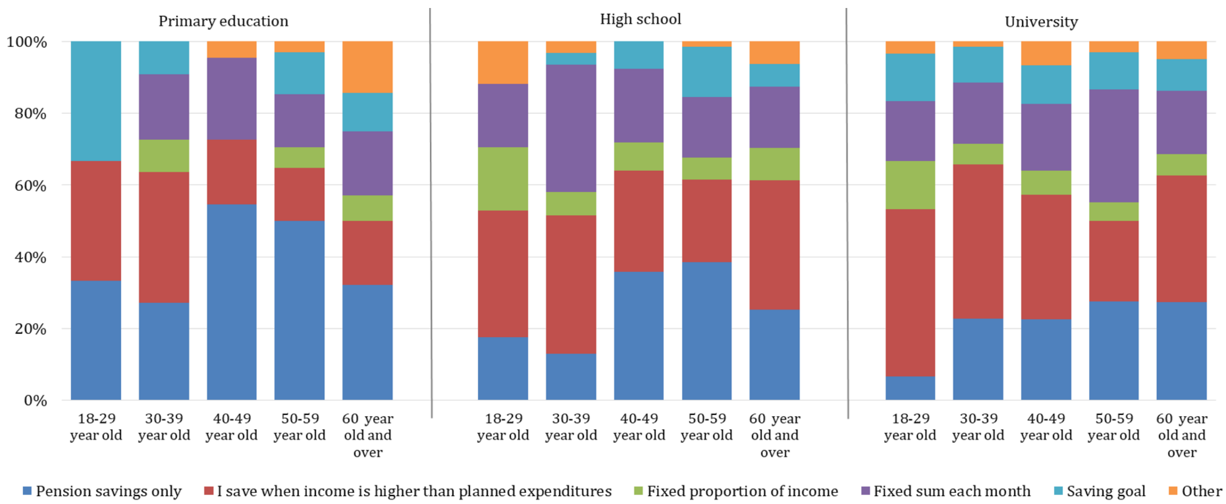
The second question is:

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 7 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. 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 7: Saving behavior, by education and age



Notes: Figure 7 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.[18]

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

[18]The dummy variable *saving capacity* is derived from a survey question asking, "Which of the following 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.

Table 5: Survey Data, Logit Regression Results

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

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, the MPC is lowest among university-educated individuals.

8 Concluding remarks

We have studied differences in consumption smoothing across education groups using administrative tax records from Iceland. We find that university-educated households have lower marginal propensities to consume out of transitory income shocks than households with primary or secondary education. Within university education, fields with higher monetary rates of return are associated with lower marginal propensities to consume and greater liquidity. Much of this difference reflects higher income and greater liquidity among the university educated, but the remaining patterns are also consistent with educational choices reflecting differences in intertemporal preferences.

To interpret these findings, we proposed a model in which individuals with different rates of time preference sort into different educational fields. More patient individuals choose fields with higher expected returns, accumulate larger liquidity buffers, and smooth consumption to a greater extent. Our empirical findings are consistent with these predictions. The survey evidence also points in the same direction. University-educated households are more likely to report saving in order to smooth future consumption, while less-educated households are more likely to rely mainly on mandatory pension saving.

Our interpretation is that educational choices partly reflect differences in underlying time preferences. An alternative interpretation, following Becker and Mulligan (1997), is that education itself lowers the rate of time preference. Our evidence does not distinguish between these mechanisms, and both imply a positive relationship between education and consumption smoothing.

More generally, our findings suggest that education is associated not only with higher lifetime earnings but also with differences in household saving behavior, liquidity, and consumption smoothing. They also suggest that heterogeneity in household consumption behavior may partly reflect differences in intertemporal preferences associated with educational choices. Whether education reflects differences in time preferences or changes them, our results suggest that educational choices contain useful information about household saving behavior and consumption smoothing.

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Appendix

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 both members have a primary education (this is the same sample as in our main specification), households in which both members have a secondary school education, and households in which both 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 A2 to A6 show the MPC in response to positive and negative transitory income shocks across education groups, by wealth, income, and liquidity. Figure A7 shows the time variation in the MPC out of negative income shocks in panel (a) and positive income shocks in panel (b). Figure A1 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 report the estimates and standard errors underlying Figure 3.

Table A1: Sample selection

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

Notes: This table presents 2SLS estimates from Equation (9). 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 included if and only if both partners have the same educational attainment. Otherwise, they are removed from the sample. The estimates are based on 951,384 individuals, who are either single or partnered with someone with the same educational attainment, 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
$\hat{\tilde{y}}_{i,t} \times primary$	0.514***	0.514***	0.514***	0.512***
	(0.020)	(0.023)	(0.027)	(0.020)
$\hat{\tilde{y}}_{i,t} \times secondary$	0.602***	0.602***	0.602***	0.601***
	(0.013)	(0.020)	(0.021)	(0.013)
$\hat{\tilde{y}}_{i,t} \times university$	0.502***	0.502***	0.502***	0.503***
	(0.014)	(0.032)	(0.032)	(0.014)
R^2	0.032	0.032	0.032	0.032

Notes: This table presents 2SLS estimates from Equation (9). 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 individuals 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: Share of observations with negative consumption by age and income

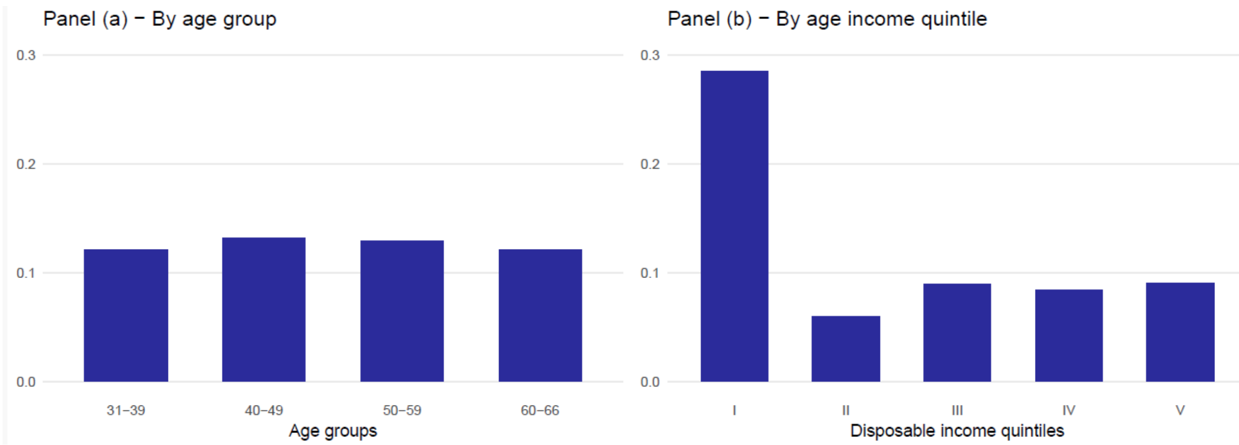
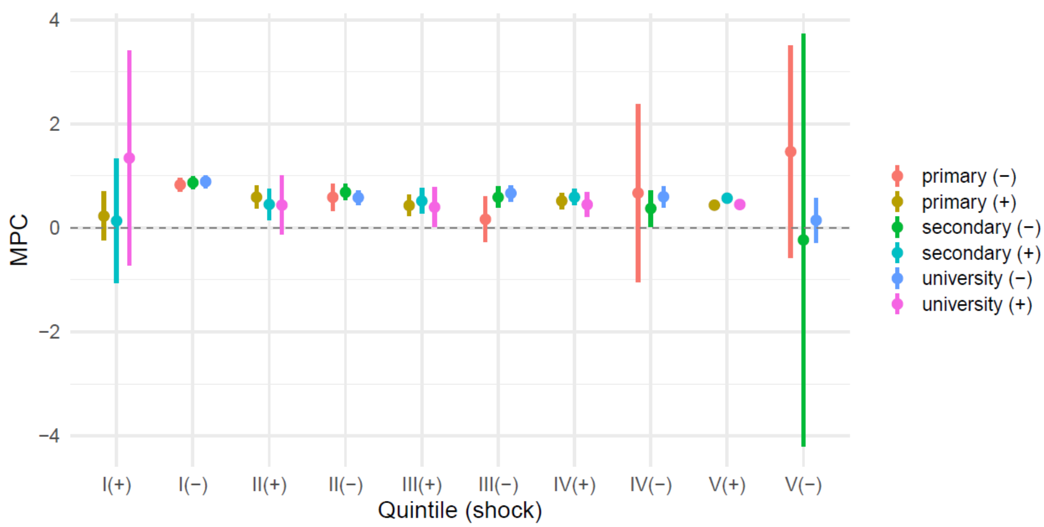
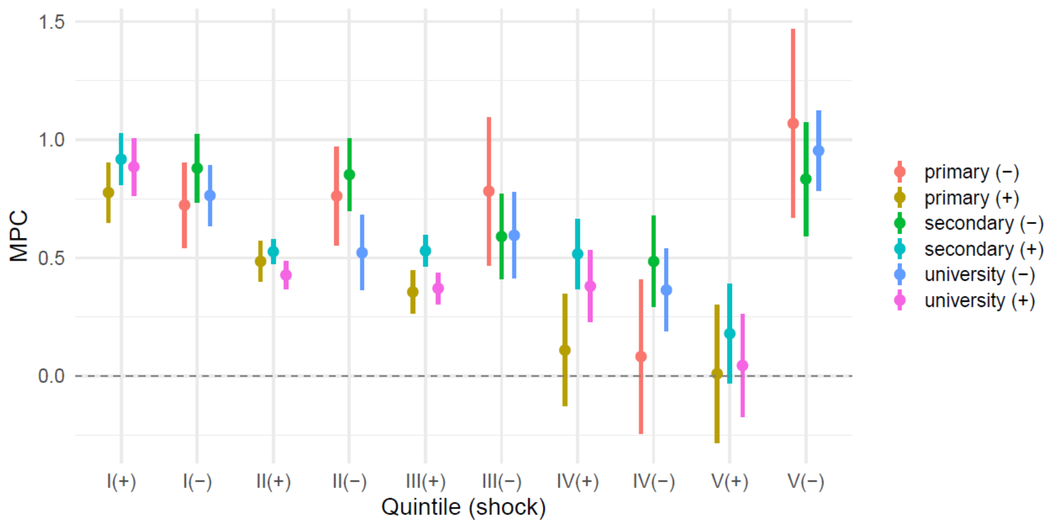


Figure A2: MPC by education and disposable income



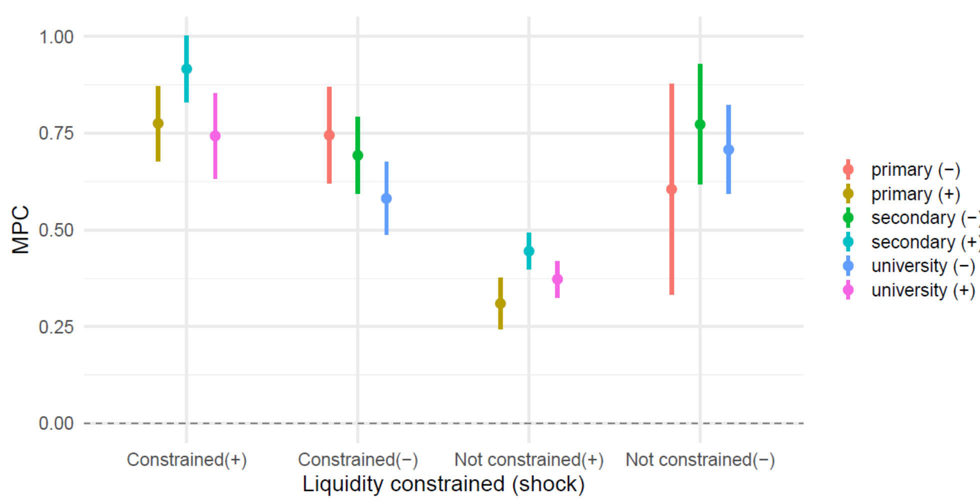
Notes: The figure shows the MPC estimates from Equation (13) with added interactions for disposable income quintiles. The points refer to the MPC coefficient estimates, 95% confidence intervals based on standard errors clustered at the individual level are represented by the vertical lines. I(-) on the 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 net-wealth-to-income



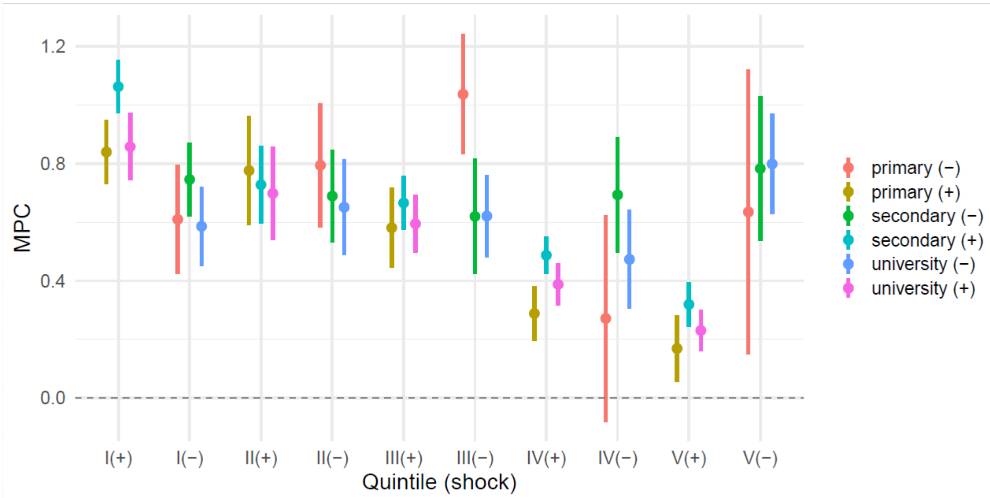
Notes: The figure shows the MPC estimates from Equation (13) with added interactions for net-wealth-to-disposable-income quintiles. The points refer to the MPC coefficient estimates, 95% confidence intervals based on standard errors clustered at the individual level are represented by the vertical lines. 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 A4: MPC by education and liquidity constraints, age 31–66



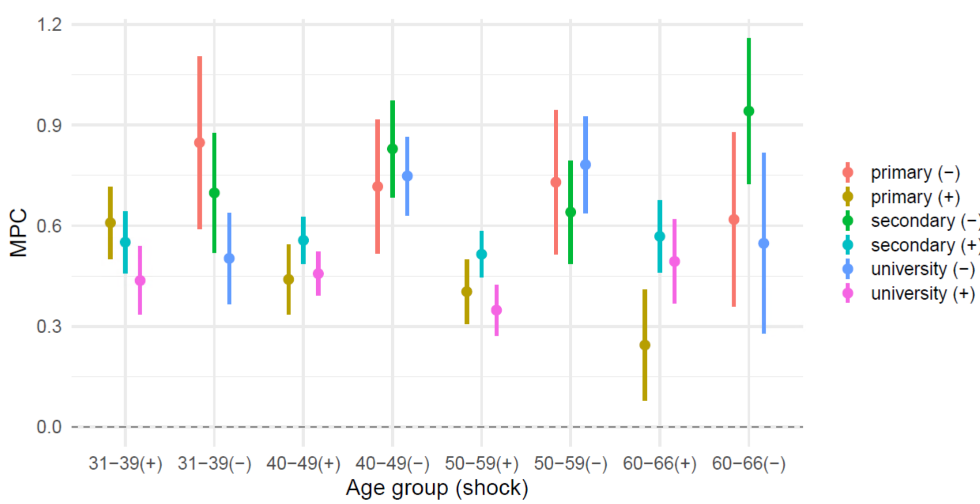
Notes: The figure shows the MPC estimates from Equation (13) with added interactions for liquidity constraints. A household is considered liquidity-constrained if the sum of bank deposits and assets in investment and savings funds is below USD 4,000 for singles and USD 8,000 for couples. The points refer to the MPC coefficient estimates. The 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 experiencing a negative transitory income shock. Constrained (+) refers to liquidity-constrained households experiencing a positive transitory income shock. Non-constrained households are represented analogously.

Figure A5: 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-wealth-to-income quintiles. The points refer to the MPC coefficient estimates. The 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 A6: MPC by education and age group



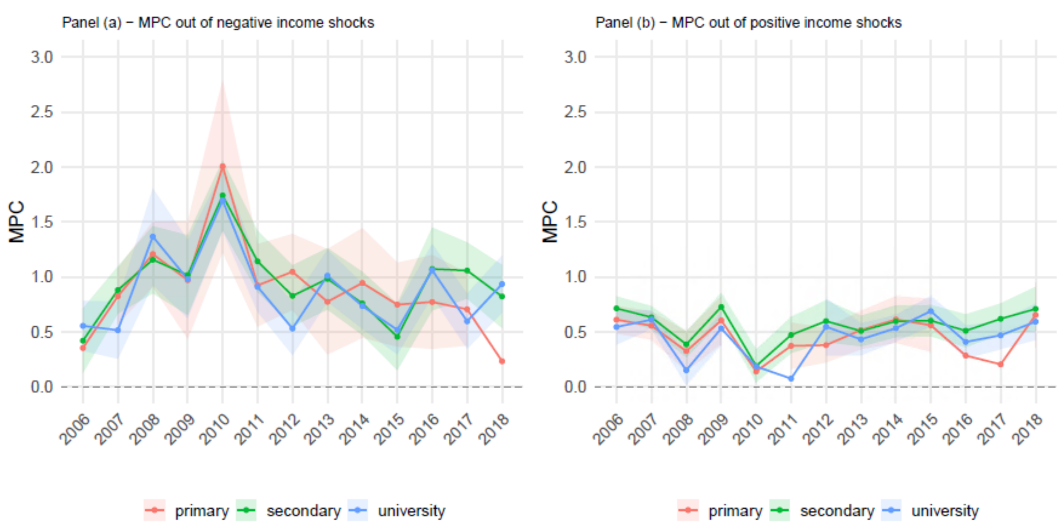
Notes: The figure shows the MPC estimates from Equation (13) with added interactions for age groups. The points refer to the MPC coefficient estimates, and 95% confidence intervals based on standard errors clustered at the individual level are represented by the vertical lines. 31-39(-) on the x-axis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

Table A3: MPC by disposable income quintiles

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

Notes: MPC estimates obtained from Equation (9) 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: 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 A4: MPC by net-wealth-to-income quintiles

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

Notes: Presents the MPC estimates obtained from Equation (9) 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^{***}	0.517^{***}	0.466^{***}
	(0.023)	(0.015)	(0.016)
$\Delta\hat{y}_{i,t} \times LC$	0.719^{***}	0.768^{***}	0.620^{***}
	(0.036)	(0.026)	(0.031)
$N = 951,384 \quad R^2 = 0.034$			

Notes: Table presents the MPC estimates obtained from Equation (9) 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^{***}	0.917^{***}	0.723^{***}
	(0.045)	(0.034)	(0.039)
$\Delta\hat{y}_{i,t} \times Q2$	0.779^{***}	0.701^{***}	0.689^{***}
	(0.065)	(0.047)	(0.051)
$\Delta\hat{y}_{i,t} \times Q3$	0.746^{***}	0.657^{***}	0.625^{***}
	(0.056)	(0.037)	(0.038)
$\Delta\hat{y}_{i,t} \times Q4$	0.298^{***}	0.537^{***}	0.426^{***}
	(0.038)	(0.025)	(0.027)
$\Delta\hat{y}_{i,t} \times Q5$	0.221^{***}	0.404^{***}	0.359^{***}
	(0.033)	(0.021)	(0.022)
$N = 951,384$ $R^2 = 0.035$			

Notes: MPC estimates obtained from Equation (9) 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^{***}	0.593^{***}	0.467^{***}
	(0.046)	(0.034)	(0.031)
$\Delta\hat{y}_{i,t} \times$ 40-49	0.513^{***}	0.632^{***}	0.550^{***}
	(0.036)	(0.023)	(0.022)
$\Delta\hat{y}_{i,t} \times$ 50-59	0.484^{***}	0.550^{***}	0.479^{***}
	(0.034)	(0.022)	(0.026)
$\Delta\hat{y}_{i,t} \times$ 60-66	0.352^{***}	0.661^{***}	0.512^{***}
	(0.052)	(0.033)	(0.045)
$N = 951,384$ $R^2 = 0.032$			

Notes: MPC estimates obtained from Equation (9) 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.