1 Parameterizing the model

This section describes how we set the various parameters of the model. First, we estimate the extent to which consumers "splurge" when receiving an income shock. We do so using Norwegian data to be consistent with the best available evidence on the time profile of the marginal propensity to consume provided by Fagereng, Holm, and Natvik (2021). For this exercise we use a version of the model calibrated to the Norwegian economy.

Second, we move on to the calibration of the full model taking the splurge-factor as given. We then have different types of agents that differ according to their level of education and their subjective discount factors. Some parameters are calibrated equally for all of these different types, while some parameters are calibrated separately for each education group. Finally, a distribution of subjective discount factors is estimated separately for each education group to match features of the wealth distribution within that group.

1.1 Estimation of the "splurge" factor

We define splurging as the free spending of available income without concern for intertemporal maximization of utility. As we will show in this section, it is necessary to allow for splurging in order to capture the shorter and longer term response of consumption to income shocks. Specifically, we show that our model can account well for the results of Fagereng, Holm, and Natvik (2021), who study the impact of lottery winnings in Norway on consumption using millions of datapoints from the Norwegian population registry. To do so we calibrate our model to reflect the Norwegian economy and estimate the splurge factor, as well as the distribution of discount factors in the population to match two empirical moments.

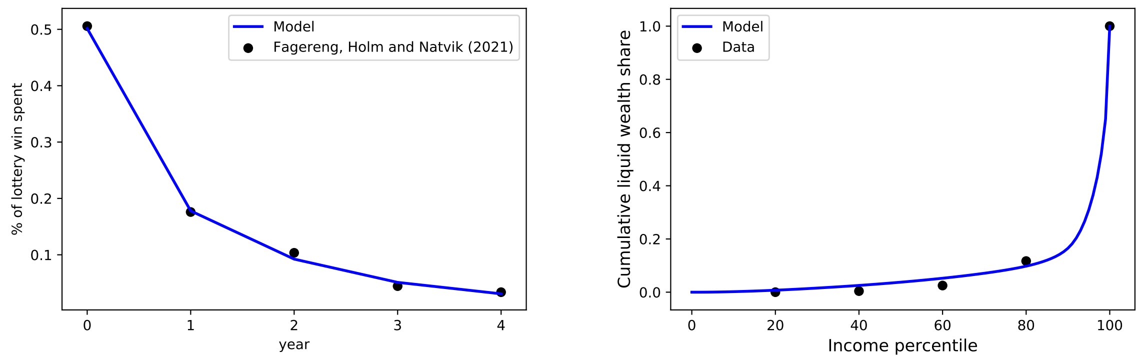
First, we take from Fagereng, Holm, and Natvik (2021) the marginal propensity to consume out of a one-period income shock. We not only target the contemporaneous response of consumption to the income shock, but also the subsequent impact on consumption in years one through four after the shock. The share of lottery winnings expended at different time horizons, as found in Fagereng, Holm, and Natvik (2021), are plotted in figure 1a.

Second, we match the steady-state distribution of liquid wealth in the model to its empirical counterpart. Due to the lack of data on the liquid wealth distribution in Norway, we resort to the corresponding data from the US - assuming that liquid wealth inequality is comparable across these countries.[1] Specifically, we impose as targets the cumulative liquid wealth share for the entire population at the 20th, 40th, 60th and 80th income percentile, which in data from the Survey of Consumer Finance in 2004 equal 0.03 percent, 0.35 percent, 1.84 percent, and 7.42 percent.[2] Hence, 92.6 percent of the total liquid wealth is held by the top income quintile. The data is plotted in figure 1b.

For this estimation exercise, the remaining model parameters are calibrated to reflect the Norwegian economy. Specifically, we set the real interest rate to 2 percent annually and the unemployment rate to 4.4 percent, in line with Aursland, Frankovic, Kanik, and Saxegaard (2020). The quarterly probability to survive is calibrated to $1 - 1/160$, reflecting an expected working life of 40 years. Aggregate productivity growth is set to 1 percent annually following Kravik and Mimir (2019). The unemployment net replacement rate is calibrated to 60 percent following OECD (2020). Finally, we set the real interest rate on liquid debt to 13.6 percent and the borrowing constraint to 80 percent

[1] Data from the Norwegian tax registry contains information on liquid assets, but not liquid debt. Only total debt is reported, and this is mainly mortgage debt. Therefore, we cannot construct liquid wealth as in for example Kaplan and Violante (2014).

[2] See section 1.2 for details.



(a) Share of lottery win spent

(b) Distribution of liquid wealth

Figure 1: Targets and model moments from the estimation

of permanent income following data from the Norwegian debt registry Gjeldsregistret (2022).[3]

Estimates of the standard deviations of the permanent and transitory shocks are taken from Crawley, Holm, and Tretvoll (2022) who estimate an income process on administrative data for Norwegian males from 1971 to 2014. The estimated annual variances for the permanent and transitory shocks are 0.004 and 0.033, respectively.[4] As in Carroll, Crawley, Slacalek, Tokuoka, and White (2020), these are converted to quarterly values by multiplying the permanent and transitory shock variances by 1/4 and 4, respectively. Thus, we obtain quarterly standard deviations of $XX = 0.0316$ and $XX = 0.363$.

Using the calibrated model, unexpected lottery winnings are simulated and the share of the lottery spent in each year is calculated. Specifically, each simulated agent receives a lottery win in a random quarter of the first year of the simulation. The size of the lottery win is itself random and spans the range of lottery sizes found in Fagereng, Holm, and Natvik (2021). The estimation procedure minimizes the distance between the target and model moments by selecting the splurge factor and the distribution of discount factors in the population, where the latter are assumed to be uniformly distributed in the range $[\beta - \nabla, \beta + \nabla]$. We approximate the uniform distribution of discount factors with a discrete approximation and let the population consist of 7 different types.

The estimation yields a splurge factor of 0.32 and a distribution of discount factors described by $\beta = 0.986$ and a $\nabla = 0.0174$. Given these estimated parameters and the remaining calibrated ones, the model is able to replicate the time path of consumption in response to a lottery win from Fagereng, Holm, and Natvik (2021) and the targeted distribution of liquid wealth very well, see figure 1.

1.2 Data on liquid wealth and permanent income

We use data on the distribution of liquid wealth from the 2004 wave of the Survey of Consumer Finance (SCF). We restrict our attention to households where the the head of the household is of

[3]Specifically, we determine the average volume-weighted interest rate on liquid debt, which consists of consumer loans, credit and payment card debt and all other unsecured debt. To determine the borrowing limit on liquid debt we determine the ratio between total credit card limit divided by total wage income in Norway. We use data from December 2019. Note that although these data let us pin down aggregate quantities, they do not solve the issue referred to in footnote 1, since we cannot link them to the tax registry at the individual level.

[4]As shown in Crawley, Holm, and Tretvoll (2022), an income process of the form that we use here should be estimated using moments in levels not differences. Hence, we take the numbers from column 3 of their Table 4.

working age which we define to be in the range from 25 to 62. The SCF-variable "normal annual income" is our measure of the household's permanent income, and to exclude outliers we drop the observations that make up the bottom 5 percent of the distribution of this variable. The smallest value of permanent income for households in our sample is thus $16,708.

Liquid wealth is defined as in Kaplan and Violante (2014) and consists of cash, money market, checking, savings and call accounts, directly held mutual funds, stocks and bonds. We subtract off liquid debt which is the revolving debt on credit card balances. Note that the SCF does not contain information on cash holdings, so this is imputed with the procedure described in Appendix B.1 of Kaplan and Violante (2014) which also describes the credit card balances that are considered part of liquid debt. We drop any households that have negative liquid wealth.

Households are classified into three educational groups. The first group "Dropout" applies to households where the head of household has not obtained a high school diploma, the second group "Highschool" includes heads of households that have a high school diploma and those who in addition have some years of college education without obtaining a bachelor's degree, and the third group "College" consists of heads of households who have obtained a bachelor's degree or higher. With this classification of the education groups, the "Dropout" group makes up 9.3 percent of the population, the "Highschool" group 52.7 percent, and the "College" group 38.0 percent.

With our sample selection criteria we are left with a sample representing about 61.3 million US households.

1.3 Calibrated parameters

With households divided into the three education groups, some parameters, presented in table 1, are calibrated equally across all groups, while other parameters, presented in table 2, are education-specific. Households are also assumed to be ex-ante heterogeneous in their subjective discount factors in addition to their level of education.

All households are assumed to have log preferences over consumption, so the coefficient of relative risk aversion is set to XX=1. We also assume that all households have the same propensity to splurge out of transitory income gains and set XX=0.32. However, each education group is divided into types that differ in their subjective discount factors. The distributions of discount factors for each education group are estimated to fit the distribution of liquid wealth within that group, and this is described in detail in section 1.4.

When households are born, they receive an initial level of permanent income. This initial value is drawn from a log-normal distribution, and for all education groups the standard deviation of the initial draw of the log of permanent income is set to XX=0.4. The mean of the distribution depends on the education level the household is born with. For the "Dropout" group the mean initial value of quarterly permanent income is $5,000, for the "Highschool" group it is $7,500, and for the "College" group it is $12,000.

While households remain employed, their income is subject to both permanent and transitory idiosyncratic shocks. These shocks are distributed equally for the three education groups with the standard deviation of the transitory shock set to XX=0.12 and the standard deviation of the permanent shock set to XX=0.003. Permanent income also grows on average with a growth rate XX that depends on the level of education. These average growth rates are based on numbers from Carroll, Crawley, Slacalek, and White (2020) who construct age-dependent expected permanent income growth factors using numbers from Cagetti (2003) and fit the age-dependent numbers to their life-cycle model. We construct the average quarterly growth rates of permanent income in our perpetual youth model by taking the average of the age-dependent growth rates during a household's working life. The average gross quarterly growth rates that we obtain for the three education groups are then $XX_d = 1.0036$, $XX_h = 1.0045$, and $XX_c = 1.0049$.

Households also face the risk of becoming unemployed. In the unemployment state in normal times, the unemployment benefits replacement rate is set to XX=0.3 for all households. When benefits run out, the unemployment income without any benefits is set to XX=0.05. The replacement rates are set as a share of the households' permanent income. The probability of transitioning out of unemployment is also the same for all households, and is set to XX=2/3. This implies that the average duration of an unemployment spell in normal times is 1.5 quarters. The duration of unemployment benefits in normal times is set to 2 quarters. However, the different education groups do differ in the probability of transitioning into unemployment in the first place. These probabilities are set to match the average US unemployment rate by education group in 2004.[5] This average was 8.5 percent for the "Dropout" group, 5 percent for the "Highschool" group, and 4 percent for the "College" group. This implies that the probability of transitioning into unemployment in normal times are $XX_d = 6.2$ percent, $XX_h = 3.5$ percent and $XX_c = 2.8$ percent.

risk-free rate and survival

Parameter	Notation	Value
Risk aversion		1.0
Splurge		0.32
Survival probability, quarterly		0.994
Risk free interest rate, quarterly		1.01
Standard deviation of transitory shock		0.346
Standard deviation of permanent shock		0.0548
Unemployment benefits replacement rate (share of PI)		0.3
Unemployment income w/o benefits (share of PI)		0.05
Avg. duration of unemp. spell in normal times (quarters)		1.5
Avg. duration of unemp. benefits in normal times (quarters)		2

Table 1: Calibrated parameters that apply to all types. "PI" refers to permanent income.

Parameters calibrated for each education group			
	Dropout	Highschool	College
Percent of population	9.3	52.7	38.0
Avg. quarterly PI of "newborn" agent ($1000)	6.2	11.1	14.5
Std. dev. of log(PI) of "newborn" agent	0.32	0.42	0.53
Avg. quarterly gross growth rate of PI	1.0036	1.0045	1.0049
Unemployment rate in normal times (percent)	8.5	4.4	2.7

Table 2: Parameters calibrated for each education group. "PI" refers to permanent income.

1.4 Estimating the discount factor distributions

The parameters that remain

[5] Source: Statista.com.

1.4.1 Estimation

In our estimation procedure we aim to fit the distribution of liquid wealth within each of the three educational groups. To do so, we allow households within each group to consist of a set of different types where the types differ in their subjective discount factor, β. The discount factors within each group $e \in \{d, h, c\}$ are assumed to be uniformly distributed in the range $[\beta_e - \nabla_e, \beta_e + \nabla_e]$. The parameters β_e and ∇_e are chosen for each group separately to match the median liquid wealth to permanent income ratio and the 20^{th}, 40^{th}, 60^{th}, and 80^{th} percentile points of the Lorenz curve for liquid wealth for that group. We approximate the uniform distribution of discount factors with a discrete approximation and let each education group consist of 7 different types.

Panel (B) Estimation targets

	Dropout	Highschool	College
Median LW/PI (data)	4.64	30.2	112.8
Median LW/PI (model)	4.64	30.2	112.8
$[20, 40, 60, 80]$ pctiles of Lorenz curve (data)	$[0, 0.01, 0.6, 3.6]$	$[0.06, 0.6, 3.0, 11.6]$	$[0.2, 0.9, 3.3, 10.3]$
$[20, 40, 60, 80]$ pctiles of Lorenz curve (model)	$[0.0, 0.0, 0.5, 3.6]$	$[0.04, 0.9, 3.7, 11.3]$	$[0.3, 1.5, 4.0, \ 9.9]$

Panel (C) Non-targeted moments

	No highschool	Highschool	College	Population
Percent of total wealth (data)	0.8	17.9	81.2	100
Percent of total wealth (model)	1.6	21.2	77.3	100
Average MPC (model)	0.63	0.38	0.14	0.31

References

Aursland, T. A., I. Frankovic, B. Kanik, and M. Saxegaard (2020): "State-dependent fiscal multipliers in NORA - A DSGE model for fiscal policy analysis in Norway," *Economic Modelling*, 93, 321–353.

Cagetti, M. (2003): "Wealth accumulation over the life cycle and precautionary savings," *Journal of Business & Economic Statistics*, 21(3), 339–353.

Carroll, C. D., E. Crawley, J. Slacalek, K. Tokuoka, and M. N. White (2020): "Sticky Expectations and Consumption Dynamics," *American Economic Journal: Macroeconomics*, 12(3), 40–76.

Carroll, C. D., E. Crawley, J. Slacalek, and M. N. White (2020): "Modeling the consumption response to the CARES act," *Covid Economics*, 10, 62–86.

Crawley, E., M. B. Holm, and H. Tretvoll (2022): "A Parsimonious Model of Idiosyncratic Income," .

Fagereng, A., M. B. Holm, and G. J. Natvik (2021): "MPC Heterogeneity and Household Balance Sheets," *American Economic Journal: Macroeconomics*, 13(4), 1–54.

Gjeldsregistret (2022): "Nøkkeltall fra Gjeldsregisteret," *Gjeldsregistret nettside*, Url: https://www.gjeldsregisteret.com/pages/nokkeltall.

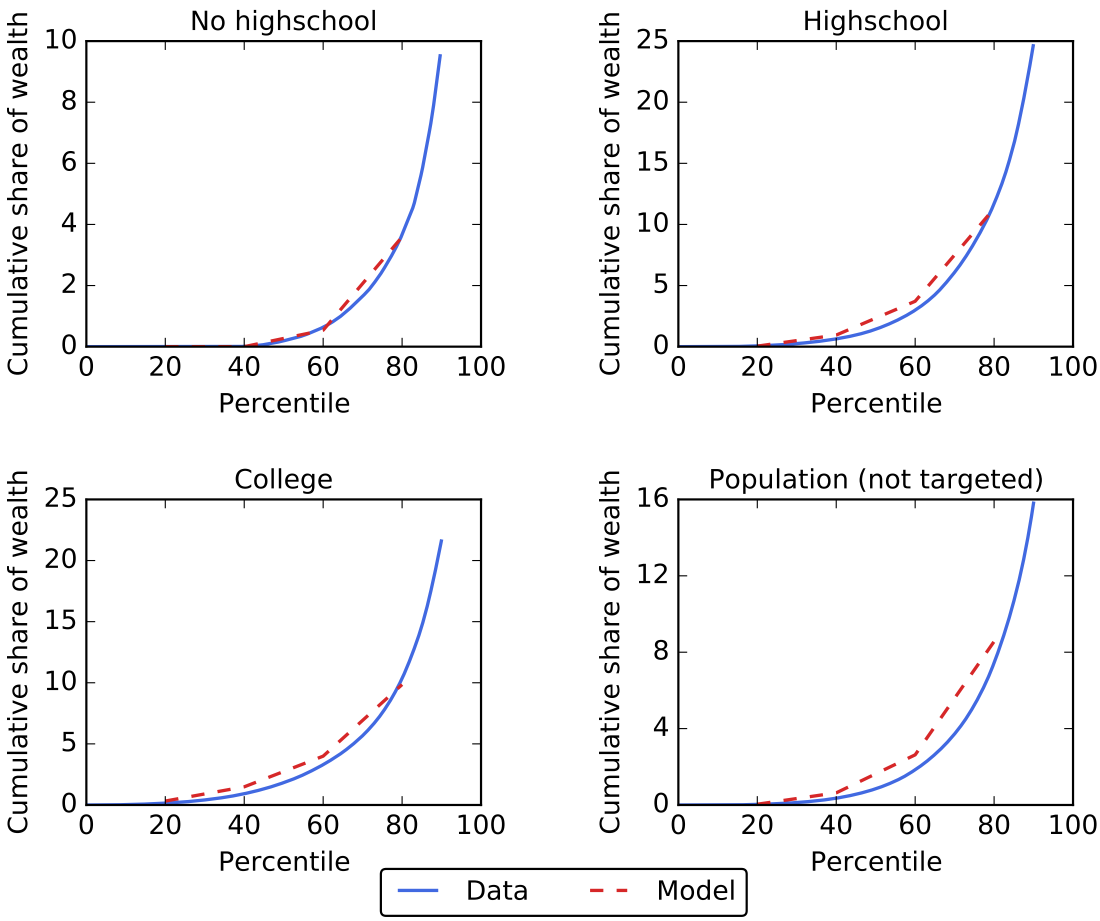


Figure 2: Distributions of liquid wealth within each educational group and for the whole population from the 2004 Survey of Consumer Finance and from the estimated model.

KAPLAN, G., AND G. L. VIOLANTE (2014): "A model of the consumption response to fiscal stimulus payments," *Econometrica*, 82(4), 1199–1239.

KRAVIK, E. M., AND Y. MIMIR (2019): "Navigating with NEMO," *Norges Bank Staff Memo*, 5.

OECD (2020): "Net replacement rate in unemployment," *OECD statistics "Social Protection and Well-being"*, Url: https://stats.oecd.org/Index.aspx?DataSetCode=NRR.