How do People Respond to Small Probability Events with Large, Negative Consequences?

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Introduction

- A central question in economics is: how do people respond to risk?
  - Crucial consideration in design of public policy to deal with small probability events like epidemics, environmental disasters, and terrorism.

- Can governments rely on people to take actions commensurate with the risks associated with those events?

- By nature, difficult to gather a substantial amount of data on small probability events.

- Outbreak of epidemic provides natural experiment for assessing how people react to small probability events, like dying from COVID-19.
  - Ex-ante epidemic is a very rare event.
  - During the epidemic death is a small probability event for most people.

COVID-19: a natural experiment

- Probability of dying from COVID-19 low for young people, rising with age for people older than 50 (e.g. Dowd et al. (2020)).
- People of all ages can reduce infection probability by cutting expenditures on goods and services that require social contact (e.g., sports events and restaurant meals).
- Using a *unique administrative dataset*, we study how younger and older people changed level and composition of consumption expenditures in response to changes over time in infection risk.

Introduction

- People might reduce consumption in response to epidemic for two reasons.
  - They lost their jobs or are worried about losing their jobs because of COVID-19 recession.
  - They want to reduce infection risk.

- We focus on public servants' consumption behavior. Their income is likely to have been relatively unaffected by the crisis. So, their consumption behavior should primarily reflect the influence of infection risk.

- We compare our empirical results with the predictions of a canonical model of risk-taking behavior.

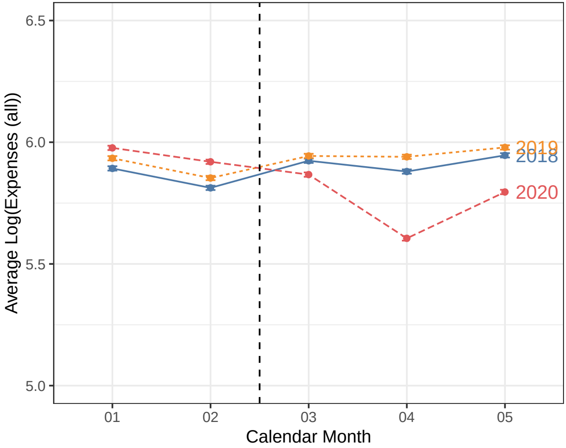
Outline

- Introduction
- Data and Empirical Results
- Model of Risk-Taking Behavior
- Conclusions

Administrative data

- Unique administrative data set from Portugal with *anonymized* monthly data on individual itemized consumer expenditures.
- Anonymized data include age, income bracket, and gender of all people in the sample, and education and occupation of a subset of people.
- Sample January 2018 to May 2020. Anonymized data for 500.000 Portuguese randomly sampled from a total of 6.3 million people.
- For every person in our sample, we construct individual total monthly consumption expenditures.
  - Expenditure data based on electronic receipts that firms provide to tax authority as part of value-added tax (VAT) reporting.
  - Each receipt can be matched to a particular person because it contains the person's anonymized fiscal number.

Average expenditures, trend and seasonality patterns



Case-fatality rates, COVID-19 in Portugal

Age group	Infected	Deceased	Case-fatality rate
0-19	$4,034$	0	0.0%
20-49	$24,230$	24	0.1%
50-59	$7,628$	55	0.7%
60-69	$5,053$	152	3.0%
70-79	$3,505$	332	9.5%
$\geq$80	$5,781$	$1,155$	20.0%

Empirical specification:

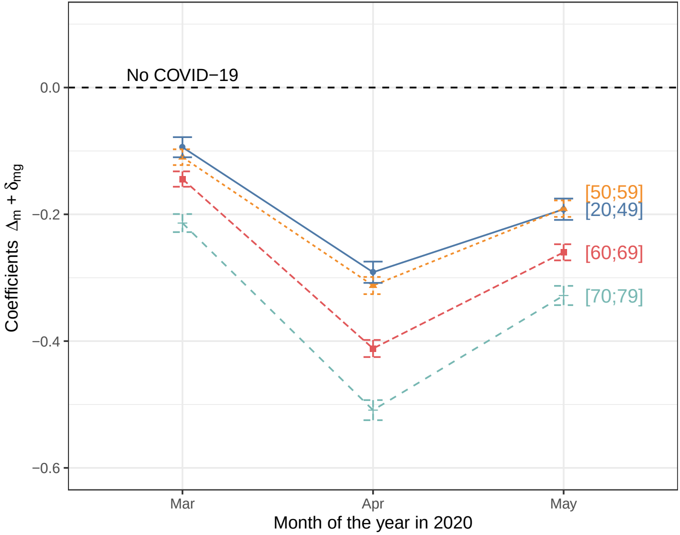
$$log(Expenses_{it}) = \sum_{y=2019}^{2020} \Lambda_y \mathbf{1}\{Year_t = y\} + \sum_{m=Feb}^{May} \lambda_m \mathbf{1}\{Month_t = m\} + \boldsymbol{\theta_i} + \boldsymbol{\Psi_{it}} +$$

$$\sum_{m=Mar}^{May} \Delta_m After_t \times \mathbf{1}\{Month_t = m\} +$$

$$\sum_{m=Mar}^{May} \sum_{g \in AgeGroup \setminus [20;49]} \delta_{mg} After_t \times \mathbf{1}\{Month_t = m\} \times \mathbf{1}\{AgeGroup_i = g\}$$

$$+ \epsilon_{it}$$

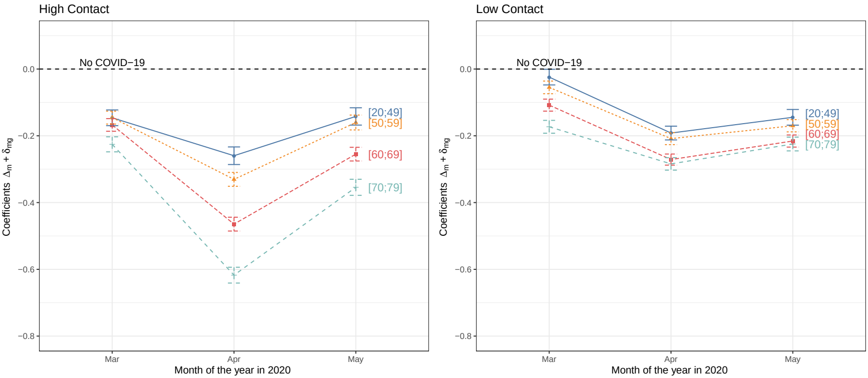
Key result: the old respond more to risk than the young.



High- and low-contact goods and services

- Portugal implemented containment between March and May.
- Does containment explain sensitivity of consumption by age?
  - Yes, if those measures affect goods consumed primarily by older people.
- Suppose that containment was only driver of change in consumption of high-contact goods, the riskiest form of consumption.
  - Then, percentage decline should be *same* for people of different ages.
- But, suppose, older people cut expenditures on high-contact goods by more than younger people.
  - Then, we would infer age-dependency in consumption was driven by infection risk.

High- and low-contact goods and services



(A)

(B)

Key result also robust to:

- Differences in income levels.
- Comorbidity effects.
- Retirees instead of public servants.
- Alternative models of seasonal and trend effects.

A model of risk-taking behavior

- Are people's consumption decisions consistent with standard model of risk-taking behavior?
- What fraction of consumption drop was due to people's risk-avoidance behavior as opposed to government containment measures?
- We use a partial-equilibrium approach
  - Allows to confront people of different ages and health status with real wages, real interest rates, and infection probabilities that mimic those observed in data using minimal assumptions.

Model Features

- Two age groups: old and young.
- Epstein-Zin preferences (standard preferences for modelling risk).
- Stochastic aging. Natural and epidemic mortality risk.
- Standard SIR framework: four possible health states.
  - Susceptible (no immunity against the virus).
  - Infected
  - Recovered (acquired immunity against the virus).
  - Deceased.

A model of risk-taking behavior

Budget constraint of person of age a and health status h

$$b'_a = w + (1+r)b_a - (1+\mu)c_a^h,$$

Probability that a person in age group a becomes infected at time t:

$$\tau_a = \pi_1 c_a^h I + \pi_2 I,$$

Example of value function:

Value function of a young susceptible person, $U^s_{y,t}(b_t)$, is

$$\begin{aligned} U^s_{y,t}(b_t) &= z + \{(1-\beta)(c^s_{y,t})^{1-\rho} + \beta[(1-\tau_y)(1-\delta_y - v)\left(U^s_{y,t+1}(b_{t+1})\right)^{(1-\alpha)} \\ &\quad + (1-\tau_y)\, v \left(U^s_{o,t+1}(b_{t+1})\right)^{(1-\alpha)} + \tau_y(1-\delta_y - v)\left(U^i_{y,t+1}(b_{t+1})\right)^{(1-\alpha)} \\ &\quad + \tau_y v \left(U^i_{o,t+1}(b_{t+1})\right)^{1-\alpha} + \delta_y B(b_{t+1})^{1-\alpha}]^{(1-\rho)/(1-\alpha)}\}^{1/(1-\rho)}, \end{aligned}$$

Similar structure for value functions of susceptible old, infected young and old, recovered young and old.

Calibration and Estimation

- We calibrate the model to Portuguese data.
- To solve and simulate the model, people in the model must compute probability of getting infected at each point in time.
  - Those probabilities depend on number of infected people, I.
- We estimate total deaths due to COVID-19 and use an estimate of the case-fatality rate to back out time series for total infections, I.
  - We input total infections, I and containment rates μ.

Comparison of Data vs. Model

Consumption (%), Young

	Data	Model: Epi+Containment	Containment only
March	-10	-13	0
April	-30	-30	-21
May	-19	-18	-12

Consumption (%), Old

	Data	Model: Epi+Containment	Containment only
March	-17	-29	0
April	-45	-42	-21
May	-29	-27	-12

- Model accounts well for data: old cut consumption more than young.
- While containment had some effect, much of the difference in behavior of young and old people reflects response to infection risk.

Conclusions

- Small probability events play important role in many economic models and are focus of many policy debates on topics such as epidemics, environmental disasters and terrorism.
- How to model people's behavior with respect to such events remains controversial issue.
- Our results suggest that people respond in a way that is commensurate with risks they face.
  - Results surprising in light of literature that highlights difficulties that people have in assessing small probability events (e.g. Slovic (2000) and Sunstein (2003)).

Conclusions

- The fact that, according to our results, people behave, on average, rationally in face of such events, does *not* imply that there is no role for government intervention during the current epidemic.
- Eichenbaum, Rebelo and Trabandt (2020) argue that, in an epidemic, the competitive equilibrium is not socially optimal.
  - Infected people dont fully internalize effect of their economic decisions on virus spread.
  - That *externality* implies that government policies like containment, mandatory testing and quarantines can be welfare enhancing.

Thank you for your attention.

Annex

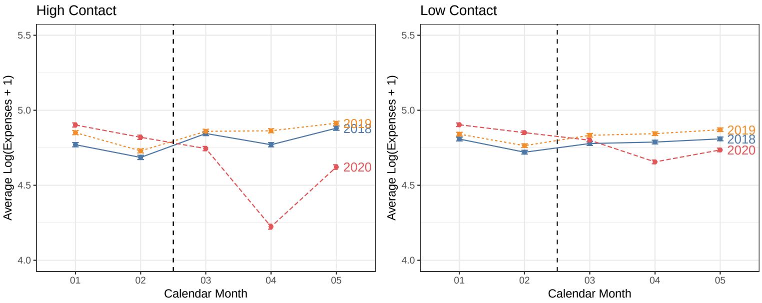
Descriptive statistics

Table: January 2018 - May 2020

Statistic	Mean	St. Dev.	Pctl(25)	Median	Pctl(75)
Complete Sample					
Number of sellers	8.2	6.2	4.0	7.0	11.0
Expense p. month (All)	618.5	2,125.3	120.8	283.3	568.1
Expense p. month (High Contact)	268.5	984.3	19.6	101.6	280.5
Expense p. month (Low Contact)	282.4	1,295.7	43.4	120.4	266.4
Expense p. month (Pharmacy)	18.2	35.9	0.0	4.8	24.3
Public Servants					
Number of sellers	10.6	6.5	6.0	9.0	14.0
Expense p. month (All)	673.9	1,639.4	211.4	417.7	731.8
Expense p. month (High Contact)	307.3	554.5	64.0	191.9	396.4
Expense p. month (Low Contact)	297.1	1,046.4	68.7	158.9	315.7
Expense p. month (Pharmacy)	26.1	43.4	0.0	11.8	36.1

Note: Pctl() denotes percentile; St. Dev. denotes the standard deviation.

Trend and seasonality patterns, high- and low-contact expenditures



Interpreting the results

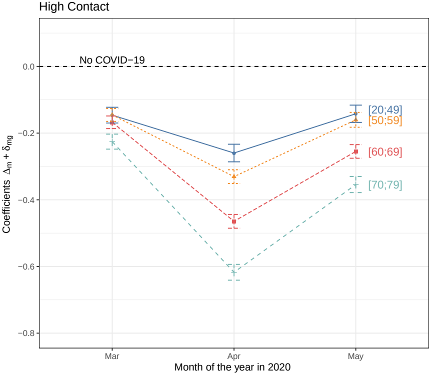
- Are these results driven by containment measures?
  - It is possible that containment measures affected more sectors overrepresented in the consumption of older people.

- For this reason, we classify expenditures into low- and high-contact goods and services and study how these expenditures change as a function of age.

High- and low-contact goods and services

- Some consumers have zero expenditures on high-contact goods in some of the epidemic months.
- The distribution of expenditures features overdispersion, i.e. the conditional variance is larger than the conditional mean.
- For these reasons, we adopt a negative-binomial version of regression model.

High- and low-contact goods and services



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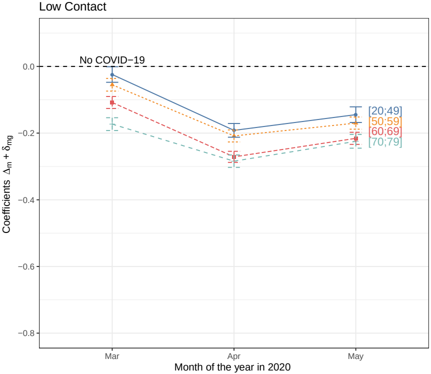
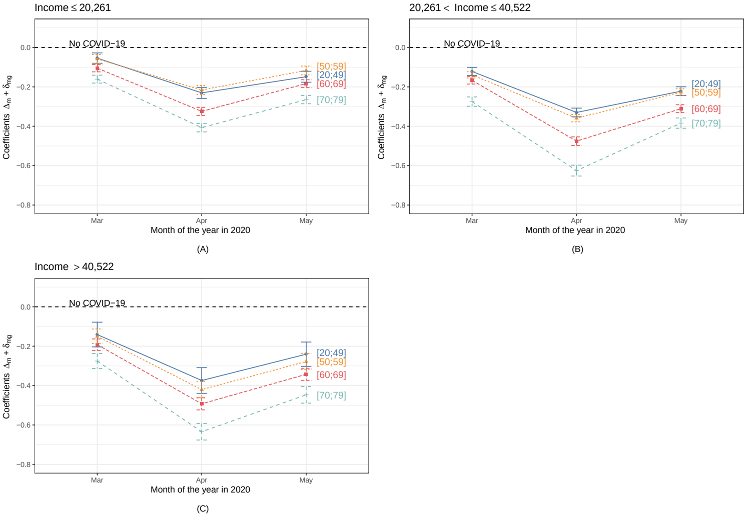


(B)

Income effects

- Older people might have higher income than younger people, so results might conflate effects of age and income.
- We estimate results for separate income groups.
- This procedure allows for separate time trends in the expenditures of each income group.
- Conditional on peoples age, the higher is their income, the larger is the decline in their consumption expenditures.
  - Consistent Chetty et al. (2020) and Carvalho et al. (2020) who use home address ZIP codes to proxy for income.

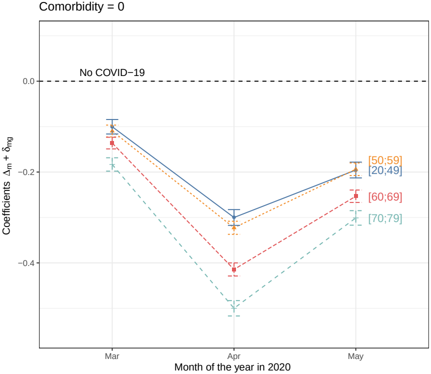
Income effects



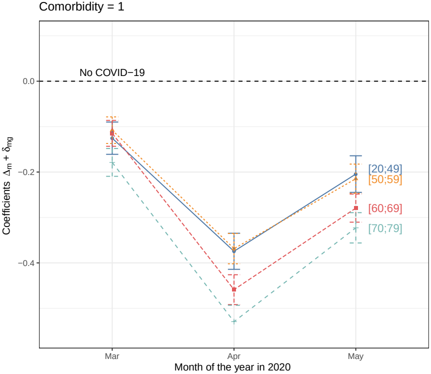
Comorbidity effects

- People with underlying health conditions such as heart problems, cancer, obesity, and type-2 diabetes are at greater risk of dying from COVID-19.
- Do people with comorbidities react to that risk by reducing consumption more than people who do not have comorbidities?
- We proxy for comorbidities using expenditures on pharmaceutical drugs.
- We split sample in two.
  - Comorbidity sample includes people whose expenditures on pharmaceutical drugs is in the top decile of the 2018 distribution of these expenditures for the persons age group.
  - Non-comorbidity sample, contains the remaining people.

Comorbidity effects



(A)

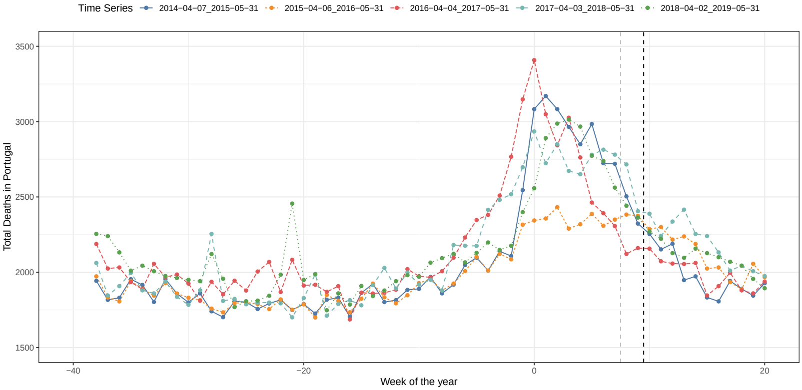


(B)

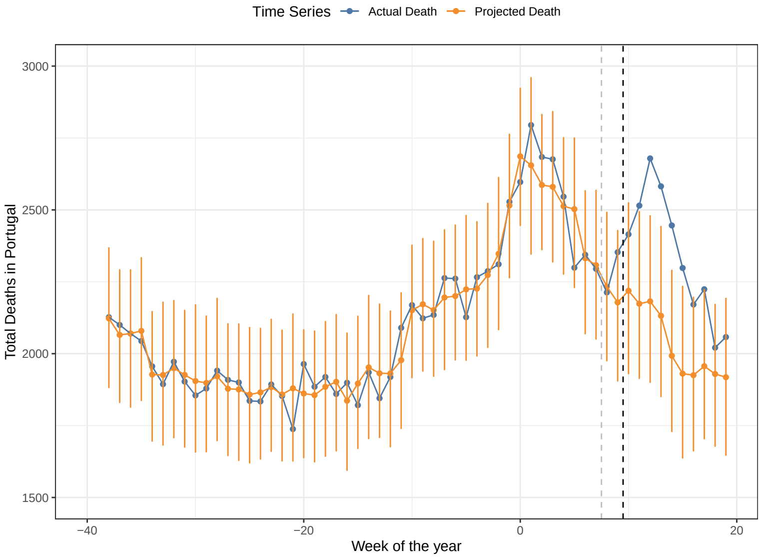
Estimating excess mortality

- Our time-series model for deaths in the absence of COVID-19 is the Bayesian model proposed by Scott and Varian (2014) and Brodersen et al. (2015).
- This model has a state equation that relates the observed data to a vector of latent variables and a transition equation that describes how the latent state evolves through time.

Total deaths in Portugal



Excess mortality



Computing the time series for infections in Portugal

- We estimate the total number of weekly deaths that would have occurred without COVID-19.
- We subtract these estimates from actual weekly deaths to obtain excess deaths. Since congestion of the health care system was not an important factor in Portugal, we attribute these excess deaths to the impact of COVID-19.
- We assume that infections result in deaths or recovery 18 days later and that the case-fatality rate is 0.5 percent.
- To eliminate high-frequency noise, we smooth the resulting time series with a monthly moving average. We use the resulting time series for infected people as a state variable in people's optimization problems.

Utility from bequests

- $B(b')$ is the utility from bequests

$$B(b') = \theta_0 + \theta_1 (b')^{1-\rho},$$

- Consistent with three empirical observations if $\theta_0, \theta_1 > 0$
  - Many people die with large amounts of assets.
  - The consumption expenditures of older people are lower than those of younger people.
  - Bequests are a superior good.

Value functions

Value function of an old, susceptible person

$$\begin{aligned} U_o^s(b,I) &= z + \{(1-\beta)(c_o^s)^{1-\rho} + \beta[(1-\tau_o)(1-\delta_o)\left(U_o^s(b',I')\right)^{1-\alpha} \\ &\quad +\tau_o(1-\delta_o)\left(U_o^i(b')\right)^{1-\alpha} + \delta_o B(b')^{1-\alpha}]^{(1-\rho)/(1-\alpha)}\}^{1/(1-\rho)}, \end{aligned}$$

Value function of a young, infected person

$$\begin{aligned} U_y^i(b) &= z + \{(1-\beta)(c_y^i)^{1-\rho} + \beta[(1-\pi_{yr}-\pi_{yd})(1-\delta_y-v)\left(U_y^i(b')\right)^{1-\alpha} + \\ &\quad (1-\pi_{yr}-\pi_{yd})v\left(U_o^i(b')\right)^{1-\alpha} \\ &\quad +\pi_{yr}(1-\delta_y-v)\left(U_y^r(b')\right)^{1-\alpha} + \pi_{yr}v\left(U_o^r(b')\right)^{1-\alpha} \\ &\quad +[\delta_y+\pi_{yd}(1-\delta_y)]B(b')^{1-\alpha}]^{(1-\rho)/(1-\alpha)}\}^{1/(1-\rho)}. \end{aligned}$$

Value functions

Value function of an old infected person

$$
\begin{aligned}
U_o^i(b) &= z + \{(1-\beta)(c_o^i)^{1-\rho} + \beta[(1-\pi_{or}-\pi_{od})(1-\delta_o)\left(U_o^i(b')\right)^{1-\alpha} \\
&\quad + \pi_{or}(1-\delta_o)\left(U_o^r(b')\right)^{1-\alpha} + [\delta_o + \pi_{od}(1-\delta_o)]B(b')^{1-\alpha}]^{(1-\rho)/(1-\alpha)}\}^{1/(1-\rho)}
\end{aligned}
$$

Value function of a young recovered person

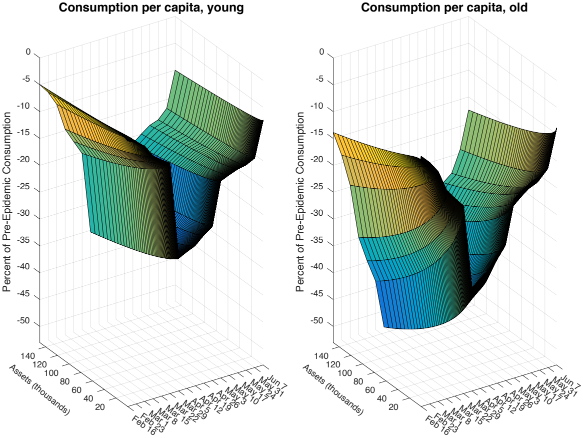
$$
\begin{aligned}
U_y^r(b) &= z + \{(1-\beta)[(c_y^r)^{1-\rho} + \beta[(1-\delta_y-v)\left(U_y^r(b')\right)^{1-\alpha} \\
&\quad + v\left(U_o^r(b')\right)^{1-\alpha} + \delta_y B(b')^{1-\alpha}]^{(1-\rho)/(1-\alpha)}\}^{1/(1-\rho)}.
\end{aligned}
$$

Value functions

Value function of an old recovered person

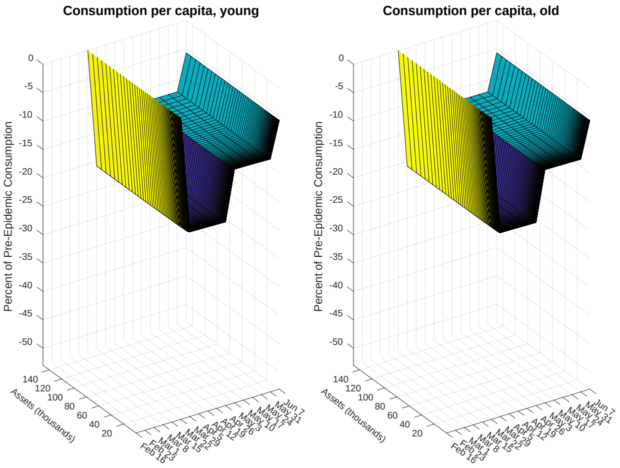
$$U_o^r(b) = z + \{(1-\beta)(c_o^r)^{1-\rho} + \beta[(1-\delta_o)\left(U_o^r(b')\right)^{1-\alpha} + \delta_o B(b')^{1-\alpha}]^{(1-\rho)/(1-\alpha)}\}^{1/(1-\rho)}.$$

Key model result: old respond more to risk than young.

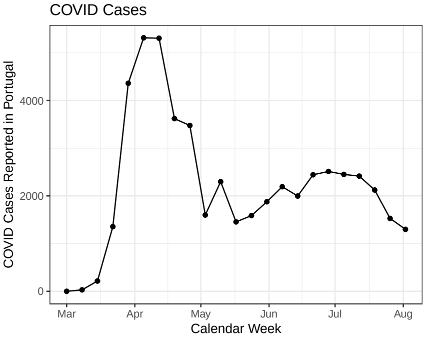


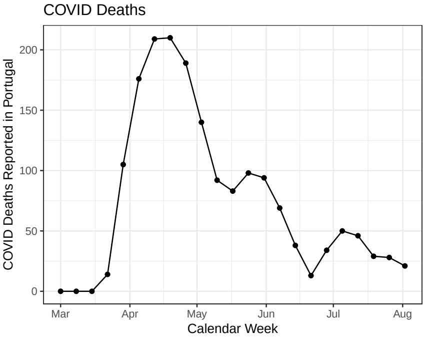
Containment only (no epidemic) counterfactual: consumption decision rules

Figure 3: Counterfactual: Consumption with Containment only



The epidemic in Portugal





Calibration, weekly parameters

Real interest rate	$1 + r$	$1.01^{1/52}$
Non-covid mortality young	δ_y	$1/(51 \times 52)$
Non-covid mortality old	δ_o	$1/(13 \times 52)$
Average recovery prob., young	π_{ry}	0.387
Average recovery prob., old	π_{ro}	0.377
Case fatality rate young	π_{dy}	$0.005 \times 7/18$
Case fatality rate old	π_{do}	$0.03 \times 7/18$
Aging probability	υ	$1/(28 \times 52)$
Discount rate	β	$0.97^{1/52}$
Initial share of young	s_y	0.7
Initial assets	b_0	75.000
Coef. rel. risk aversion	α	2
Elast. of int. substitution	ρ	$1/1.5$

Calibration

Epidemiology parameters		
Transmission parameter	π_1	5.6247×10^{-4}
Transmission parameter	π_2	0.3983

Targets	
Percent of pop. exposed with no containment	60%
Percent of infections from non-economic interaction	2/3

Utility parameters			Targets	
Bequest parameter	θ_0	120	Ratio of cons. young to old	1.18
Bequest parameter	θ_1	4	Average savings rate	6.7%
Const. utility	z	2	Value of life	890,000 EUR

Containment rate mu:

March	April	May	June
100*mu0	17	9	4

Calibration (weekly), selected parameters

Case fatality rate young	π_{dy}	$0.005 \times 7/18$
Case fatality rate old	π_{do}	$0.03 \times 7/18$
Average recovery prob., young	π_{ry}	0.387
Average recovery prob., old	π_{ro}	0.377
Coefficient of relative risk aversion	α	2
Elasticity of intertemporal substitution	ρ	1/1.5

Calibration

Epidemiology transmission parameter	π_1	5.6247×10^{-4}
Epidemiology transmission parameter	π_2	0.3983

Implied: 60% of population exposed eventually and
2/3 of infections from non-economic interaction.

Containment rate μ (based on share of business closures):

March	April	May	June
0	0.17	0.09	0.04