# Expectations, Infections, and Economic Activity*

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**Abstract**

This paper develops a quantitative theory of how people weigh the risks of infections against the benefits of engaging in social interactions that contribute to the spread of infectious diseases. Our framework takes into account the interrelated yet distinct effects of public policies and private behavior on the spread of the disease. We evaluate the model using a novel micro data set on consumption expenditures in Portugal. The estimated model accounts for the cross-sectional consumption response of individuals of different ages at a given time, as well as the time-series response of consumption of the young and old across the first three waves of Covid. Our model highlights the critical role of expectations in shaping how human behavior influences the dynamics of epidemics.

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# 1 Introduction

It is now widely recognized that human behavior influences the dynamics of epidemics. But how should we incorporate the impact of human actions into quantitative epidemiological models?

In our view, a successful approach requires a quantitative theory of how people weigh the risks of infections against the benefits of engaging in social interactions that contribute to the spread of infectious diseases. The resulting model should also account for the interrelated yet distinct effects of public policies and private behavior on the spread of the disease.

We develop such a model and evaluate its plausibility using a novel micro data set on consumption expenditures in Portugal. In so doing, we encounter two key challenges. The first is to account for the cross-sectional consumption response of individuals of different ages at a given point in time. This response is consistent with a full-information, rational expectations (FIRE) model in which the old rationally fear that they are more likely than the young to die from an infectious disease. The second challenge is to account for the time-series response of consumption of the young and old across the first three waves of Covid. The consumption responses in the first and third waves are similar, but deaths per capita were much larger in the third wave than in the first. At the same time, government-imposed containment measures were similar in the first and third waves. These observations are inconsistent with a simple FIRE model.

We develop a quantitative model that meets the challenges discussed above. In so doing, we face a set of difficulties likely to be encountered by any researcher modeling an epidemic in a specific location and the observed behavioral responses to disease threats over extended time horizons. These difficulties include how to (i) model the evolution over time of individual beliefs about the risks presented by a new disease; (ii) model the evolution over time of beliefs that individuals have about the persistence of this risk; (iii) model individual beliefs about the impact of the actions that they can take to mitigate the risks of infection; (iv) isolate the separate roles of risk aversion (uncertainty over health outcomes) and intertemporal substitution in shaping behavior; (v) model the extent to which individuals care about dying (the value of bequests versus the value of living); (vi) reconcile the large short-run impact of Covid on consumption expenditures with the small corresponding impact of the secular decline in mortality from infectious diseases and (vii) separate the quantitative impacts of public policy such as lockdowns and private behavior on economic and disease outcomes.

We model lockdowns as a wedge in the consumers' utility and assume that the magnitude of this wedge is proportional to an index of the severity of lockdowns in Portugal constructed by an external source. We estimate and judge the importance of lockdowns by the impact of changes in the proportionality factor on model fit. Our approach to modeling containment is equivalent, in many contexts, to an absolute prohibition on purchases of certain goods (see Appendix B.3).

Our answers to the previous questions are not definitive. But we hope our analysis is a useful step in quantifying the different forces at work that any behavioral epidemiological model will have to incorporate.

Our paper makes five specific contributions to the literature. First, we use micro data to document the empirical response of consumption expenditures to Covid by people of different ages, comorbidity statuses, and incomes.

Second, we estimate our structural model using micro data on consumption expenditures. The key parameters that we estimate include old and young people's prior beliefs about case-fatality rates and the speed with which they change their views. We find that all people had pessimistic prior beliefs about case-fatality rates but learned the actual case-fatality rates over time.

Third, we highlight the importance of deviations from full-information rational expectations in accounting for the empirical response of consumption to the Covid epidemic.

Fourth, we use the empirically validated model to assess how much people of different ages and incomes would be willing to pay to avoid the epidemic. Naturally, people's expectations about mortality rates play a crucial role in their willingness to pay. We also explore the distinct roles of intertemporal substitution and risk aversion in determining the willingness to pay.

Fifth, we suggest a way to reconcile the large short-run and small long-run effects on consumption of changes in mortality rates associated with contagious diseases. Our suggestion highlights the critical role of expectations about case-fatality rates in such a reconciliation. To keep our analysis tractable, we abstract from long-run supply issues possibly arising from changes in fertility and education decisions.

Our paper is organized as follows. Section 2 briefly reviews the related literature. Section 3 describes our data. Section 4 contains our empirical results. Section 5 presents a simple model used to develop intuition about the mechanisms at work in our quantitative model. Section 6 describes the quantitative model and estimation procedure. Section 7 summarizes our estimation results. Section 8 contains a general equilibrium model of endemic Covid. This model extends our partial-equilibrium analysis along three dimensions. First, we embed it in a general equilibrium framework with endogenous labor supply and capital accumulation. Second, we allow for vaccination. Third, we modify the epidemiology assumptions so that people who have natural immunity or are vaccinated lose their immunity over time. We conclude in Section 9.

# 2 Related literature

There is, by now, an extensive literature on the macroeconomic impact of epidemics. Examples include Alvarez, Argente, and Lippi (2020), Eichenbaum, Rebelo, and Trabandt (2021), Faria-e-Castro (2021), Farboodi, Jarosch, and Shimer (2021), Krueger, Uhlig, and Xie (2020), Jones, Philippon, and Venkateswaran (2021), Krueger, Uhlig, and Xie (2020), Guerrieri, Lorenzoni, Straub, and Werning (2022), Piguillem and Shi (2022), and Toxvaerd (2020). There is also a sizable epidemiology literature on the interaction between Covid and age. Examples include Dessie et al. (2021), Doerre and Doblhammer (2022), and Sorensen et al. (2022). We do not attempt to survey these literatures here. Instead, we discuss the papers most closely related to ours in the sense that they study the impact of age on people's consumption behavior. The three key papers are as follows.

Glover et al. (2021) analyze a two-sector model (essential and luxury) with young workers and retirees. The epidemic creates significant distributional effects because the luxury sector contracts more than the essential sector. In addition, containment measures redistribute welfare from the young to the old. The old benefit from the reduced risk of infection produced by containment, while the young suffer the adverse employment consequences.

Brotherhood et al. (2021) use a calibrated model of the pandemic that features age heterogeneity and individual choice, allowing agents to choose rationally how much social distancing to undertake, considering future infection risk, and prospects for vaccine arrival.

Acemoglu et al. (2021) study targeted lockdowns in a multi-group SIR model where infection, hospitalization, and fatality rates vary between groups—in particular between the young, middle-aged, and old.

## 3 Data

Our dataset comes from Statistics Portugal, the national statistical authority. A software system called "e-fatura" which the Portuguese government adopted in 2013 to reduce tax evasion, generates the data. The decree-law no. 198/2012 published on August 24, 2012, requires firms to report their invoice data electronically. This decree covers all individuals or legal entities with headquarters, stable establishment, or tax domicile in Portuguese territory that conduct operations subject to value-added tax (VAT). Durable goods purchases, such as cars, refrigerators, and televisions, are included in our dataset because they are subject to VAT. However, we cannot separate purchases of durable and non-durable goods because we cannot access itemized invoices that specify the nature of the goods purchased.

Goods and services exempt from VAT are excluded from the data.[1] The most important exempt categories are health services provided by medical doctors, childcare services provided by kindergartens, residential homes, day centers for the elderly, rent and property investments, and services provided by non-profit organizations that operate facilities for art, sports, or recreation activities. Our data covers approximately 75 percent of the per capita consumption expenses included in the national income accounts.

Our data includes anonymized information for five hundred thousand Portuguese people randomly sampled from a set of 6.3 million people who meet two criteria. First, they were at least 20 years old in 2020. Second, they filed income taxes as Portuguese residents in 2017. The data set includes a person's age, income bracket, and gender. In addition, for a subset of people, the data includes education and occupation in 2017.

For every person in our sample, we construct total monthly consumption expenditures using the electronic receipts that firms provide to the tax authority as part of their value-added tax (VAT) reporting. Each receipt is matched to a particular person using their anonymized fiscal number. We also compute individual pharmacy expenditures, which we use as a proxy for comorbidity.

Portuguese consumers have four incentives to include their fiscal number in expenditure receipts. First, they can deduct from their income taxes, up to a limit, expenditures on health, education, lodging, nursing homes, and general-household spending. Second, the government rebates 15 percent of the VAT from documented expenditures on public transportation passes, lodging, restaurants, and automobile and motorcycle shops. Third, for

[1] See article nine of the VAT code for an exhaustive list.

every ten euros of reported spending, consumers receive a coupon for a weekly lottery in which the prize is a one-year treasury bond with a face value of 35 thousand euros. Fourth, the law obliges consumers to request invoices for all purchases of goods and services. Consumers who fail to comply are subject to fines ranging from 75 to 2,300 euros.

Young people might have purchased goods and services for their parents and reported them under their own fiscal number. But it is in general not in their interest to do so because there are caps on the VAT rebates that taxpayers can receive and on the VAT expenses that taxpayers can deduct from their income taxes.

The data includes online purchases from Portuguese businesses but excludes online purchases from foreign companies. The latter types of purchases are likely to be small and not negatively affected by Covid. Since young people are more likely to engage in such purchases, including them would likely strengthen the result, documented below, that older people cut their consumption by more than young people.

We exclude from the sample in a given month people who do not have any receipts associated with their fiscal number for that month. We also remove from the sample 21,814 people who were unemployed or inactive in 2017. These people are unlikely to pay taxes, so they have less incentive to include their fiscal number in receipts. Finally, we dropped all persons older than 80 from the sample because their expenditure patterns suggest that many of them live in nursing homes. We also exclude people younger than 20 because they make few independent consumption decisions. The resulting dataset contains 421,337 people and 12,218,773 person-month observations aggregated over 97,363,250 buyer-seller pairs.

We identify two groups in our sample whose incomes are likely to have been relatively unaffected by the Covid recession: public servants (58,598 people) and retirees (93,839 people). These groups overlap because we do not exclude retirees from the population of public servants. There are roughly 22,000 retired public servants in our sample.[2]

Our sample covers the period from January 2018 to April 2021. We end our sample in April 2021 for two reasons. First, vaccines became available to the general population after April 2021. Before April, only the elderly and people with comorbidities were vaccinated first. Second, according to CISAID data, there were no reported cases of the delta variant, which was arguably more contagious than previous variants.[3]

[2]In 2011, Portugal entered into an adjustment program with the International Monetary Fund, the European Central Bank, and the European Commission (see Eichenbaum, Rebelo, and Resende (2017) for a discussion). This reduction led to a large increase in the number of retired public servants.

[3]Data downloaded from https://covariants.org

Table 6 in the appendix reports descriptive statistics for monthly expenses net of VAT. For public servants, the average per capita monthly expenditure on consumption goods and services is 687.8 euros, of which 25.6 euros is spent on pharmacy items. These expenditures are roughly similar for the sample of the population as a whole: the average per capita monthly expenditure on consumption goods and services is 629.3 euros, of which 17.9 euros is spent on pharmacy items. Retirees have lower levels of overall expenditure. They spend, on average, 437.8 euros on consumption goods and services, of which 24.3 euros is spent on pharmacy items.

Table 7 in the appendix reports the same statistics as Table 6 broken down by income and age groups. Income groups are based on the 2017 income-tax brackets used by Portugal's Internal Revenue Service (IRS). We group people according to their ages so that they have similar Covid case-fatality rates. Our estimates of this risk are based on the statistics reported by the Portuguese health authority (DGS) on July 28, 2020. Table 1 displays case-fatality rates (the ratio of Covid deaths to people infected) by age cohort for Portugal. Two key results emerge from Table 1. First, people aged 20 to 49 all have low case-fatality rates. Second, case-fatality rates rise non-linearly with age for people older than 50.

Table 1: Covid infection-fatality rates (averages May 14-June 14, 2020)

| Age Group | Infected | Deceased | Infection-fatality rate |
|---|---|---|---|
| $[0;9]$ | 672 | 0 | 0.0% |
| $[0;19]$ | 1,085 | 0 | 0.0% |
| $[20;29]$ | 4,245 | 1.5 | 0.03% |
| $[30;39]$ | 4,869 | 0.6 | 0.01% |
| $[40;49]$ | 5,420 | 15.3 | 0.28% |
| $[50;59]$ | 5,336 | 43.6 | 0.82% |
| $[60;69]$ | 3,519 | 122.1 | 3.5% |
| $[70;79]$ | 2,576 | 265.9 | 10.3% |
| $\geq 80$ | 4,522 | 926 | 20.5% |

Computed with data from the Portuguese Health Authority.

# 4 Empirical results

This section has two parts. In the first subsection, we provide an overview of the evolution of the epidemic in Portugal and the government's containment measures. We also discuss the evolution of per capita consumption expenditures in our sample. In the second subsection, we present formal econometric evidence of how Covid impacted the consumption expenditures of people of different ages and comorbidity conditions.

## 4.1 The epidemic in Portugal

Figure 1 depicts the weekly time series of infected people and Covid deaths in Portugal. We refer to March 2020 through April 2021 as the "epidemic dates." There were three waves of Covid deaths during this period. The peaks of these waves occur in April 2020, December 2020, and January 2021. The broad pattern of Covid cases is consistent with the facts documented by Atkeson et al. (2020) for a cross-section of countries.

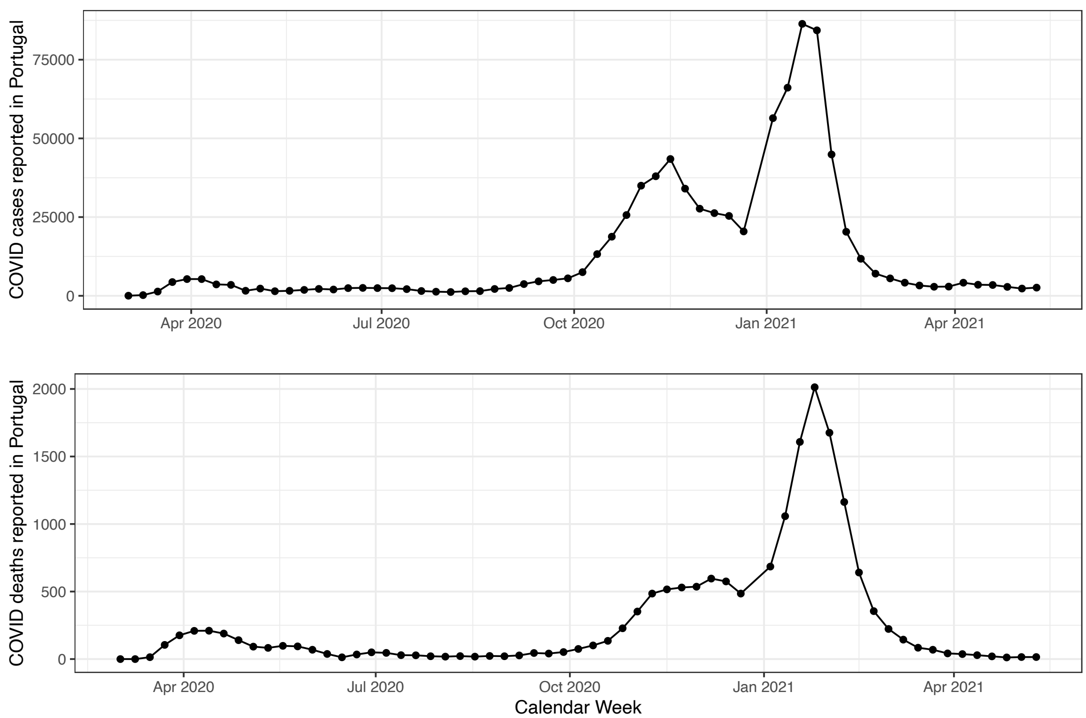



Figure 1: Covid-19 cases and deaths reported by the Portuguese Health Authority (May 20, 2021).

The vaccination campaign started on January 8, 2021. The initial campaign focused on people over 80 with comorbidities. Vaccination of the general population began on April 23, 2021, very close to the end of our sample (April 30, 2021).

Over the period from March 2020 to April 2021, the government implemented various containment measures. These measures vary in intensity and sectoral coverage. For concreteness, we summarize the severity of these measures using an index of the full or partial closing of non-essential shops, restaurants, and cafés.[4] Figure 2 displays this containment index. Containment rose quickly in mid-March 2020 and started to decline at the beginning of May 2020. It then dropped to low levels in the summer of 2020. In mid-November 2020, containment was partially reimposed in response to the second wave. The third epidemic wave led to the strengthening of containment measures from January to March 2021. As the number of infections waned, containment measures were eased. Note that the peak containment rates are the same in the first and third waves.

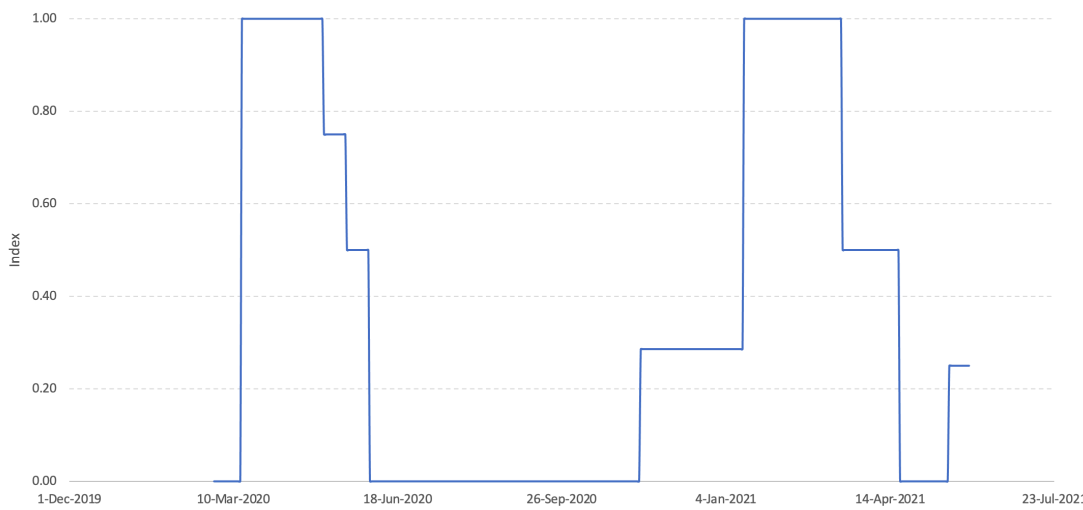



Figure 2: Severity of Covid-19 containment measures over time.

Figure A.1 in the appendix depicts the average logarithm of public servants' monthly consumption expenditures from January 2018 to April 2021. Three features emerge from this figure. First, there are pronounced drops in consumption around the peak months of the first and third waves. There is a more muted decline in consumption during the months around the peak of the second wave. Second, there is a clear seasonal pattern in the pre-Covid sample. This pattern is similar in 2018 and 2019. Third, per-capita spending was growing before the Covid shock. Our econometric procedure considers the latter two features in creating a counterfactual for what spending would have been in 2020 absent the Covid shock. We estimate a seasonal effect and time trend for each age and income group using data from January 2018 to February 2020.

[4]To construct this index, we use data from https://ourworldindata.org and https://dre.pt/legislacao-covid-19-upo. We attribute the values 1, 0.5, 2/7, and zero to full closing, partial closing, closing on weekends, and open. The containment index is the average of the indexes for non-essential shops and restaurants and cafés.

## 4.2 Age and the impact of Covid on consumer expenditures

Our empirical specification focuses on the differential consumption response by people of different ages. This specification is given by:

$$\begin{aligned}\ln(Expenses_{it}) &= \Lambda \times Year_t + \sum_{m=Feb}^{Dec} \lambda_m \mathbf{1}\{Month_t = m\} + \boldsymbol{\theta_i} + \boldsymbol{\Psi_{it}} + \epsilon_{it} \\ &\sum_{d=Mar,2020}^{Apr,2021} \Delta_d After_t \times \mathbf{1}\{Date_t = d\} + \\ &\sum_{d=Mar,2020}^{Apr,2021} \sum_{g \in AgeGroup \setminus [20;49]} \delta_{dg} After_t \times \mathbf{1}\{Date_t = d\} \times \mathbf{1}\{AgeGroup_i = g\}.\end{aligned} \tag{1}$$

Subscripts $i$ and $t$ denote person $i$ and calendar month $t$, respectively. The coefficient $\Lambda$ represents a linear growth trend in consumption expenditures. $Year_t$ is a variable that takes the value $1+t$ for year $2018+t$ for $t = 0, 1, 2, 3$. The coefficients $\lambda_m$ control for seasonality in consumption. The vector $\boldsymbol{\Psi_{it}}$ includes interaction terms that allow seasonal effects to vary with individual characteristics (age, income bracket, gender, education, and occupation). The coefficients $\boldsymbol{\theta_i}$ denote time-invariant individual fixed effects. $After_t$ is a dummy variable equal to one during the epidemic dates (beginning March 2020). The coefficients $\Delta_d$ represent the change in spending for people in the reference group (aged 20-49) during the epidemic date $d$. The coefficient $\delta_{dg}$ measures the additional change in spending for age group $g$ in epidemic date $d$.[5] The variable $\epsilon_{it}$ is an idiosyncratic error term. As long as the inflation rate for the consumption baskets of different age cohorts is the same, any inflation effects cancel out from the difference in nominal responses, and we are left with the real differential response. We estimate equation (1) using a fixed effects (FE) estimator and cluster standard errors by person, as suggested in Bertrand et al. (2004).[6]

Column 4 of Table 14 reports our parameter estimates. Figure 3 displays our estimates of the impact of Covid on consumption expenditures of different age groups ($\Delta_d$ for the reference group and $\Delta_d + \delta_{dg}$ for the other groups) obtained from estimating equation (1). The bars around the point estimates represent 95 percent confidence intervals. Our key findings are as follows. First, all consumers reduced their expenditures during the three waves of the epidemic. Second, older people cut their expenditures by much more than younger people.

[5] We keep age groups constant based on a person's age in 2020.

[6] Because of our large sample size, we estimate the FE models using the method of alternating projections implemented in R by Gaure (2013) and in STATA by Guimaraes and Portugal (2010) and Correia (2016).

The non-linear effect of age on consumer expenditures mirrors the non-linear dependency of case-fatality rates on age. Third, the decline in consumption for each age group was similar in the first and third waves.

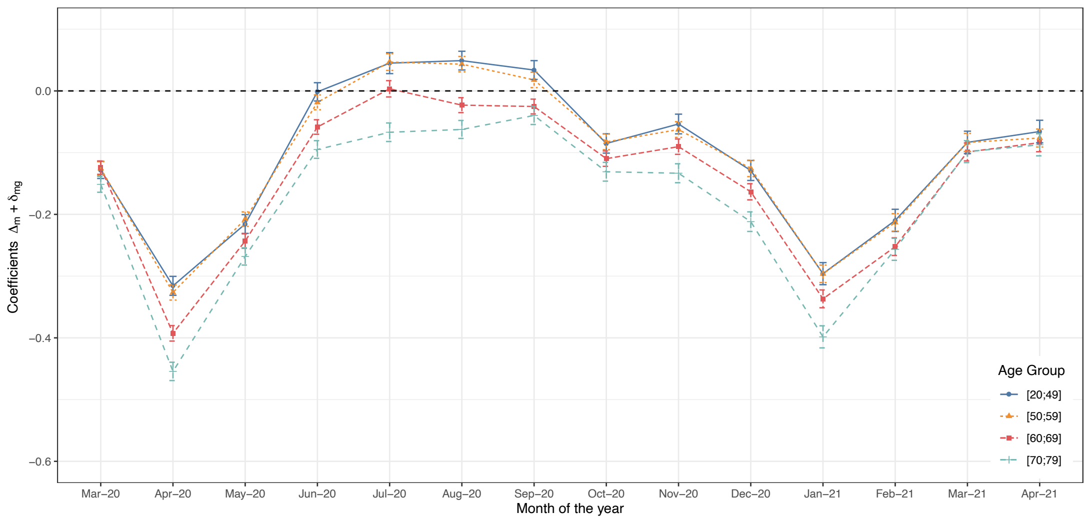



Figure 3: Changes in expenditures of public servants during the epidemic relative to a counterfactual without Covid.

## 4.3 The response of people with different income

The economic model discussed in Section 6 implies that high-income people cut their expenditures by more than low-income people to reduce the risk of infection. According to the model's logic, rich people have more to lose from becoming infected than poor people. Since older people might have a higher income than younger people, the results reported in Section 4.2 might conflate the effect of age and income.

Table 15 in Appendix A reports our parameter estimates. Figure 4 displays our estimates of the impact of Covid on consumption expenditures of different age groups ($\Delta_d$ for the reference group and $\Delta_d + \delta_{dg}$ for the other groups) obtained from estimating equation (1) for separate income groups. Two key results emerge from this figure. First, our results about the impact of age on consumption expenditures are very robust to controlling for income. Older people cut their expenditures by much more than younger people for all income groups. Second, controlling for age, high-income people reduce their consumption by more than low-income people.

The finding that expenditure cuts are an increasing function of income complements the

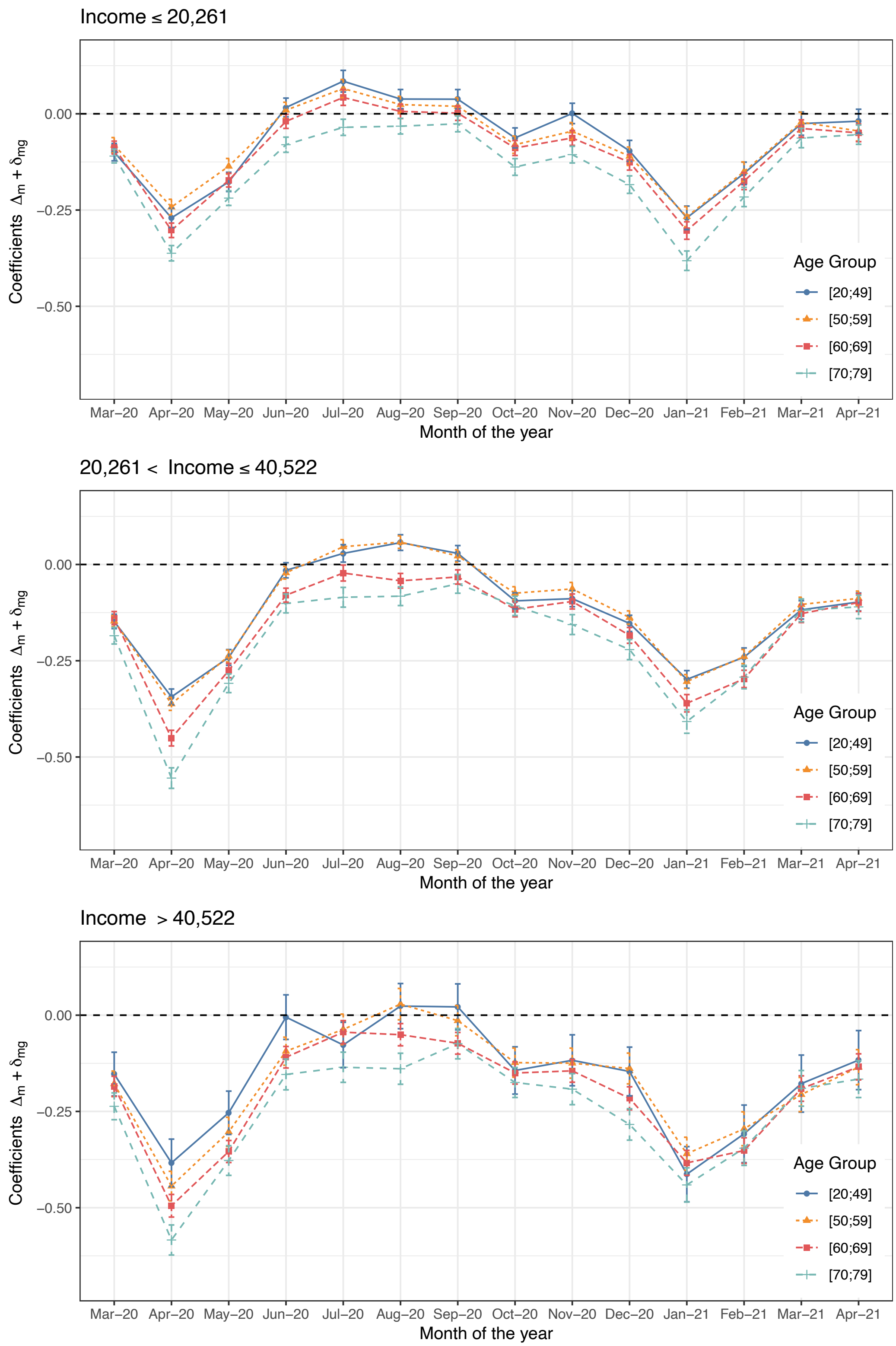



Figure 4: Changes in expenditures of public servants in different income groups during the epidemic relative to a counterfactual without Covid.

evidence in Chetty et al. (2020) and Carvalho et al. (2020), which relies on home-address ZIP codes to proxy for income.

### 4.4 Robustness

In Appendix A, we report the results of six robustness checks. First, we provide evidence in favor of the assumption that the seasonal effects for January 2020 through April 2021 are the same as for the 2018-19 period.

Second, we redo our benchmark analysis allowing for different monthly expenditure time trends for each age cohort. We find a similar pattern for the impact of age on the response of expenditures to the Covid shock.

Third, we redo our empirical analysis for retirees instead of public servants. Retirees are another group whose income is likely to have remained relatively stable during the epidemic. Our results are similar to those that we obtain for public servants. We find that conditioning on age, the consumption expenditures of civil servants and retirees respond similarly to Covid.

Fourth, we find that our results are robust to running regression (1) using the year-on-year growth rate ($\ln(Expenses_{it}/Expenses_{it-12})$) instead of the log-level of expenditures as the dependent variable.

Fifth, we study a potential reason why the consumption expenditures of old and young people responded differently to Covid: these groups purchase different goods and services that were differentially affected by lockdowns. To investigate this possibility, we estimate the change in consumption expenditures for different age groups in sectors of the economy that were least affected by lockdowns. We base this sector classification on the information reported in the appendix to law 78-A/2020 approved September 29, 2020. Figure A.4, which is the analog to Figure 3, presents our results. Two features are worth noting. First, all groups cut their consumption expenditures by about the same amount in the epidemic's first and third waves. Second, the old cut their consumption by more than the young in the epidemic's first, second, and third waves.

Sixth, we re-do our analysis excluding two sectors where adaptations were most likely to have reduced the risk of infections: restaurants (people could order take out instead of eating at the restaurant) and supermarkets (people could ask for delivery instead of going to the store). Figures A.5 and A.6 in Appendix A show that our results are robust to excluding these two expenditure categories.

Finally, we use data on expenditures on pharmaceutical drugs to investigate the effect of comorbidities that increase the risk of dying from COVID. We find that people with comorbidities cut their consumption more than those without comorbidities.

# 5 A simple model of mortality risk and consumption decisions

In this section, we consider a simple two-period model to develop intuition about the key features of our quantitative model presented in Section 6. Consistent with the latter, we make three assumptions. First, the probability of dying depends on current consumption. Second, people derive utility from leaving a bequest when they die. Third, people's utility has the recursive form proposed by Kreps and Porteus (1978), Weil (1989), and Epstein and Zin (1991). These preferences allow us to study the different roles that risk aversion and intertemporal substitution play in our model.

In the first period of their life, a person receives an endowment, $y$, which they can consume in period one ($c_1$) or two ($c_2$). Their resource constraint is:

$$y = c_1 + c_2. \tag{2}$$

The period-one utility is given by the following version of equation (8) in Section 6,

$$U_1(y) = \left\{(1-\beta)c_1^{1-\rho} + \beta[E(U_2^{1-\alpha})]^{(1-\rho)/(1-\alpha)}\right\}^{1/(1-\rho)}. \tag{3}$$

The certainty equivalent of period-two utility is

$$\left[E(U_2^{1-\alpha})\right]^{1/(1-\alpha)} = \{[1-\delta(c_1)]\, c_2^{1-\alpha} + \delta(c_1)(\omega_0 + \omega_1 b^{\mu})^{1-\alpha}\}^{1/(1-\alpha)},$$

where $\delta(c_1)$ is the probability of dying before consuming in period two. To capture the basic mechanism at work in our epidemiological model, we assume that $\delta(c_1)$ is an increasing, linear function of $c_1$

$$\delta(c_1) = \Gamma_0 + \Gamma_1 c_1, \tag{4}$$

where $\Gamma_0$ and $\Gamma_1$ are positive constants. A person who survives in period two consumes $c_2$. A person who dies leaves their planned consumption, $c_2$, as a bequest: $b = c_2$. The representative person chooses $c_1$, $c_2$, and $b$ to maximize (3) subject to (2), (4), and $b = c_2$.

To derive the first-order conditions, it is useful to consider the following monotonic transformation of the Epstein-Zin utility function: $V_1 = \frac{U_1^{1-\rho}}{1-\rho}$. The first-order conditions are as follows:

$$(1-\beta)c_1^{-\rho} + \frac{\beta}{1-\alpha}\left[E(U_2^{1-\alpha})\right]^{(1-\rho)/(1-\alpha)-1}\delta'(c_1)[(\omega_0+\omega_1 c_2^{\mu})^{1-\alpha} - c_2^{1-\alpha}] = \lambda,$$

$$\beta\left[E(U_2^{1-\alpha})\right]^{(1-\rho)/(1-\alpha)-1}\{[1-\delta(c_1)]\,c_2^{-\alpha} + \delta(c_1)(\omega_0+\omega_1 c_2^{\mu})^{-\alpha}\mu\omega_1 c_2^{\mu-1}\} = \lambda,$$

where $\beta$ is the discount factor, $\alpha$ is the coefficient of relative risk aversion for static gambles, and $\rho$ is the inverse of the elasticity of intertemporal substitution (EIS) with respect to deterministic income changes. The case of $\rho = \alpha$ and $z = 0$ corresponds to standard time-separable expected discounted utility.

In the absence of death ($\Gamma_0 = \Gamma_1 = 0$), the optimal value of the ratio $c_2/c_1$ is

$$\frac{c_2}{c_1} = \left(\frac{\beta}{1-\beta}\right)^{1/\rho}. \tag{5}$$

As $\rho$ goes to infinity (zero EIS), $c_2$ converges to $c_1$. Suppose that $\beta > 0.5$, so people place a larger weight on the future than on the present. When $\rho$ goes to zero (infinite EIS), $c_1$ converges to zero and $c_2$ to $y$, that is, all consumption takes place in period 2.

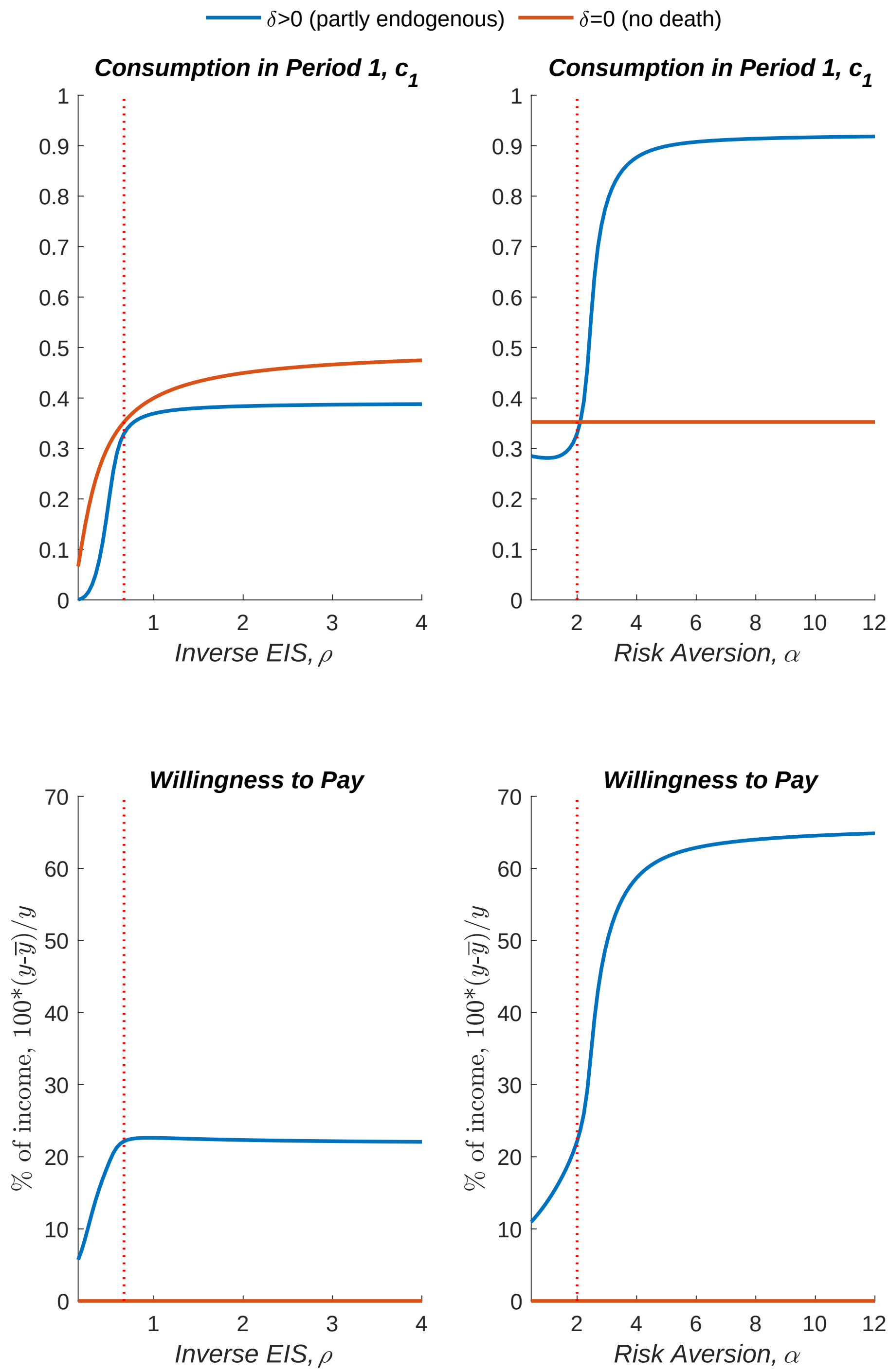
For positive values of $\Gamma_0$ and $\Gamma_1$, the model has no analytical solution. We explore the key mechanisms using a series of numerical examples. We choose parameters so that $c_2 > \omega_0 + \omega_1 b^{\mu}$. This condition, emphasized by Bommier et al. (2020, 2021), implies that people prefer to live rather than die in the second period of their lives.

The benchmark parameters in our example are as follows: $\rho = 1/1.5$, $\alpha = 2$, $\mu = 1-\rho$, $\omega_0 = 0.0865$, $\omega_1 = 0.1276$, $\Gamma_0 = 0.02$, $\Gamma_1 = 0.5462$. We normalize the initial income, $y$, to one. Since period two represents the future, we choose $\beta = 0.6$ so that more consumption occurs in the future than in the present. Given our choices of $\beta$ and $\rho$, $c_2/c_1$ is equal to 1.8.

The benchmark values of $\rho$, $\alpha$, and $\mu$ are the same as in our quantitative model. The rationale for these values is discussed in Section 6.1. We choose $\omega_0$ and $\omega_1$ so that the following ratios coincide with the corresponding values for a weighted average of recovered young and old people in the estimated benchmark model.

$$\frac{\omega_0}{\omega_0 + \omega_1 b^{\mu}} = 0.44, \quad \frac{c_2}{\omega_0 + \omega_1 b^{\mu}} = 3.38. \tag{6}$$

To illustrate the impact of the probability of dying on consumption, we choose values of $\Gamma_0$ and $\Gamma_1$ that are sufficiently large that the results of our experiment are clearly visible in Figure 5. In our simple example, the probability of dying, evaluated at the optimum level of consumption, is quite high (20 percent) as is the endogenous component ($\Gamma_1 c_1$) of




Note: $100*(y\text{-}\overline{y})/y$ denotes percent of income someone is willing to pay to remain in $\delta$=0 economy instead of going to $\delta$ >0 economy.

Figure 5: Two-period example.

the probability of dying (90 percent). In our quantitative model, both of these numbers are much lower.

Figure 5 shows the effects of varying the EIS and risk aversion in the simple model. For each value of $\rho$ and $\alpha$ we recompute the values of $\omega_0$ and $\omega_1$ so that conditions (6) hold. The red line corresponds to the case in which the probability of dying in period two is zero ($\Gamma_0 = \Gamma_1 = 0$). The blue line corresponds to the case where the probability of dying is positive and a function of $c_1$ ($\Gamma_0$, $\Gamma_1 > 0$).

The upper left-hand entry of Figure 5 shows how $c_1$ varies with the inverse of the EIS, $\rho$. The dotted vertical line corresponds to the $\rho$ value in our benchmark calibration. In general, there are two forces at work governing the impact of $\rho$ on $c_1$. First, if a person dies, they leave a bequest equal to their planned period-two consumption. The utility of leaving this bequest is lower than that of consuming in period two. When the EIS is high, a person reacts to the risk of dying in period two by reducing planned $c_2$ and increasing $c_1$. The higher is the EIS, the larger this effect is. Second, because $\delta$ is endogenous, people have an incentive to cut $c_1$ to reduce the probability of dying in period two. In our example, the second effect dominates the first effect so that, for all values of $\rho$, $c_1$ is lower than when $\delta = 0$, that is the blue line is below the red line.

The upper right-hand entry of Figure 5 shows how $c_1$ varies with the coefficient of relative risk aversion, $\alpha$. When $\delta = 0$ , there is no risk, so $c_1$ does not depend on $\alpha$ (the red line is flat). When $\Gamma_0$, $\Gamma_1 > 0$, there are two forces governing the impact of $\alpha$ on $c_1$. First, people respond to the risk of death by raising $c_1$ relative to the $\delta = 0$ case. The higher is risk aversion, the higher is $c_1$. The reason is that deferring consumption to period two is a risky gamble relative to consuming in period one. This effect is emphasized in Bommier et al. (2020). Second, in our model people have an incentive to lower $c_1$ to reduce $\delta$. For moderate degrees of risk aversion, the second effect dominates, so $c_1$ is lower than when $\delta = 0$. As risk aversion gets larger, the first effect dominates, so $c_1$ is higher than when $\delta = 0$.

We now turn to the question of how risk aversion and the EIS affects people's willingness to pay to eliminate the risk of death. To compute the willingness to pay, we solve the following equation, $U_1(y) = \bar{U}_1(\bar{y})$, where $\bar{U}_1$ is lifetime utility in an economy with $\delta = 0$. The level of $\bar{y}$ that solves this equation is

$$\bar{y} = \frac{U_1(y)}{(1-\beta)^{1/(1-\rho)}\left(1 + [\beta/(1-\beta)]^{1/\rho}\right)^{\frac{\rho}{1-\rho}}}.$$

The bottom left-hand entry of Figure 5 displays the fraction of income $(y - \bar{y})/y$ that people would be willing to pay to eliminate the risk of death as a function of the EIS. People's willingness to pay is low when the EIS is high (low value of $\rho$) because it is less costly to reduce the probability of death by cutting $c_1$. For values of $\rho$ exceeding one, the willingness to pay is insensitive to the EIS.

The bottom right-hand entry of Figure 5 reports the analog results as we vary the coefficient of relative risk aversion, $\alpha$. Not surprisingly, the willingness to pay is monotonically increasing in $\alpha$. The key result is that the willingness to pay to avoid the risk of death is much more sensitive to $\alpha$ than to $\rho$. As we vary $\rho$, the willingness to pay ranges from roughly 8 percent to 22 percent. In contrast, as we vary $\alpha$, the willingness to pay ranges from roughly 11 percent to 65 percent.

In sum, the previous discussion highlights the key mechanisms at work in our quantitative model: risk aversion, intertemporal substitution, people's beliefs about the probability of dying, and bequest motives.

# 6 A model of consumer behavior in an epidemic

In this section, we develop a quantitative model of how people changed their consumption behavior in response to Covid. We use the model to address the question: how much would people be willing to pay to avoid the risk of death associated with Covid? Answering this question revolves around two issues. The first is people's beliefs about case-fatality rates. The second is the fraction of the drop in consumption due to people's risk-avoidance behavior as opposed to government-imposed containment measures.

We use a partial-equilibrium approach that allows us to confront people of different ages and health statuses with real wages, real interest rates, and infection probabilities that mimic those observed in the data using a minimal set of assumptions. By partial-equilibrium analysis, we mean that we study the consumption decisions of people of different ages and incomes given exogenous processes for real wages, real interest rates, and infection probabilities. In Section 8, we consider a general equilibrium model in which we fully specify the environment (preferences, technology, market structure, and epidemic dynamics) and solve for the equilibrium values of real wages, real interest rates, and infection probabilities.

Consistent with the evidence in Sorensen et al. (2022), we assume that actual case-fatality rates fall over time due to improvements in medical treatments (see subsection 6.1.2 for details). Throughout, we assume that people know the objective probability of becoming infected. However, they don't know their age group's actual, time-varying case-fatality rate. They begin with a prior, which they update over time. This prior and the rate at which it converges to the objective probability play a critical role in our analysis. We could have assumed that people also do not know the objective probability of becoming infected. But we could not credibly identify all the free parameters associated with this specification. As it turns out, focusing on uncertainty about the true case-fatality rate is sufficient to allow the model to account for the key features of the data.

To compute the probability of being infected, people need to form expectations about the path of infections in the economy. We assume the economy is in the pre-epidemic steady state in the first four weeks of March 2020. Then, on the 5th week of March, people learn about the first wave of the epidemic. To simplify, we assume that people have perfect foresight with respect to the first wave of infections and expect the epidemic to end in week 17 (the week of June 21, 2020). Then, in week 18 (the week of June 28, 2022), people learn that there will be two more waves. From that point on, people have perfect foresight with respect to these waves. We could allow for uncertainty about the number of infections at the cost of making the model more complex and introducing free parameters that would be difficult to identify. To add perspective on the role played by intertemporal substitution, we also consider the case in which people know there will be three waves.

We divide the population into two groups: people younger than 60 with no comorbidities and people older than 60 or younger than 60 but with comorbidities. For ease of exposition, we refer to these groups as young and old. We assume that a person in the first group joins the second group with a constant probability per period, $v$. This assumption makes the analysis more tractable because the model has only two types of people. With deterministic aging, we would need to keep track of 61 age cohorts (from 20 to 80 years old). The critical difference between people in the two groups is the subjective and objective risk of dying from Covid or other causes.

As in Kermack and McKendrick (1927)'s SIR model, people are in one of four possible health states: susceptible (those with no immunity against the virus), infected, recovered (those who recovered from the infection and have acquired immunity against the virus), and deceased. In studying the first three waves of the epidemic, we assume that recovered people have permanent immunity. This assumption is incorrect in light of recent mutations of the Covid virus and associated breakthrough infections. However, this possibility was not widely discussed during the first three Covid waves. So, to simplify, we assume in this section that people think that once they recover from the infection, they have permanent immunity. We relax this assumption in Section 8, in which we discuss the implications of endemic Covid.

Each period in our model represents a week. Since our empirical work relies on data for public servants, we assume that people's labor supply decisions are exogenous and the real wage rate is constant. We normalize the number of hours worked to one. The budget constraint of a person with assets $b_t$ who consumes $c_t$ is

$$b_{t+1} = w + (1 + r)b_t - c_t,$$

where $w$ is the real wage rate and $r$ is the rate of return on assets. People differ in their health status, age, and initial assets. To simplify the notation, we omit in the budget constraint the subscripts $a$ and $h$.

The probability of a susceptible person in age group $a$ becoming infected at time $t$, $\tau_{a,t}$, is given by the transmission function:

$$\tau_{a,t} = \pi_1 c^h_{a,t} I_t + \pi_2 I_t, \tag{7}$$

where $h$ denotes a person's health status and $I_t$ is the number of infected people in the population at time $t$. The terms $\pi_1 c^h_a I_t$ and $\pi_2 I_t$ represent the probability of becoming infected through consumption- and non-consumption-related activities, respectively. As in Eichenbaum, Rebelo, and Trabandt (2021), this function embodies the assumption that people meet randomly and that susceptible people can reduce their infection probability by cutting their consumption.

People are uncertain about case-fatality rates. At the beginning of the epidemic, people believe that the case-fatality rate for a person of age $a$ is $\pi_{ad,0}$. They update these beliefs using a parsimonious constant-gain learning algorithm:[7]

$$\pi_{ad,t} = \pi_{ad,t-1} + g_a(\pi^*_{ad,t} - \pi_{ad,t-1}).$$

Here, $\pi^*_{ad,t}$ is the true case-fatality rate for people of age $a$ at time $t$. The parameters $g_a \in [0, 1]$ control how quickly people update their beliefs.[8] These beliefs converge in the long run to $\pi^*_{ad,t}$. Implicitly, this specification assumes that, in every period, people see the

[7] See Evans and Honkapohja (2012) and Eusepi and Preston (2011) for discussions of the properties of this learning algorithm.

[8] In principle, one could entertain more complex information structures in which people receive noisy signals about infections and deaths in each period and use those signals optimally in solving their maximization problem. For computational reasons, we abstract from these types of information structures.

actual ratio of Covid deaths to infections and use it to update their beliefs. At each point in time, people expect the case-fatality rate to remain constant: $\pi_{ad,t+j} = \pi_{ad,t}$.[9]

The variable $\delta_a$ denotes the time-$t$ probability that a person of age $a$ dies of non-Covid causes. The variable $\pi_{ar,t}$ denotes the probability that a person of age $a$ who is infected at time $t$ recovers at time $t+1$. The probability of exiting the infection state, $\pi_{ar,t} + \pi_{ad,t}$ is constant over time, so time variation in people's beliefs about $\pi_{ad,t}$ induces time variation in their beliefs about $\pi_{ar,t}$.

As in the simple model, people's utility has the recursive form proposed by Kreps and Porteus (1978), Weil (1989), and Epstein and Zin (1991). The lifetime utility of a person with age $a$ and health status $h$ at time $t$ is

$$U^h_{a,t} = \max_{c^h_{a,t}, b_{t+1}} \left\{ z + \left[ (1-\beta)((1-\mu_t)c^h_{a,t})^{1-\rho} + \beta \left\{ E_t \left[ \left( U^h_{a,t+1} \right)^{1-\alpha} \right] \right\}^{(1-\rho)/(1-\alpha)} \right]^{1/(1-\rho)} \right\}. \tag{8}$$

Here, $z$ is a constant that influences the value of life (see Hall and Jones (2007)). The expectations operator, $E_t$, takes into account all the stochastic elements of the environment, including the possibility of death. People take as given the sequence of aggregate infections, $\{I_t\}_{t=0}^{\infty}$. We use time variation in $\mu_t$ to model exogenous changes in consumption demand associated with government-imposed containment measures. This variable represents the consumption wedge introduced by containment measures. The higher is $\mu_t$, i.e., the more containment there is, the lower the marginal utility of consumption. In Appendix B.3, we show that there is an equivalence between modeling containment as a wedge on utility and a model where containment implies that some goods cannot be consumed.

The value functions for all people depend on the value of their assets, $b_t$, and calendar time. This time dependence reflects deterministic time variation in $\mu_t$, $I_t$, $\pi_{ad,t}$, and the person's time-$t$ belief about the case-fatality rates for old and young. Recall that when solving their optimization problem at time $t$, people assume that future values of the case-fatality rate equal their current beliefs.

[9] This assumption implies that we are working with a version of Kreps (1988)' anticipated utility.

The value function of a susceptible young person at time $t$ is[10]

$$\begin{aligned} U_{y,t}^{s}(b_t) &= \max_{c_{y,t}^{s},b_{t+1}} \Big\{ z + \{(1-\beta)((1-\mu_t)c_{y,t}^{s})^{1-\rho} + \beta[(1-\tau_{y,t})(1-\delta_y-v)\left(U_{y,t+1}^{s}(b_{t+1})\right)^{(1-\alpha)} + \\ &\quad (1-\tau_{y,t})\, v \left(U_{o,t+1}^{s}(b_{t+1})\right)^{(1-\alpha)} + \tau_{y,t}(1-\delta_y-v)\left(U_{y,t+1}^{i}(b_{t+1})\right)^{(1-\alpha)} + \\ &\quad \tau_{y,t} v \left(U_{o,t+1}^{i}(b_{t+1})\right)^{1-\alpha} + \delta_y B(b_{t+1})^{1-\alpha}]^{(1-\rho)/(1-\alpha)}\}^{1/(1-\rho)} \Big\}. \end{aligned}$$

Recall that $v$ is the probability of a young person becoming old. $U_{yt}^{i}$ and $U_{ot}^{i}$ are the value functions of a young and old infected person, respectively. The value function reflects the possible changes in health and age status at time $t+1$. A young, susceptible person at time $t$ can remain in that state at time $t+1$ with probability $(1-\tau_{y,t})(1-\delta_y-v)$, not get infected but become old with probability $(1-\tau_{y,t})\, v$, get infected and stay young with probability $\tau_{y,t}(1-\delta_y-v)$, get infected and become old with probability $\tau_{y,t}v$, or die of non-Covid causes with probability $\delta_y$.

The function $B(b_{t+1})$ represents the utility from leaving a bequest $b_{t+1}$ upon death. We assume that this function takes the form:

$$B(b_{t+1}) = \omega_0 + \omega_1(b_{t+1})^{\mu},$$

where $\omega_0 > 0$ and $\omega_1 > 0$. The bequest motive allows the model to be consistent with two empirical observations. First, many people die with large asset holdings (see, e.g., Huggett (1996) and De Nardi and Yang (2014)). Second, older people's consumption expenditures are lower than younger people's. The latter pattern obtains in the model because, as people age, bequests receive a higher weight in the utility function relative to consumption. People of all ages and health statuses choose their consumption and asset holdings to maximize their expected lifetime utility. We solve their optimization problem using value function iteration. In Appendix B, we display the value functions for old, susceptible people, young infected people, old infected people, young recovered people, and old recovered people.

## 6.1 Parameters of quantitative model

We partition the parameters of our quantitative model into two sets. The first set is estimated with Bayesian methods. The second set is calibrated to micro data.

[10] This formulation and the others in Appendix B involve a slight abuse of notation. The perceived value function $U_{a,t+1}^{h}$ is computed at time $t$ assuming that $\pi_{ad,t+j} = \pi_{ad,t}$ for all $j$. The realized value function at time $t+1$, is computed assuming that $\pi_{ad,t+1+j} = \pi_{ad,t+1}$ for all $j$. Our notation does not distinguish between these two types of value functions. In solving the model, we do take into account this distinction.

### 6.1.1 Econometric methodology

We estimate younger and older people's initial prior beliefs about case-fatality rates ($\pi_{yd,0}$ and $\pi_{od,0}$), the gain parameters ($g_y$ and $g_o$), and the parameter $\mu$. The latter parameter controls the impact of containment on the marginal utility of consumption. We assume that the containment wedge $\mu_t$ is given by $\mu_t = \mu\xi_t$, where $\mu$ is a scalar and $\xi_t$ is the time series for containment measures depicted in Figure 2. The maximum value of $\xi_t$ is normalized to one.

We calibrate the basic reproduction number, $\mathcal{R}_0$ to equal 2.5, the value preferred by the Center for Disease Control.[11] In our model $\mathcal{R}_0$ is given by:

$$\mathcal{R}_0 = \frac{\pi_1[c_{ys}s_y + c_{os}(1-s_y)] + \pi_2}{\pi_{yr}s_y + \pi_{or}\,(1-s_y) + \pi^*_{yd}s_y + \pi^*_{od}(1-s_y)},$$

where $s_y$ is the pre-epidemic share of young people in the population, and $c_{ys}$ and $c_{os}$ are the pre-epidemic levels of consumption of susceptible young and old, respectively.

We estimate $\kappa$, an auxiliary parameter that represents the average share, for young and old, of infections generated by consumption activities at the beginning of the epidemic:

$$\kappa = \frac{\pi_1[c_{ys}s_y + c_{os}(1-s_y)]}{\pi_1[c_{ys}s_y + c_{os}(1-s_y)] + \pi_2}.$$

Given the value of $\mathcal{R}_0$ and the estimate of $\kappa$, we solve for the implied estimates of $\pi_1$ and $\pi_2$.

Let the vector $\psi$ denote the time series of the response to Covid of the consumption expenditures of younger and older people in our model from March 2020 to April 2021. Let $\hat{\psi}$ denote our estimate of $\psi$ for these two groups of people obtained using regression (1). Table 12 in Appendix A reports the estimated regression parameters. The results are displayed in Figure 8 below.

Our estimation criterion focuses on the consumption response of young and old with a net wealth of 75 thousand euros. According to the Survey of Household Financial Conditions Statistics-Portugal (2017) and Costa and Farinha (2012), the average net wealth of Portuguese households over the period 2013-2017 is 150 thousand euros. We divide this number by two because there are, on average, two adults per household in Portugal.

We estimate the model's predictions for people with this level of assets for two reasons. First, we do not observe the wealth distribution for people in our sample. Second, it is computationally daunting to compute the consumption behavior of people with different wealth levels in every iteration of the estimation algorithm.

[11] See COVID-19 Pandemic Planning Scenarios, Center for Disease Control, March 19, 2021.

The logic of the estimation procedure is conceptually the same as in Christiano, Trabandt, and Walentin (2010). Suppose that our structural model is true. Denote the true values of the model parameters by $\theta_0$. Let $\psi(\theta)$ denote the mapping from values of the model parameters to the time series of the impact of Covid on the consumption expenditures of younger and older people. The vector $\psi(\theta_0)$ denotes the true value of the time series whose estimates are $\hat{\psi}$. According to standard classical asymptotic sampling theory, when the number of observations, $T$, is large,

$$\sqrt{T}\left(\hat{\psi} - \psi(\theta_0)\right) \overset{a}{\sim} N(0, W(\theta_0)).$$

It is convenient to express the asymptotic distribution of $\hat{\psi}$ as

$$\hat{\psi} \overset{a}{\sim} N(\psi(\theta_0), V). \tag{9}$$

Here, $V$ is a consistent estimate of the precision matrix $W(\theta_0)/T$. Following Christiano, Trabandt, and Walentin (2010), Christiano, Eichenbaum, and Trabandt (2016), and Fernández-Villaverde, Rubio-Ramírez, and Schorfheide (2016), we assume that $V$ is a diagonal matrix. In our case, the diagonal elements are the variances of the percentage responses of consumption of younger and older people at each point in time, reported in Column 4 of Table 12 in Appendix A.

Our analysis treats $\hat{\psi}$ as observed data. We specify priors for $\theta$ and then compute the posterior distribution for $\theta$ given $\hat{\psi}$ using Bayes' rule. This computation requires the likelihood of $\hat{\psi}$ given $\theta$. Our asymptotically valid approximation of this likelihood is motivated by (9):

$$f\left(\hat{\psi}|\theta, V\right) = (2\pi)^{-\frac{N}{2}} |V|^{-\frac{1}{2}} \exp\left[-0.5\left(\hat{\psi} - \psi(\theta)\right)' V^{-1}\left(\hat{\psi} - \psi(\theta)\right)\right]. \tag{10}$$

The value of $\theta$ that maximizes this function is an approximate maximum likelihood estimator of $\theta$. It is approximate for two reasons. First, the central limit theorem underlying (9) only holds exactly as $T \to \infty$. Second, our proxy for $V$ is guaranteed to be correct only for $T \to \infty$.

Treating the function $f$ as the likelihood of $\hat{\psi}$, it follows that the Bayesian posterior of $\theta$ conditional on $\hat{\psi}$ and $V$ is:

$$f\left(\theta|\hat{\psi}, V\right) = \frac{f\left(\hat{\psi}|\theta, V\right) p(\theta)}{f\left(\hat{\psi}|V\right)}. \tag{11}$$

Here, $p(\theta)$ denotes the prior distribution of $\theta$ and $f\left(\hat{\psi}|V\right)$ denotes the marginal density of $\hat{\psi}$:

$$f\left(\hat{\psi}|V\right) = \int f\left(\hat{\psi}|\theta, V\right) p(\theta)\, d\theta.$$

Because the denominator is not a function of $\theta$, we can compute the mode of the posterior distribution of $\theta$ by maximizing the value of the numerator in (11). We compute the posterior distribution of the parameters using a standard Monte Carlo Markov chain (MCMC) algorithm. We evaluate the relative empirical performance of different models by comparing their implications for the marginal likelihood of $\hat{\psi}$ computed using the Laplace approximation.

We assume uniform $[0, 7/14]$ priors for $\pi_{yd,0}$ and $\pi_{od,0}$, and uniform $[0, 1]$ priors for $\mu$, $g_y$, $g_o$, and $\kappa$. We assume that it takes on average 14 days to either die or recover from an infection, so $\pi_{yd,0} + \pi_{yr,0} = 7/14$ and $\pi_{od,0} + \pi_{or,0} = 7/14$.

### 6.1.2 Calibration

In addition to $\mathcal{R}_0$, we calibrate the following parameters: $\pi^*_{yd,t}$, $\pi^*_{od,t}$, $r$, $\alpha$, $\rho$, $\beta$, $\delta_y$, $\delta_o$, $z$, $\omega_0$, and $\omega_1$. We set the actual weekly case-fatality rates ($\pi^*_{yd,t}$ and $\pi^*_{od,t}$) for the week of July 26, 2020 to $7 \times 0.001/14$ and $7 \times 0.035/14$, respectively. These values correspond to the case-fatality rates for the median younger (age 39.5) and older (age 64.5) person (see Table 1).

Sorensen et al. (2022) estimate the population-wide time trend in the infection-fatality rate from April 2020 to January 2021. These estimates imply that the infection-fatality rate fell by 36 percent between March 2022 and April 2021. We use these estimates to compute the values of $\pi^*_{yd,t}$ and $\pi^*_{od,t}$ for periods before and after July 26, 2020. We assume that the values of $\pi^*_{yd,t}$ and $\pi^*_{od,t}$ are such that, on average, infected people recover or die in two weeks ($\pi^*_{or,t} + \pi^*_{od,t} = \pi^*_{yr,t} + \pi^*_{yd,t} = 7/14$). We make the same assumption for the beliefs of case-fatality rates, i.e., $\pi_{or,t} + \pi_{od,t} = \pi_{yr,t} + \pi_{yd,t} = 7/14$. The blue-dashed lines in Figure 7 show the resulting time series for $\pi^*_{yd,t}$ and $\pi^*_{od,t}$. See subsection B.4 of the Appendix for a more detailed description of how we incorporate the Sorensen et al. (2022) estimates into our calibration.

The annual real interest rate, $r$, is set to 1 percent. This value corresponds roughly to the realized real yield on 10-year Portuguese government bonds from March 2020 to April 2021.

We use the life-expectancy tables produced by Statistics Portugal to calibrate non-COVID-related mortality rates for younger and older people. We obtain $\delta_y = 1/(51 \times 52)$

and $\delta_o = 1/(13 \times 52)$. Since the average age difference between old and young people is 28 years, we set the weekly probability of aging, $\nu$, to $1/(28 \times 52)$. Consistent with Portuguese demographic data, we assume that the population between 20 and 59 years old is 70 percent of the population between 20 and 79 years old.

We set the coefficient of relative risk aversion ($\alpha$) to 2 and the EIS ($1/\rho$) to 1.5. These parameter values correspond to the estimates in Albuquerque et al. (2016), obtained using data on the equity premium and other moments of financial-market data. These data are particularly relevant to our analysis because they reflect people's attitudes toward risk. The weekly discount factor, $\beta$, is set equal to $0.97^{1/52}$, which is consistent with the values used in the literature on dynamic stochastic general equilibrium models (see, e.g., Christiano et al. (2005)).

The level parameter in the utility function ($z$) and the two parameters that control the utility of bequests ($\omega_0$ and $\omega_1$) are chosen so that the model is consistent with three features of the Portuguese data. First, the ratio of younger to older people's consumption is roughly 1.2. Second, the average savings rate is 6.7 percent. Third, the value of life is about 900 thousand euros, which is consistent with the value used in cost-benefit analyses of Portuguese public works (see, e.g., Ernst and Young (2015)). These conditions imply that $\omega_0 = 159.51$, $\omega_1 = 4.88$, and $z = 2.66$. A value of life of 900 thousand euros equals 6.8 times annual consumption. For comparison, Hall, Jones, and Klenow (2020), henceforth HJK, consider values of life measured in units of consumption ranging from 5 to 7.

In our sample, the average after-tax income of people younger and older than 60 in 2018 is very similar ($18,900$ and $19,400$ euros, respectively). To simplify, we assume that both groups earn $19,000$ euros per year.

# 7 Empirical results

Figure 6 depicts priors and posteriors for the parameters we estimate. The figure shows that the data is very informative relative to our priors. Table 2 reports the mean and 95 percent probability intervals for the priors and posterior of the estimated parameters.

Several features are worth noting. First, the posterior modes of $\pi_{yd,0}$ and $\pi_{od,0}$ are 0.087 and 0.413, respectively. Recall that case-fatality rates for young and old are $\pi_{yd} = 7 \times 0.001/14 = 0.0005$ and $\pi_{od} = 7 \times 0.035/14 = 0.0175$, respectively. So, according to the model, both younger and older people greatly overestimated their case-fatality rates at the

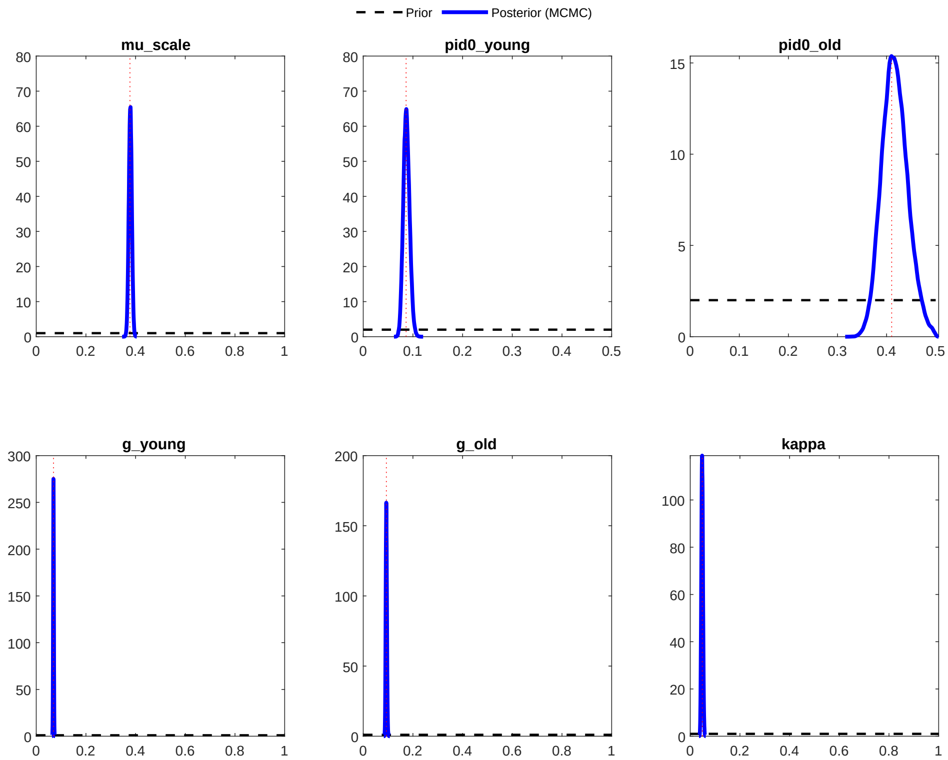



Figure 6: Priors and posteriors of estimated parameters.

Table 2: Priors and Posteriors of Parameters: Baseline Model vs. FIRE/no learning Model.

| | | Baseline Model | FIRE/no learning Model |
|---|---|---|---|
| | Prior Distribution $D$, Mean, [2.5-97.5%] | Posterior Distribution Mode, [2.5-97.5%] | Posterior Distribution Mode, [2.5-97.5%] |
| Initial belief, mortality rate, young, $\pi_{yd,0}$ | $U$, 0.50, [0.025 0.975] | 0.087, [0.075 0.100] | - |
| Initial belief, mortality rate, old, $\pi_{od,0}$ | $U$, 0.50, [0.025 0.975] | 0.413, [0.371 0.474] | - |
| Learning speed parameter, young, $g_y$ | $U$, 0.50, [0.025 0.975] | 0.069, [0.066 0.072] | - |
| Learning speed parameter, old, $g_o$ | $U$, 0.50, [0.025 0.975] | 0.092, [0.088 0.098] | - |
| Initial share of cons.-based infections, $\kappa$ | $U$, 0.50, [0.025 0.975] | 0.048, [0.041 0.054] | 0.069, [0.065 0.074] |
| Containment parameter, $\mu$ | $U$, 0.50, [0.025 0.975] | 0.380, [0.366 0.391] | 0.525, [0.518 0.532] |
| Memo Item | | | |
| Log Marginal Likelihood (Laplace): | | -532.3 | -1704.9 |

Notes: For model specifications where particular parameter values are not relevant, the entries in this table are blank. Posterior mode and parameter distributions are based on a standard MCMC algorithm with a total of 500,000 draws (10 chains, 10 percent of draws used for burn-in, draw acceptance rates about 0.2). $U$ denotes the prior for the uniform distribution for which the mean is reported instead of the mode.

beginning of the epidemic. Second, the posterior mode of the gain parameters, $g_y$ and $g_o$, are 0.069 and 0.092, respectively. Figure 7 displays the implied time series of $\pi_{yd,t}$ and $\pi_{od,t}$. By the end of the sample, $\pi_{yd,t}$ and $\pi_{od,t}$ have essentially converged to their true values. As discussed below, this feature is critical to the model's ability to account for the data. Third, the posterior mode of the parameter $\mu$ is equal to 0.380. So, at their peak, containment measures reduced the marginal utility of consumption by roughly 38 percent. Fourth, $\kappa$, the fraction of infections associated with consumption activities is 4.6 percent. Taken together, these values imply that $\pi_1 = 0.000170$ and $\pi_2 = 1.1921$.

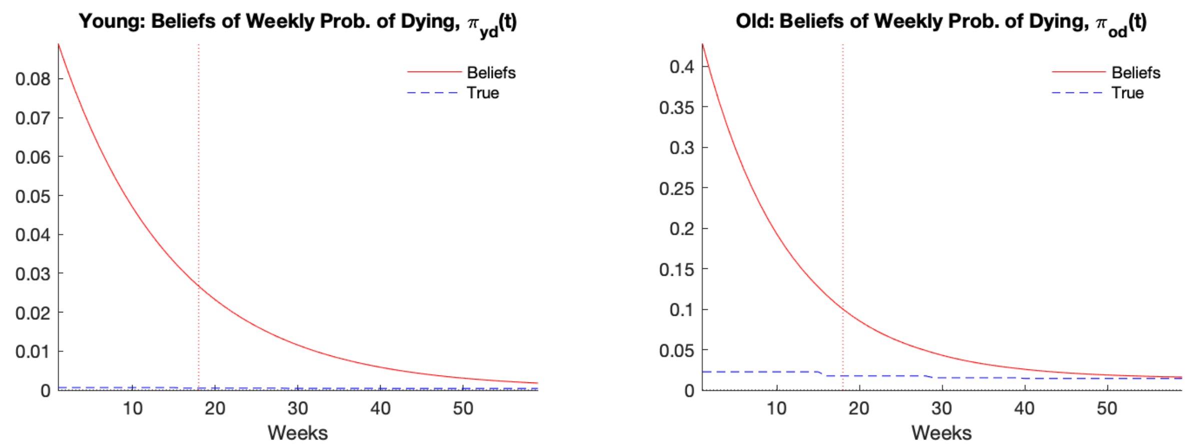



Figure 7: Evolution over time of beliefs about case-fatality rates of old and young.

The dashed red and blue lines in Figure 8 display our regression-based estimates of how the consumption of old and young people responded to Covid. The bars around point estimates represent the 95 percent confidence intervals. The solid red and blue lines are the corresponding model implications computed using the posterior mode of the estimated parameters. These implications are computed by comparing the model's dynamics with and without Covid.

Figure 8 shows that the model does quite well at accounting for the consumption behavior of older people over the entire sample. In particular, the model generates the steep decline during the first wave, the recovery in the summer of 2020, the subsequent reduction beginning in the fall of 2020, as well as the recovery in the winter of 2021. Critically, the model is consistent with the fact that consumption of the old falls by more in the first wave than in the second wave, even though the risk of infection was higher in the second and third waves.

With two exceptions, the model does quite well at accounting for the consumption behavior of the young. The first exception is that it does not fully explain the rise in consumption

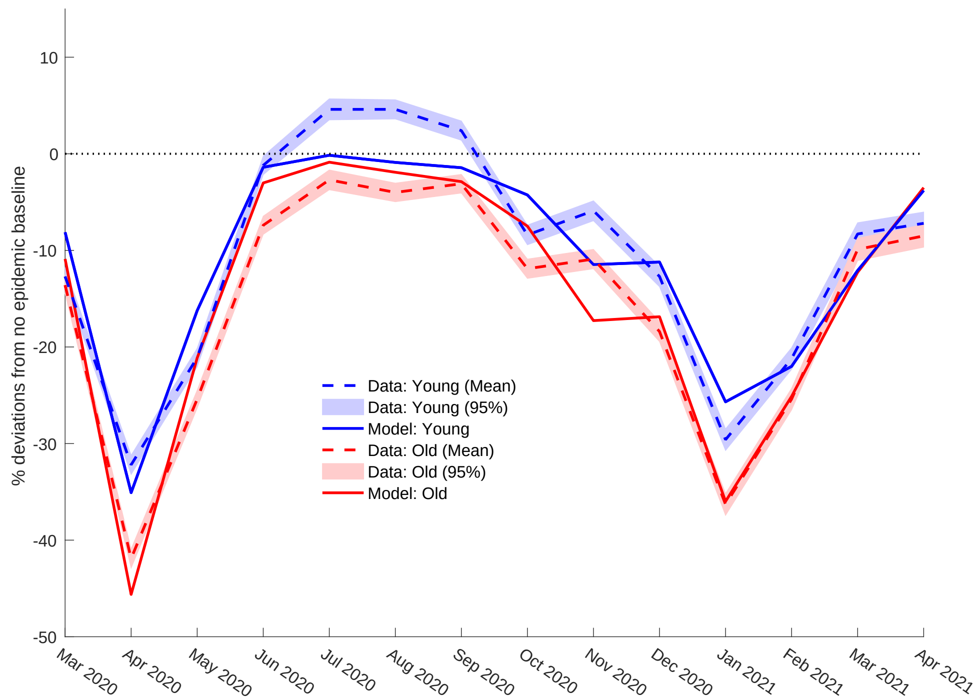



Figure 8: Consumption of young and old in the epidemic. Baseline estimated model and data implications for changes in expenditures of old and young during the epidemic relative to a counterfactual without Covid.

of the young during the summer of 2020. The second exception is that the model understates the peak decline in the consumption of the young during the second wave. An important success of the model is that it implies that consumption expenditures of the young fall by more in the first wave than in the second and third waves.

We conduct the following experiment to gain insight into intertemporal substitution's role in consumption choices. In our baseline specification, the second and third waves come as a surprise to people. Suppose, instead, people knew about the second and third waves at the beginning of the epidemic. Other things equal, the more important intertemporal substitution is, the more we would expect consumption choices to be affected by this information. It turns out that in this case, people's consumption choices are very similar to the baseline case (see Figure B.8 in Appendix B).

## 7.1 Identifying $\kappa$ and $\mu$

In this subsection, we discuss the key features of the data that allow us to identify $\kappa$ and $\mu$. Consider first $\kappa$, the fraction of infections attributed to consumption. To account for the behavior of consumers in the first and the third waves in the face of differential infections, the model assumes that initially, people have pessimistic beliefs about case-fatality rates. These beliefs converge to the truth by the third wave (see Figure 7 and subsection 7.2). Given this convergence, the estimation algorithm chooses $\kappa$ so that the model matches the consumption of old and young in the third wave.

To understand how our model identifies $\mu$, the parameter that controls the importance of containment, we proceed as follows. We re-estimate the model, setting $\mu$ to zero. The model's fit deteriorates significantly: the marginal log likelihood falls from $-532$ to $-2,007$. Regarding parameter estimates, the main impact of setting $\mu$ to zero is twofold. First, it increases the value of $\kappa$, the parameter that governs the effect of consumption on the probability of being infected. Second, it reduces $\pi_{od,0}$, old people's prior about the case-fatality rate.

To understand these effects, suppose we set $\mu$ to zero without changing $\kappa$ or $\pi_{od,0}$. Without containment, the consumption of the young would drop by much less than in the benchmark model. The estimation algorithm increases $\kappa$ to better fit the drop in the consumption of the young. But increasing $\kappa$ exacerbates the decline in the consumption of the old. To offset this effect, the estimation algorithm reduces $\pi_{od,0}$, so that the old view Covid as less lethal. The deterioration in model fit is most notable at the end of the third wave. By then, people's priors about case-fatality rates have converged to their true values, and there are few infected people in the economy. In the absence of containment, consumption of young and old are counterfactually high.

We also re-estimated the model by fixing $\mu$ at 10 percent higher than its estimated value. Even this small change in $\mu$ leads to a sizable deterioration in the marginal log-likelihood, which falls from $-532$ to $-559$. This deterioration reflects the model's poor fit at the end of the sample–consumption is counterfactually low relative to the data. We experimented with larger values of $\mu$ and found that the algorithm pushed parameters like $\kappa$ and $\pi_{od,0}$ to their boundary values.

An alternative way of studying the role of containment is to compute the counterfactual fall in expenditures that would have occurred if the government had imposed containment measures, but there were no infections. The difference between the consumption policy functions with and without containment allows us to estimate the impact of containment per se. This estimate relies on the assumption that, to a first order, the observed behavior of expenditures is the sum of people's response to containment and the risk of becoming infected.

The solid blue line in Figure 9 displays the consumption of old and young in a version of the model with containment but no infections. In this scenario, the changes in consumption expenditures of young and old people are the same. Figure 9 shows that the containment measures in isolation would have led to a 21 percent drop in consumption of the young and the old in the trough of the first and third waves. In the data, the actual declines in consumption are much larger. So, while containment had a substantial impact, most of the decrease in consumption for both groups reflects their response to the risk of dying from Covid. These results are consistent with the findings of Arnon et al. (2020), Chetty et al. (2020), Chernozhukov et al. (2021), Goolsbee and Syverson (2020), and Villas-Boas et al. (2020).

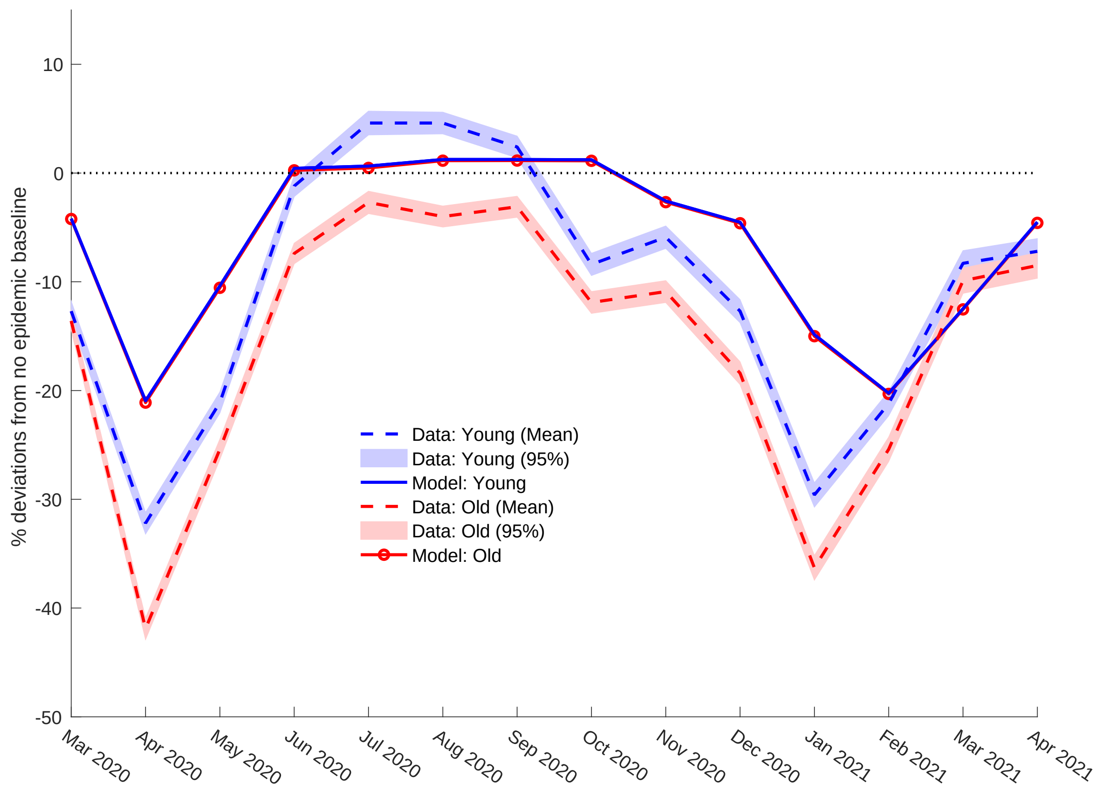



Figure 9: Consumption of young and old in model with containment and no Covid epidemic.

Our results are also consistent with those in Sheridan et al. (2020). Denmark and Sweden were similarly exposed to the pandemic, but only Denmark imposed significant containment measures. Sheridan et al. (2020) find that consumption of the young dropped by more in Denmark, presumably because of containment measures. Consumption of the old dropped by more in Sweden, presumably because the absence of containment increased the risk of infection.

## 7.2 The importance of time-varying beliefs

Learning plays a critical role in allowing the model to account for the key patterns in the data across the different Covid waves. In the data, the troughs of consumption are the same in the first and third waves for each age group. But the risk of becoming infected is much larger in the third wave. Other things equal, a model in which people know their true case-fatality rate at the beginning of the epidemic cannot account for these facts.

To formally substantiate this claim, we estimate a version of the model with full-information rational expectations (FIRE). In this version of the model, people know the true case-fatality rates at the beginning of the epidemic. This assumption is standard in the Covid literature (e.g., Alvarez, Argente, and Lippi (2021), Eichenbaum, Rebelo, and Trabandt (2021), and Jones, Philippon, and Venkateswaran (2021)).

In this version of the model, the only estimated parameters are $\mu$ and $\kappa$. The last column of Table 2 reports the mean and 95 percent probability intervals for the prior and posterior of $\mu$ and $\kappa$. Interestingly, the posterior mode of $\mu$ and $\kappa$ are higher than the corresponding value in the benchmark model. These higher values improve model fit during the first wave but do not help the model explain the differential response of old and young.

We evaluate the performance of this model relative to the learning model by computing its implications for the marginal log-likelihood. The marginal log-likelihood of the no-learning model is a dramatic 1,173 points lower than that of the learning model. To understand this result, consider Figure 10, which displays the implications of the re-estimated model with no learning for the consumption expenditures of young and old. First, the model substantially understates the drop in consumption expenditures of old people during the first wave of the epidemic. Second, for the period up to November 2020, the model does not account for the fact that consumption expenditures of the old dropped by much more than those of the young. After that period, the model does generate a larger consumption drop for the old compared to the young. Third, the model counterfactually predicts that the decline in consumption expenditures of the old is larger in the second and third waves than in the first wave.

## 7.3 Consumption response for different income groups

In Section 4.3, we discuss our estimates of the consumption response of different income groups to the epidemic. Recall that consumption expenditures fell more for higher-income

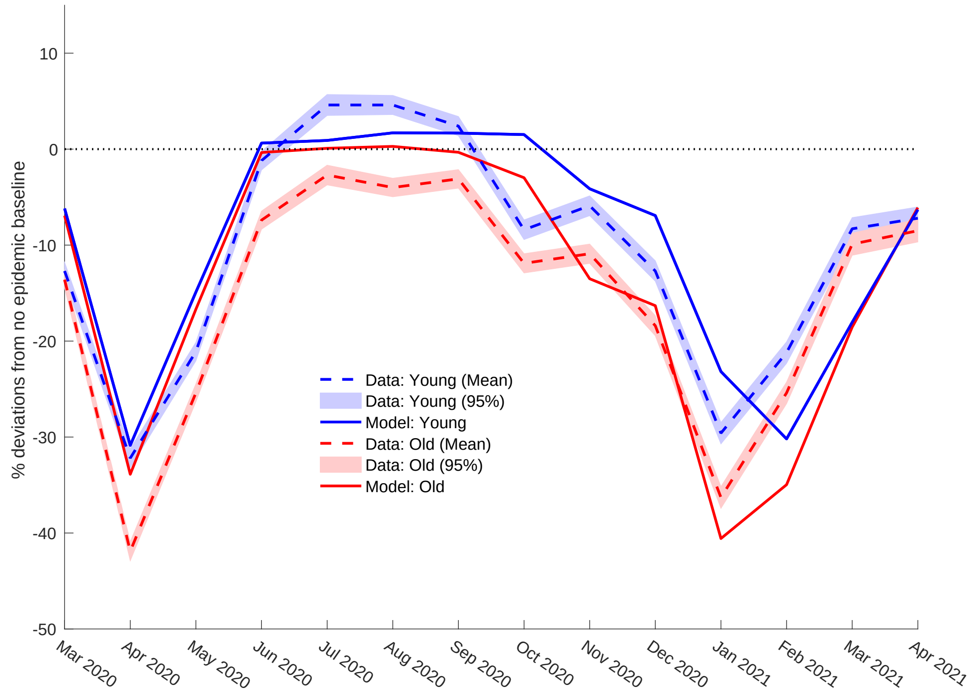



Figure 10: Consumption of young and old in the epidemic. Model with FIRE/no learning and data implications for changes in expenditures of young and old during the epidemic relative to a counterfactual without Covid.

groups than for lower-income groups. Our model is qualitatively consistent with this response pattern because higher-income households have a higher value of life, so they have more to lose from dying from Covid. In this subsection, we compare the quantitative implications of our model with our empirical estimates. To do so, we change the value of real labor income, $w$, to be consistent with the mean income of each of the three groups considered in Section 4.3 ($12,481$ EUR, $28,566$ EUR, and $59,419$ EUR). We solve and simulate the model for these three income groups, keeping all parameters equal to our baseline estimates.

Figure 11 shows the model implications and the 95 percent confidence intervals estimated in Section 4.3. This figure provides an important post-estimation check on the model because these data are not used in the estimation. Except for the lower income group during the first wave, the model fits quite well the consumption behavior of the different income groups. Introducing a subsistence level of consumption and targeted transfers to the lowest income group would help the model better fit the consumption behavior of this group during the first wave.

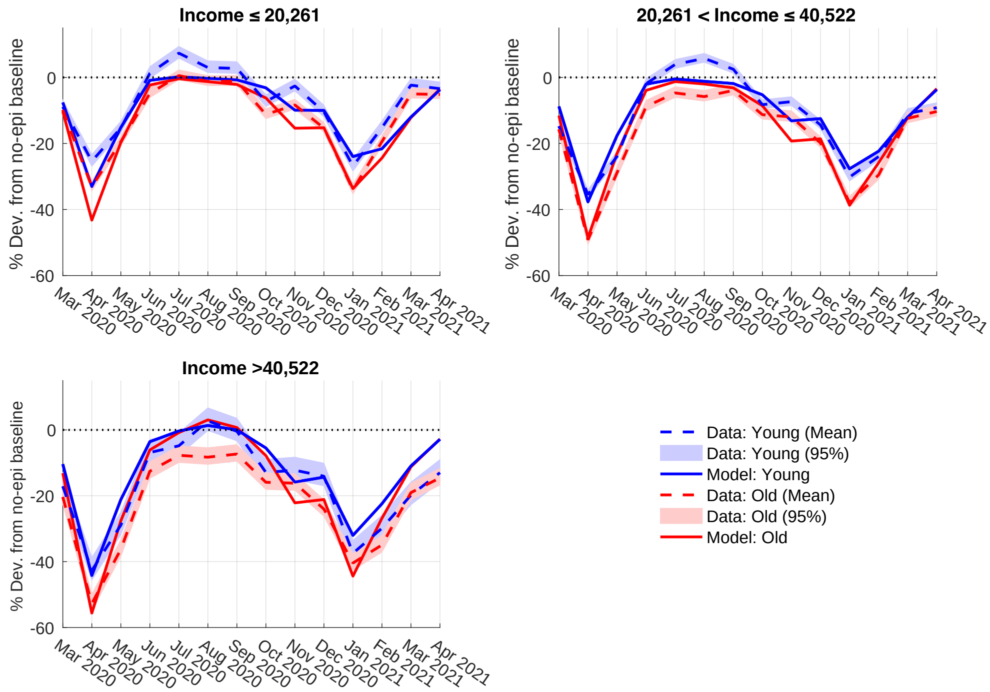



Figure 11: Consumption of young and old in the epidemic by income groups. Model with different levels of income and data implications for changes in expenditures of young and old with different incomes during the epidemic relative to a counterfactual without Covid.

## 7.4 The alpha variant

As a robustness check, we study the impact of alpha, the only important variant of the ancestral virus in our sample. That variant is estimated to be roughly 50 percent more contagious than the original strain (e.g., Yang and Shaman (2021) and Tabatabai et al. (2023)). Brainard et al. (2022) estimate that the alpha variant and the ancestral virus case-fatality rates are roughly the same.

According to GISAID data, this variant was detected in Portugal in the week of December 7, 2020, and consistently accounted for more than half of the sequenced viruses between February 2020 and April 2021.

To compute an upper bound on how much this variant affected consumption expenditures, we assume that there was an unanticipated increase of 50 percent in $\pi_1$ and $\pi_2$ after December 7, 2020. Figure B.9 in Appendix B shows that consumption by old and young falls by more in the second and third waves than in our benchmark model. This modification improves the model's fit in terms of the young's consumption expenditures and somewhat deteriorates the fit in terms of the old's consumption expenditures. Incorporating the alpha variant into the analysis does not affect our results concerning the importance of learning about case-fatality rates.

### 7.5 The impact of declining case-fatality rates

In this subsection, we study the impact of the decline in case-fatality rates estimated in Sorensen et al. (2022) which are embedded in our benchmark model. Recall that these estimates imply that the case-fatality rate falls 36 percent between March 2020 and January 1, 2021. We solve a version of the model where the case-fatality rate is constant and equal to the March 2020 values keeping all other model parameters at their estimated baseline values. As in the baseline model, people learn the constant true case-fatality rate over time. Figure B.10 in Appendix B displays the implications of this version of the model. The fit to the data is similar in the first wave but somewhat worse in the second and third waves. The higher case-fatality rate during the second and third waves generates slightly larger consumption drops than in the baseline model. Overall, the decline in case-fatality rates has a modest impact on the consumption dynamics implied by the model. The intuition for this result is that, while case-fatality rates declined, they did so from very low levels.

### 7.6 Willingness to pay to avoid the epidemic

In this subsection, we study the following question: how much would people of different ages and incomes be willing to pay to avoid the epidemic? In what follows, we refer to an epidemic as including associated containment measures.

We first discuss the impact of age on the willingness to pay. The lifetime utility of a susceptible person with assets $b$ at the beginning of the epidemic is $U_a^s(b)$. The lifetime utility of a person with assets $b$ in an economy without an epidemic is $U_a(b)$. In general, $U_a^s(b) < U_a(b)$, that is, the epidemic reduces lifetime utility. We compute the value of initial assets $\bar{b}$ in the economy without an epidemic that makes people indifferent between living in an economy with and without an epidemic: $U_a^s(b) = U_a(\bar{b})$.

The annual income of a person of age $a$ at time zero, $y_{a,0}$, is given by: $y_{a,0} = 52 \times (w + rb)$. In the spirit of HJK and Murphy and Topel (2006), we report for young and old $\Delta \equiv (b - \bar{b})/y$, i.e., the fraction of one year's income that a person would be willing to give up to avoid the epidemic.

Table 3 contains our results. In the baseline model, young and old people are willing to give up 45 and 80 percent of a year's income to avoid the epidemic. These large values reflect the pessimistic priors implied by the consumption behavior observed in the data. Containment increases people's willingness to pay to avoid the epidemic, but this effect is relatively small in the baseline model. Removing containment reduces the willingness to pay from 45 to 40 percent for young and from 80 to 77 percent for old.

When people know their actual case fatality rate (FIRE/no learning), their willingness to pay to avoid the epidemic is significantly reduced to 9 and 15 percent of a year's income for young and old, respectively. Since the true case fatality rate is very low for the young, most of their willingness to pay to avoid the epidemic reflects their desire to avoid the containment measures associated with the epidemic. For the old, roughly half of the willingness to pay reflects the desire to avoid containment measures.[12]

In their analysis for the U.S., HJK compute that the willingness of the representative person to pay to avoid the epidemic in a model with FIRE, no learning, and no containment. Depending on the case fatality rate, they find that a representative person would be willing to pay between 28 and 41 percent of one year's income to avoid the epidemic. The comparable value implied by our model is 2 percent. Several differences between our model and HJK's affect people's willingness to pay. The two major differences are as follows.[13] First, HJK assume there is no bequest motive, so dying results in a much larger utility loss in their model. Second, HJK assume that the probability of dying increases by 0.81 of a percentage point for one year due to Covid. Their calculation corresponds to a scenario in which everybody is infected at the beginning of the epidemic and dies from Covid with probability 0.81. In our model, only a relatively small fraction of the population is infected and is at risk of dying from Covid. In our sample, the probability of dying from Covid for the overall population is 0.17 percent.

To illustrate the importance of two of these factors, we proceed as follows. First, we consider a version of the model with no bequests ($\omega_0 = \omega_1 = 0$) and no containment ($\mu_t = 0$). We find that the average willingness to pay is 10 percent of income (6 percent for the young and 18 percent for the old). Second, we assume that the number of infected is five times larger, so the probability of dying from Covid in the first year is 0.81 percent. We find that the average willingness to pay is 43 percent (29 percent for the young and 74 percent for the

[12]Our results on the difference in the willingness to pay of young and old are complementary to the estimates of the value of a statistical life produced by Greenberg et al. (2021) for young people in the U.S. who enlist in the army.

[13]Other differences, less important from a quantitative point of view, are as follows. First, the statistical value of life and income are lower in Portugal than in the U.S. Second, HJK assume no discounting of future utility ($\beta = 1$) and time-separable expected discounted utility.

Table 3: Willingness to pay to avoid the epidemic.

| $100 \times \Delta_a$ | Baseline Model | | FIRE/no learning Model | |
|---|---|---|---|---|
| | *Epidemic & Containment* | *No Containment* | *Epidemic & Containment* | *No Containment* |
| Young | 45 | 40 | 9 | 1 |
| Old | 80 | 77 | 15 | 7 |
| Weighted Average | 54 | 51 | 10 | 2 |

Table 4: Willingness to pay to avoid the epidemic by income (as a fraction of initial assets).

| Income in euros (thousands) | 12,481 | 19,000 | 28,566 | 59,490 |
|---|---|---|---|---|
| *Euros (thousands)* | | | | |
| Young | 8 | 9 | 11 | 16 |
| Old | 14 | 16 | 18 | 25 |
| *Fraction of own income* | | | | |
| Young | 58 | 45 | 36 | 26 |
| Old | 110 | 80 | 62 | 41 |

old), a number in the range of those reported by HJK.

Table 4 shows how much people in different income groups would pay to avoid the epidemic. Three results emerge. First, for all income levels, the young are willing to pay less than the old, both in absolute terms and as a fraction of their income. This result reflects the fact that the young are less likely to die than the old due to the epidemic. Second, the higher a person's income is, the more they are willing to pay in absolute terms to avoid the epidemic. This finding reflects the fact that the value of life is increasing in income. Third, the higher a person's income, the lower the fraction of their income they are willing to pay. This result reflects the fact that preferences are non-homothetic due to the presence of two terms in the utility function ($z$ and $\omega_0$) that do not depend on income. These terms imply that the value of life as a fraction of income is a decreasing function of income.

# 8 The economic impact of endemic Covid

In this section, we explore one way to reconcile the large short-run and small long-run effects on consumption of changes in mortality rates associated with contagious diseases. To do so, we investigate the economic costs of endemic Covid in an economy where people know the actual case-fatality rates. We modify our model in three ways. First, we modify our epidemiology model so that Covid becomes endemic. As in Eichenbaum, Rebelo, and Trabandt (2022b) and Abel and Panageas (2020), we modify social dynamics so that recovered people become susceptible with probability $\pi_s$. This modification implies that the pool of susceptible people gets replenished, so there are always new people who can get infected. As a result, the steady-state number of infected people is positive, i.e., Covid is endemic. Second, we allow for vaccination. Third, we assume, for tractability, that people are organized into households, each with a continuum of identical members. This household structure introduces limited sharing of health risks. Fourth, we embed that model in a general equilibrium framework with endogenous labor choice and capital accumulation. The model is described in detail in Appendix C.

Our analysis focuses on the economy's steady state, where it seems natural to assume that people's posteriors about case-fatality rates have converged to their actual values. As might be anticipated from our previous results, this assumption has a major impact on the model's implications for the economic consequences of endemic Covid. We compare the economic costs of Covid in this model with a counterfactual in which people have high prior values for $\pi_{yd,0}$ and $\pi_{od,0}$ and do not update them.

### 8.0.1 Steady-state results

The first column of Table 5 compares consumption and hours worked in the pre-epidemic steady state with the steady state in which Covid is endemic. Aggregate output, hours worked, and consumption fall by about 0.26 percent relative to the pre-epidemic steady state. Consumption falls by 0.86 percent for old people and barely falls for young people. Hours worked fall by 0.72 percent for older people and only 0.07 percent for younger people.

The lower response of consumption relative to the partial equilibrium model discussed in Section 7 reflects four factors. First, people know the true case-fatality rate. Second, consistent with the estimates in Sorensen et al. (2022), this rate is 36 percent lower than at the beginning of the epidemic. Third, this model includes vaccines that reduce the probability

Table 5: Effect of case-fatality rate on percent change of allocations in endemic Covid steady state relative to pre-epidemic steady state.

| | Case-fatality rate equal to... | |
|---|---|---|
| | *Actual long-run value* | *Initial estimated beliefs* |
| Percent change of ... | | |
| Aggregate output | -0.26 | -4.93 |
| Aggregate consumption | -0.26 | -4.93 |
| Aggregate hours worked | -0.26 | -4.93 |
| Consumption young | -0.003 | -4.16 |
| Consumption old | -0.86 | -6.74 |
| Hours worked young | -0.07 | -4.20 |
| Hours worked old | -0.72 | -6.65 |
| Capital stock | -0.26 | -4.93 |

of infection. Fourth, there are no containment measures.

We interpret these results as an upper bound on the economic cost of endemic Covid. The reason is that our model abstracts from ways in which economies can adapt to Covid. Examples include the adoption of remote work and e-commerce (see Jones et al. (2021) and Krueger et al. (2020) for discussions).

The steady-state economic impact of endemic Covid is minimal compared to the massive decline in economic activity experienced in 2020. In the steady state Covid reduces life expectancy at birth by 1.5 percent and reduces aggregate output by 0.26 percent relative to the pre-epidemic steady state.

Interpreted through the lens of our model, the differential short- and long-run impact of endemic Covid on economic activity reflects people's beliefs about case-fatality rates. The steady-state calculations above assume that people's beliefs correspond to the objective case-fatality rate. Our empirical results indicate that in early 2020 people's initial beliefs about case-fatality rates were much higher than the true case-fatality rates.

To quantify the impact of people's beliefs on economic activity, we re-solve for the steady state assuming that people make decisions based on our estimates of their March 2020 beliefs. The objective case-fatality rates drive actual population dynamics. Technically, in the first-order conditions for $i_{a,t+1}$, the values of $\pi_{ad}$ and $\pi_{ar}$ are set to the estimated initial beliefs in

Section 6.1.

The second column of Table 5 compares consumption and hours worked in this steady state and the pre-epidemic steady state. We see large falls in consumption and hours worked relative to the pre-epidemic steady state. Aggregate consumption, hours worked, and physical capital fall by 4.93 percent. Consumption falls by 6.74 percent for old people and 4.2 percent for young people. Hours worked fall by 6.65 percent for older people and only 4.2 percent for younger people.

Taken together, our results suggest a way of reconciling the large economic impact of Covid relative to the historical evidence presented by Acemoglu and Johnson (2007). Our reconciliation highlights the critical role of expectations about case-fatality rates in determining the dynamic economic impact of an epidemic.

# 9 Conclusion

Our analysis highlights the importance of expectations in determining the economic impact of infectious diseases like Covid. According to our estimates, people's prior beliefs about Covid case-fatality rates were very pessimistic. These pessimistic prior beliefs led to sizable consumption declines in the first wave of the epidemic. People's beliefs converged to the true case-fatality rates by the third wave of the epidemic. So, even though the risk of becoming infected was much larger in the third wave, consumption expenditures fell by about the same as in the first wave.

The fact that estimated expectations converged is important for thinking about the economic consequences of the secular declines in the mortality rate associated with infectious diseases. We expect people to eventually learn about these declines and adjust their behavior accordingly. Once this learning occurs, the impact of infectious diseases is relatively small. Our model is consistent with the large impact of Covid on economic activity and the small effect of the secular fall in mortality rates associated with other infectious diseases.

If the government and consumers have full information, rational expectations about case-fatality rates, then there is a clear argument for implementing some form of containment. As discussed, for example, in Eichenbaum, Rebelo, and Trabandt (2021), there is an externality associated with market activities that can be corrected with containment measures. However, suppose that consumers overestimate case-fatality rates at the beginning of an epidemic. If the government had better information than consumers, containment might be a mistake. The reason is that consumers are overreacting to the possibility of getting infected, and market activity is falling by more than warranted by the objective case-fatality rate. Introducing containment could further exacerbate this overreaction.

It is unclear to us that the government had better information about case-fatality rates at the beginning of the epidemic than consumers. To the extent that the government understands that it does not know the actual case-fatality rates, optimal policy design should draw on the insights of the literature on decision-making under Knightian uncertainty (see, e.g., Gilboa and Schmeidler (1989) and Cosmin and Schneider (2022) for a recent review).

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# A Appendix A: empirical results

This appendix is organized as follows. The first subsection contains tables with descriptive statistics. The second subsection provides evidence of the empirical plausibility of the assumption used in our empirical specification that seasonal effects for January through April 2021 are the same as the common seasonal effects in 2018 and 2019. The third subsection provides results estimated by age cohort and results obtained using data for retirees instead of public servants. The fourth subsection reports results regarding the impact of comorbidities on consumption behavior. The fifth subsection provides results estimated to contrast with the economic model of consumer behavior. The final subsection provides the regression results that support the construction of the figures we present in the main body of the paper.

## A.1 Descriptive statistics

Table 6: Descriptive statistics, January 2018 - December 2019.

| Statistic | Mean | St. Dev. | Pctl(25) | Median | Pctl(75) |
|---|---|---|---|---|---|
| *All People* | | | | | |
| Expense p. month (All) | 629.3 | 2,164.7 | 121.0 | 284.1 | 572.6 |
| Expense p. month (Pharmacy) | 17.9 | 35.4 | 0.0 | 4.9 | 24.0 |
| *Public Servants* | | | | | |
| Expense p. month (All) | 687.8 | 1,681.0 | 214.7 | 423.2 | 742.6 |
| Expense p. month (Pharmacy) | 25.6 | 42.3 | 0.0 | 11.7 | 35.6 |
| *Retirees* | | | | | |
| Expense p. month (All) | 437.8 | 1,696.1 | 79.5 | 189.5 | 417.8 |
| Expense p. month (Pharmacy) | 24.3 | 41.5 | 0.0 | 12.4 | 34.5 |

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

Because of the large sample size, the 95 percent confidence intervals are indistinguishable from the point estimates. The vertical dashed line denotes the beginning of the Covid epidemic in 2020.

## A.2 Seasonality effects

Equation (1) assumes that, in the absence of the epidemic, the seasonal effects for January through April 2021 ($\lambda_m$) are the same as the common seasonal effects in 2018 and 2019. To assess the empirical plausibility of this assumption, we estimated the following specification

Table 7: Distribution of monthly expenses by age and income, January 2018 - December 2019.

| Group | N | Mean | St. Dev | Pctl(25) | Median. | Pctl(75) |
|---|---|---|---|---|---|---|
| *All People* | | | | | | |
| $Age_{[20;49]}$ | 190,036 | 642.0 | 2051.1 | 135.3 | 310.7 | 591.8 |
| $Age_{[50;59]}$ | 85,305 | 680.2 | 2405.3 | 122.3 | 299.1 | 616.4 |
| $Age_{[60;69]}$ | 74,390 | 619.4 | 2269.8 | 98.6 | 249.5 | 547.4 |
| $Age_{[70;79]}$ | 71,605 | 436.7 | 1839.5 | 66.5 | 172.3 | 397.1 |
| $Income_{[0;7,091]}$ | 114,295 | 289.2 | 1085.7 | 43.9 | 125.4 | 286.6 |
| $Income_{]7,091;20,261]}$ | 217,381 | 477.3 | 1425.6 | 123.5 | 265.8 | 490.7 |
| $Income_{]20,261;40,522]}$ | 64,593 | 913.0 | 2093.7 | 316.8 | 557.7 | 922.4 |
| $Income_{]40,522;80,640]}$ | 19,377 | 1592.4 | 3185.1 | 474.2 | 851.1 | 1,529.6 |
| $Income_{\geq 80,640}$ | 5,690 | 5404.7 | 1,1044.1 | 712.6 | 1,659.2 | 5,745.6 |
| *Public Servants* | | | | | | |
| $Age_{[20;49]}$ | 10,007 | 779.9 | 1,944.0 | 291.0 | 504.7 | 804.5 |
| $Age_{[50;59]}$ | 15,367 | 730.0 | 1,668.9 | 255.3 | 477.5 | 797.1 |
| $Age_{[60;69]}$ | 18,837 | 675.8 | 1,647.4 | 197.4 | 399.7 | 725.7 |
| $Age_{[70;79]}$ | 14,387 | 566.7 | 1,494.9 | 147.2 | 316.0 | 613.2 |
| $Income_{[0;7,091]}$ | 1,620 | 251.8 | 734.0 | 53.1 | 126.4 | 265.4 |
| $Income_{]7,091;20,261]}$ | 24,250 | 435.0 | 1,139.7 | 140.7 | 277.4 | 486.8 |
| $Income_{]20,261;40,522]}$ | 25,651 | 772.3 | 1,694.9 | 306.2 | 528.2 | 836.5 |
| $Income_{]40,522;80,640]}$ | 6,194 | 1,158.4 | 2,347.2 | 446.9 | 762.4 | 1,221.9 |
| $Income_{\geq 80,640}$ | 883 | 2,224.0 | 4,582.2 | 649.2 | 1,159.2 | 2,014.7 |
| *Retirees* | | | | | | |
| $Age_{[20;49]}$ | 935 | 232.6 | 981.6 | 17.7 | 78.6 | 206.3 |
| $Age_{[50;59]}$ | 3,114 | 286.4 | 1,112.0 | 32.4 | 108.7 | 279.1 |
| $Age_{[60;69]}$ | 26,920 | 428.7 | 1,463.5 | 77.1 | 197.8 | 436.2 |
| $Age_{[70;79]}$ | 63,467 | 422.6 | 1,764.6 | 67.2 | 172.8 | 394.3 |
| $Income_{[0;7,091]}$ | 37,998 | 161.5 | 564.3 | 27.3 | 79.5 | 172.1 |
| $Income_{]7,091;20,261]}$ | 38,328 | 360.0 | 941.2 | 107.1 | 217.0 | 402.5 |
| $Income_{]20,261;40,522]}$ | 13,925 | 741.7 | 1,685.1 | 253.2 | 470.3 | 803.2 |
| $Income_{]40,522;80,640]}$ | 3,351 | 1,346.0 | 2,587.1 | 436.3 | 787.5 | 1,392.8 |
| $Income_{\geq 80,640}$ | 834 | 5,636.9 | 12,115.9 | 732.0 | 1,749.2 | 5,819.6 |

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

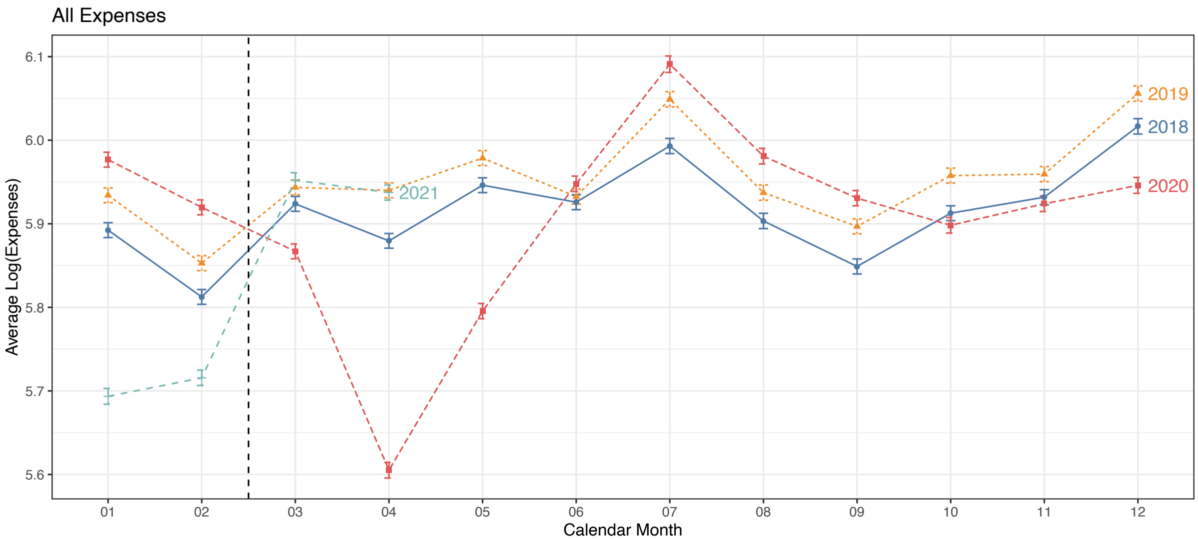


Figure A.1: Average of the logarithm of public servants' monthly expenditures.

using data from January 2018 through December 2019:

$$
\begin{aligned}
Log(Expense_{it}) = {} & \Lambda_{2019}\mathbf{1}\{Year_t = 2019\} + \\
& \sum_{m=Feb}^{Dec} \lambda_m \mathbf{1}\{Month_t = m\} + \\
& \sum_{m=Feb}^{Dec} \phi_m \mathbf{1}\{Month_t = m\} \times \mathbf{1}\{Year_t = 2019\} + \boldsymbol{\theta_i} + \epsilon_{it}
\end{aligned}
\tag{A.1}
$$

The $\phi_m$ coefficients measure the difference between seasonal effects in 2019 and 2018. Under the null hypothesis that these effects are identical in both years, all $\phi_m$ coefficients should be zero. Table 8 presents the regression coefficients.

Figure A.2 displays our estimates of $\phi_m$ along with 95 percent confidence intervals. Regardless of which age we focus on, most estimates of $\phi_m = 0$ are not statistically different from zero at a 95 percent confidence level. We reject the null hypothesis that $\phi_m s$ are jointly zero for the overall sample that includes all ages. However, the estimates of $\phi_m$ are small, especially when compared to the changes in consumption expenditures after the Covid shock.

## A.3 Robustness of empirical results

In this subsection, we report the results of additional robustness checks. First, we estimate separate versions of equation (1) for each age cohort. We consider versions with total expenditures (Table 9) as well as a version with comorbidity (Table 10). This split-sample-by-age

Table 8: Contrasting the month trends of years 2018 and 2019.

| | *Dependent variable:* | | | | |
|---|---|---|---|---|---|
| | $Log(Expenses_{it})$ | | | | |
| | All | [20;49] | [50;59] | [60;69] | [70;79] |
| | (1) | (2) | (3) | (4) | (5) |
| Feb ($\lambda_{Feb}$) | $-0.080^{***}$ | $-0.078^{***}$ | $-0.074^{***}$ | $-0.095^{***}$ | $-0.068^{***}$ |
| | (0.004) | (0.008) | (0.007) | (0.007) | (0.008) |
| Mar ($\lambda_{Mar}$) | $0.031^{***}$ | $0.022^{**}$ | $0.037^{***}$ | $0.018^{**}$ | $0.049^{***}$ |
| | (0.004) | (0.008) | (0.007) | (0.006) | (0.008) |
| Apr ($\lambda_{Apr}$) | $-0.013^{***}$ | $-0.005$ | $-0.003$ | $-0.026^{***}$ | $-0.013$ |
| | (0.004) | (0.009) | (0.007) | (0.007) | (0.008) |
| May ($\lambda_{May}$) | $0.054^{***}$ | $0.061^{***}$ | $0.061^{***}$ | $0.040^{***}$ | $0.058^{***}$ |
| | (0.004) | (0.009) | (0.007) | (0.007) | (0.008) |
| Jun ($\lambda_{Jun}$) | $0.033^{***}$ | $0.043^{***}$ | $0.043^{***}$ | $0.026^{***}$ | $0.026^{**}$ |
| | (0.004) | (0.009) | (0.007) | (0.007) | (0.009) |
| Jul ($\lambda_{Jul}$) | $0.101^{***}$ | $0.117^{***}$ | $0.117^{***}$ | $0.092^{***}$ | $0.083^{***}$ |
| | (0.004) | (0.009) | (0.007) | (0.007) | (0.008) |
| Aug ($\lambda_{Aug}$) | $0.011^{**}$ | $0.042^{***}$ | $0.042^{***}$ | $-0.014^{+}$ | $-0.012$ |
| | (0.004) | (0.009) | (0.008) | (0.007) | (0.009) |
| Sep ($\lambda_{Sep}$) | $-0.044^{***}$ | $-0.025^{**}$ | $-0.005$ | $-0.070^{***}$ | $-0.064^{***}$ |
| | (0.004) | (0.009) | (0.007) | (0.007) | (0.009) |
| Oct ($\lambda_{Oct}$) | $0.020^{***}$ | $0.013$ | $0.017^{*}$ | $0.004$ | $0.049^{***}$ |
| | (0.004) | (0.009) | (0.007) | (0.007) | (0.009) |
| Nov ($\lambda_{Nov}$) | $0.039^{***}$ | $0.032^{***}$ | $0.047^{***}$ | $0.034^{***}$ | $0.042^{***}$ |
| | (0.004) | (0.009) | (0.007) | (0.007) | (0.009) |
| Dec ($\lambda_{Dec}$) | $0.124^{***}$ | $0.140^{***}$ | $0.150^{***}$ | $0.111^{***}$ | $0.101^{***}$ |
| | (0.004) | (0.009) | (0.007) | (0.007) | (0.009) |
| $\mathbf{1}\{Year_t = 2019\}$ ($\Lambda_{2019}$) | $0.042^{***}$ | $0.064^{***}$ | $0.051^{***}$ | $0.033^{***}$ | $0.027^{**}$ |
| | (0.004) | (0.009) | (0.007) | (0.007) | (0.008) |
| $\mathbf{1}\{Year_t = 2019\} \times$ Feb ($\phi_{Feb}$) | $-0.001$ | $-0.013$ | $-0.002$ | $0.009$ | $-0.005$ |
| | (0.005) | (0.011) | (0.009) | (0.009) | (0.011) |
| $\mathbf{1}\{Year_t = 2019\} \times$ Mar ($\phi_{Mar}$) | $-0.022^{***}$ | $-0.005$ | $-0.014$ | $-0.017^{+}$ | $-0.048^{***}$ |
| | (0.005) | (0.011) | (0.009) | (0.009) | (0.011) |
| $\mathbf{1}\{Year_t = 2019\} \times$ Apr ($\phi_{Apr}$) | $0.019^{***}$ | $0.022^{+}$ | $0.018^{*}$ | $0.024^{**}$ | $0.009$ |
| | (0.005) | (0.012) | (0.009) | (0.009) | (0.011) |
| $\mathbf{1}\{Year_t = 2019\} \times$ May ($\phi_{May}$) | $-0.009^{+}$ | $-0.004$ | $-0.009$ | $-0.009$ | $-0.013$ |
| | (0.005) | (0.012) | (0.009) | (0.009) | (0.011) |
| $\mathbf{1}\{Year_t = 2019\} \times$ Jun ($\phi_{Jun}$) | $-0.035^{***}$ | $-0.020^{+}$ | $-0.011$ | $-0.046^{***}$ | $-0.057^{***}$ |
| | (0.005) | (0.012) | (0.009) | (0.009) | (0.011) |
| $\mathbf{1}\{Year_t = 2019\} \times$ Jul ($\phi_{Jul}$) | $0.014^{**}$ | $0.041^{***}$ | $0.022^{*}$ | $0.006$ | $-0.001$ |
| | (0.005) | (0.012) | (0.010) | (0.009) | (0.012) |
| $\mathbf{1}\{Year_t = 2019\} \times$ Aug ($\phi_{Aug}$) | $-0.008$ | $0.001$ | $-0.007$ | $0.0003$ | $-0.026^{*}$ |
| | (0.005) | (0.012) | (0.010) | (0.010) | (0.012) |
| $\mathbf{1}\{Year_t = 2019\} \times$ Sep ($\phi_{Sep}$) | $0.006$ | $0.017$ | $-0.007$ | $0.012$ | $0.005$ |
| | (0.005) | (0.012) | (0.010) | (0.010) | (0.012) |
| $\mathbf{1}\{Year_t = 2019\} \times$ Oct ($\phi_{Oct}$) | $0.003$ | $-0.005$ | $0.002$ | $0.012$ | $-0.002$ |
| | (0.005) | (0.012) | (0.010) | (0.010) | (0.012) |
| $\mathbf{1}\{Year_t = 2019\} \times$ Nov ($\phi_{Nov}$) | $-0.014^{**}$ | $-0.012$ | $-0.005$ | $-0.018^{+}$ | $-0.021^{+}$ |
| | (0.005) | (0.013) | (0.010) | (0.010) | (0.012) |
| $\mathbf{1}\{Year_t = 2019\} \times$ Dec ($\phi_{Dec}$) | $-0.002$ | $0.001$ | $0.007$ | $0.003$ | $-0.022^{+}$ |
| | (0.005) | (0.012) | (0.010) | (0.010) | (0.012) |
| Constant | $5.892^{***}$ | $6.086^{***}$ | $6.010^{***}$ | $5.875^{***}$ | $5.654^{***}$ |
| | (0.005) | (0.010) | (0.008) | (0.008) | (0.010) |
| $\chi^2$ ( $\phi_{Feb} = 0, \ldots, \phi_{Dec} = 0$) | 59.100 | 16.853 | 9.880 | 28.203 | 24.052 |
| p-value | 0.000 | 0.112 | 0.541 | 0.003 | 0.013 |
| Observations | 1,392,370 | 238,965 | 366,102 | 447,699 | 339,604 |
| $R^2$ | 0.003 | 0.005 | 0.004 | 0.003 | 0.002 |
| Adjusted $R^2$ | 0.003 | 0.005 | 0.004 | 0.002 | 0.002 |
| Residual Std. Error | 1.103 | 0.964 | 1.026 | 1.130 | 1.182 |

*Note:* + $p<0.1$; * $p<0.05$; ** $p<0.01$; *** $p<0.001$
All columns estimated with person fixed effects
Cluster robust standard errors in (); Errors clustered by person

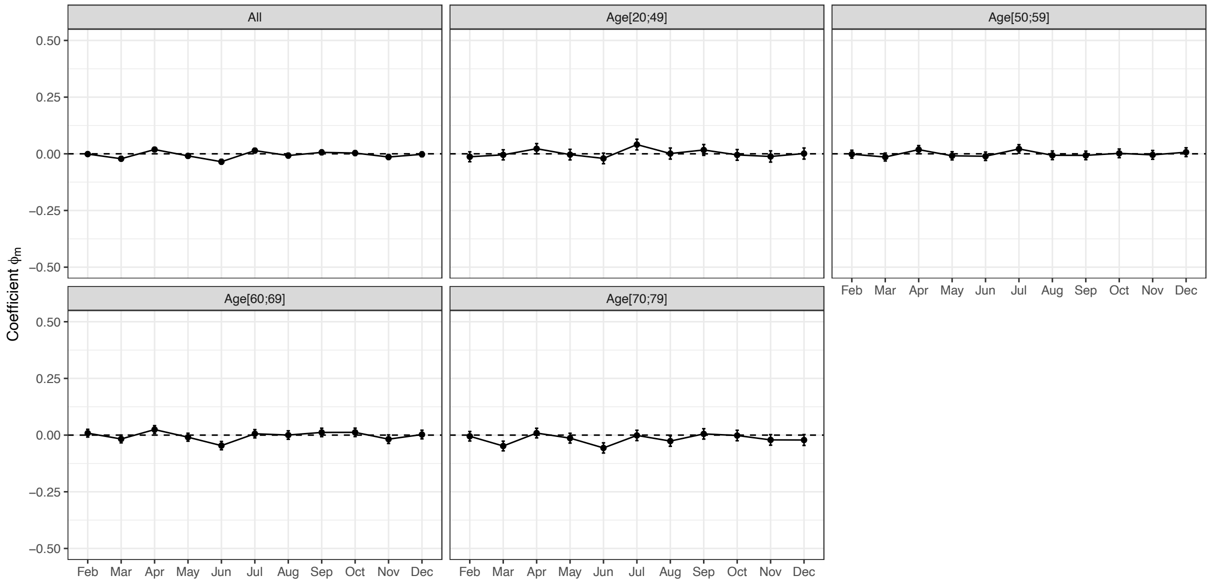


Figure A.2: Seasonality effects for different age groups.

approach allows each cohort to have different yearly growth trends and monthly seasonality in the relevant measure of consumption expenditures. We find a similar pattern for the impact of age on the response of expenditures to the Covid shock.

We re-do our main empirical analysis for retirees as opposed to public servants. Our results are similar to those we obtain for public servants. Table 11 is the analogue of Table 14. We see that the consumption expenditures of older retirees fall much more than those of younger retirees. In addition, spending declines are particularly pronounced in April, the peak month of the epidemic.

Fourth, we run regression (1) using the year-on-year growth rate ($\ln(Expenses_{it}/Expenses_{it-12})$) instead of the log-level of expenditures as the dependent variable. Figure A.3 shows that the results are similar to those obtained in our baseline specification.

Figure A.4 displays the estimates of the change in consumption expenditures for different age groups in sectors of the economy that were least affected by lockdowns.

We run our baseline regression excluding restaurant expenditures since people could have switched from eating in the restaurant to ordering take out. We display the results in Figure A.5. We also exclude restaurant and supermarket expenditures. People could have switched from shopping at supermarkets to using home delivery. Figure A.6 displays our results.

Table 9: Impact of age on consumption expenditure.

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | $log(Expenses_{it})$ | | | |
| | [20;49] | [50;59] | [60;69] | [70;79] |
| | (1) | (2) | (3) | (4) |
| $After_t \times \mathbf{1}\{Month_t = Mar20\}$ | $-0.124^{***}$ | $-0.124^{***}$ | $-0.123^{***}$ | $-0.158^{***}$ |
| | (0.008) | (0.006) | (0.006) | (0.007) |
| $After_t \times \mathbf{1}\{Month_t = Apr20\}$ | $-0.322^{***}$ | $-0.327^{***}$ | $-0.390^{***}$ | $-0.453^{***}$ |
| | (0.009) | (0.007) | (0.007) | (0.008) |
| $After_t \times \mathbf{1}\{Month_t = May20\}$ | $-0.222^{***}$ | $-0.205^{***}$ | $-0.239^{***}$ | $-0.272^{***}$ |
| | (0.009) | (0.007) | (0.007) | (0.008) |
| $After_t \times \mathbf{1}\{Month_t = Jun20\}$ | $-0.015^{+}$ | $-0.029^{***}$ | $-0.054^{***}$ | $-0.080^{***}$ |
| | (0.008) | (0.007) | (0.007) | (0.008) |
| $After_t \times \mathbf{1}\{Month_t = Jul20\}$ | $0.020^{*}$ | $0.037^{***}$ | 0.008 | $-0.044^{***}$ |
| | (0.010) | (0.008) | (0.007) | (0.008) |
| $After_t \times \mathbf{1}\{Month_t = Aug20\}$ | $0.016^{+}$ | $0.023^{**}$ | $-0.012^{+}$ | $-0.031^{***}$ |
| | (0.009) | (0.007) | (0.007) | (0.008) |
| $After_t \times \mathbf{1}\{Month_t = Sep20\}$ | 0.012 | $-0.004$ | $-0.011^{+}$ | $-0.019^{*}$ |
| | (0.009) | (0.007) | (0.007) | (0.008) |
| $After_t \times \mathbf{1}\{Month_t = Oct20\}$ | $-0.071^{***}$ | $-0.069^{***}$ | $-0.107^{***}$ | $-0.158^{***}$ |
| | (0.009) | (0.007) | (0.007) | (0.009) |
| $After_t \times \mathbf{1}\{Month_t = Nov20\}$ | $-0.046^{***}$ | $-0.066^{***}$ | $-0.092^{***}$ | $-0.133^{***}$ |
| | (0.009) | (0.007) | (0.007) | (0.009) |
| $After_t \times \mathbf{1}\{Month_t = Dec20\}$ | $-0.146^{***}$ | $-0.147^{***}$ | $-0.161^{***}$ | $-0.179^{***}$ |
| | (0.009) | (0.007) | (0.007) | (0.009) |
| $After_t \times \mathbf{1}\{Month_t = Jan21\}$ | $-0.293^{***}$ | $-0.290^{***}$ | $-0.342^{***}$ | $-0.400^{***}$ |
| | (0.009) | (0.007) | (0.007) | (0.009) |
| $After_t \times \mathbf{1}\{Month_t = Feb21\}$ | $-0.204^{***}$ | $-0.213^{***}$ | $-0.251^{***}$ | $-0.262^{***}$ |
| | (0.009) | (0.007) | (0.007) | (0.009) |
| $After_t \times \mathbf{1}\{Month_t = Mar21\}$ | $-0.084^{***}$ | $-0.085^{***}$ | $-0.095^{***}$ | $-0.101^{***}$ |
| | (0.010) | (0.008) | (0.008) | (0.010) |
| $After_t \times \mathbf{1}\{Month_t = Apr21\}$ | $-0.076^{***}$ | $-0.079^{***}$ | $-0.080^{***}$ | $-0.082^{***}$ |
| | (0.010) | (0.008) | (0.008) | (0.010) |
| $Year_t$ | $0.110^{***}$ | 0.037 | $0.045^{***}$ | $0.045^{***}$ |
| | (0.027) | (0.028) | (0.012) | (0.009) |
| Month FE | Yes | Yes | Yes | Yes |
| Individual FE | Yes | Yes | Yes | Yes |
| Income Group $\times Year_t$ ($\Psi_{it}$) | Yes | Yes | Yes | Yes |
| Observations | 398,086 | 609,606 | 744,262 | 563,048 |
| $R^2$ | 0.560 | 0.618 | 0.636 | 0.639 |
| Adjusted $R^2$ | 0.548 | 0.608 | 0.626 | 0.630 |
| Residual Std. Error | 0.654 | 0.647 | 0.697 | 0.731 |

*Note:* $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01
+ p<0.1; * p<0.05; ** p<0.01; *** p<0.001
Cluster robust standard errors in (); Errors clustered by person

Table 10: Impact of age on consumption expenditure.

| | Dependent variable: | | | |
|---|---|---|---|---|
| | $log(Expenses_{it})$ | | | |
| | [20;49] | [50;59] | [60;69] | [70;79] |
| | (1) | (2) | (3) | (4) |
| $After_t \times \mathbf{1}\{Month_t = Mar20\}(\Delta_{Mar20})$ | $-0.115^{***}$ | $-0.120^{***}$ | $-0.121^{***}$ | $-0.153^{***}$ |
| | (0.009) | (0.007) | (0.006) | (0.008) |
| $After_t \times \mathbf{1}\{Month_t = Apr20\}(\Delta_{Apr20})$ | $-0.305^{***}$ | $-0.316^{***}$ | $-0.379^{***}$ | $-0.442^{***}$ |
| | (0.009) | (0.007) | (0.007) | (0.009) |
| $After_t \times \mathbf{1}\{Month_t = May20\}(\Delta_{May20})$ | $-0.214^{***}$ | $-0.197^{***}$ | $-0.229^{***}$ | $-0.261^{***}$ |
| | (0.009) | (0.007) | (0.007) | (0.008) |
| $After_t \times \mathbf{1}\{Month_t = Jun20\}(\Delta_{Jun20})$ | $-0.005$ | $-0.020^{**}$ | $-0.043^{***}$ | $-0.069^{***}$ |
| | (0.009) | (0.007) | (0.007) | (0.009) |
| $After_t \times \mathbf{1}\{Month_t = Jul20\}(\Delta_{Jul20})$ | $0.026^{*}$ | $0.044^{***}$ | $0.014^{+}$ | $-0.041^{***}$ |
| | (0.010) | (0.008) | (0.008) | (0.009) |
| $After_t \times \mathbf{1}\{Month_t = Aug20\}(\Delta_{Aug20})$ | $0.023^{*}$ | $0.032^{***}$ | $-0.004$ | $-0.021^{*}$ |
| | (0.009) | (0.007) | (0.007) | (0.009) |
| $After_t \times \mathbf{1}\{Month_t = Sep20\}(\Delta_{Sep20})$ | $0.019^{*}$ | 0.002 | $-0.004$ | $-0.009$ |
| | (0.009) | (0.007) | (0.007) | (0.009) |
| $After_t \times \mathbf{1}\{Month_t = Oct20\}(\Delta_{Oct20})$ | $-0.068^{***}$ | $-0.065^{***}$ | $-0.103^{***}$ | $-0.151^{***}$ |
| | (0.009) | (0.008) | (0.007) | (0.009) |
| $After_t \times \mathbf{1}\{Month_t = Nov20\}(\Delta_{Nov20})$ | $-0.038^{***}$ | $-0.058^{***}$ | $-0.088^{***}$ | $-0.124^{***}$ |
| | (0.010) | (0.008) | (0.007) | (0.009) |
| $After_t \times \mathbf{1}\{Month_t = Dec20\}(\Delta_{Dec20})$ | $-0.142^{***}$ | $-0.143^{***}$ | $-0.152^{***}$ | $-0.164^{***}$ |
| | (0.010) | (0.008) | (0.008) | (0.010) |
| $After_t \times \mathbf{1}\{Month_t = Jan21\}(\Delta_{Jan21})$ | $-0.287^{***}$ | $-0.291^{***}$ | $-0.343^{***}$ | $-0.401^{***}$ |
| | (0.010) | (0.008) | (0.008) | (0.010) |
| $After_t \times \mathbf{1}\{Month_t = Feb21\}(\Delta_{Feb21})$ | $-0.192^{***}$ | $-0.200^{***}$ | $-0.238^{***}$ | $-0.243^{***}$ |
| | (0.010) | (0.008) | (0.008) | (0.010) |
| $After_t \times \mathbf{1}\{Month_t = Mar21\}(\Delta_{Mar21})$ | $-0.074^{***}$ | $-0.079^{***}$ | $-0.088^{***}$ | $-0.083^{***}$ |
| | (0.011) | (0.008) | (0.008) | (0.010) |
| $After_t \times \mathbf{1}\{Month_t = Apr21\}(\Delta_{Apr21})$ | $-0.068^{***}$ | $-0.075^{***}$ | $-0.076^{***}$ | $-0.066^{***}$ |
| | (0.011) | (0.008) | (0.008) | (0.010) |
| $After_t \times \mathbf{1}\{Month_t = Mar20\} \times Comorbidity$ | $-0.068^{***}$ | $-0.027^{+}$ | $-0.013$ | $-0.032^{*}$ |
| | (0.018) | (0.014) | (0.014) | (0.016) |
| $After_t \times \mathbf{1}\{Month_t = Apr20\} \times Comorbidity$ | $-0.117^{***}$ | $-0.074^{***}$ | $-0.080^{***}$ | $-0.068^{***}$ |
| | (0.020) | (0.016) | (0.016) | (0.019) |
| $After_t \times \mathbf{1}\{Month_t = May20\} \times Comorbidity$ | $-0.062^{**}$ | $-0.060^{***}$ | $-0.070^{***}$ | $-0.069^{***}$ |
| | (0.020) | (0.015) | (0.015) | (0.017) |
| $After_t \times \mathbf{1}\{Month_t = Jun20\} \times Comorbidity$ | $-0.068^{***}$ | $-0.061^{***}$ | $-0.079^{***}$ | $-0.065^{***}$ |
| | (0.019) | (0.015) | (0.015) | (0.017) |
| $After_t \times \mathbf{1}\{Month_t = Jul20\} \times Comorbidity$ | $-0.044^{*}$ | $-0.048^{**}$ | $-0.041^{*}$ | $-0.023$ |
| | (0.022) | (0.018) | (0.017) | (0.019) |
| $After_t \times \mathbf{1}\{Month_t = Aug20\} \times Comorbidity$ | $-0.050^{**}$ | $-0.062^{***}$ | $-0.058^{***}$ | $-0.063^{***}$ |
| | (0.019) | (0.016) | (0.016) | (0.018) |
| $After_t \times \mathbf{1}\{Month_t = Sep20\} \times Comorbidity$ | $-0.049^{*}$ | $-0.043^{**}$ | $-0.050^{***}$ | $-0.062^{***}$ |
| | (0.019) | (0.016) | (0.015) | (0.018) |
| $After_t \times \mathbf{1}\{Month_t = Oct20\} \times Comorbidity$ | $-0.026$ | $-0.029^{+}$ | $-0.028^{+}$ | $-0.045^{*}$ |
| | (0.020) | (0.016) | (0.015) | (0.018) |
| $After_t \times \mathbf{1}\{Month_t = Nov20\} \times Comorbidity$ | $-0.054^{**}$ | $-0.055^{***}$ | $-0.027^{+}$ | $-0.053^{**}$ |
| | (0.020) | (0.016) | (0.016) | (0.018) |
| $After_t \times \mathbf{1}\{Month_t = Dec20\} \times Comorbidity$ | $-0.032$ | $-0.026$ | $-0.060^{***}$ | $-0.096^{***}$ |
| | (0.020) | (0.017) | (0.016) | (0.019) |
| $After_t \times \mathbf{1}\{Month_t = Jan21\} \times Comorbidity$ | $-0.042^{*}$ | 0.007 | 0.004 | 0.004 |
| | (0.020) | (0.016) | (0.016) | (0.019) |
| $After_t \times \mathbf{1}\{Month_t = Feb21\} \times Comorbidity$ | $-0.087^{***}$ | $-0.091^{***}$ | $-0.089^{***}$ | $-0.116^{***}$ |
| | (0.021) | (0.017) | (0.017) | (0.020) |
| $After_t \times \mathbf{1}\{Month_t = Mar21\} \times Comorbidity$ | $-0.068^{***}$ | $-0.039^{*}$ | $-0.053^{***}$ | $-0.113^{***}$ |
| | (0.020) | (0.016) | (0.016) | (0.019) |
| $After_t \times \mathbf{1}\{Month_t = Apr21\} \times Comorbidity$ | $-0.058^{**}$ | $-0.033^{*}$ | $-0.026$ | $-0.099^{***}$ |
| | (0.019) | (0.016) | (0.016) | (0.020) |
| Month FE | Yes | Yes | Yes | Yes |
| Individual FE | Yes | Yes | Yes | Yes |
| Income Group $\times Year_t$ ($\Psi_{it}$) | Yes | Yes | Yes | Yes |
| Observations | 398,086 | 609,606 | 744,262 | 563,048 |
| $R^2$ | 0.560 | 0.618 | 0.636 | 0.639 |
| Adjusted $R^2$ | 0.548 | 0.608 | 0.626 | 0.630 |
| Residual Std. Error | 0.654 | 0.647 | 0.697 | 0.731 |
| *Note:* | + p<0.1; * p<0.05; ** p<0.01; *** p<0.001<br>Cluster robust standard errors in (); Errors clustered by person | | | |

Table 11: Impact of age heterogeneity on spending for retirees.

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | $log(Expense_{it})$ | | | |
| | (1) | (2) | (3) | (4) |
| $After_t \times \mathbf{1}\{Month_t = Mar20\} \times \mathbf{1}\{Age_i < 60\}(\Delta_{Mar20,<60} + \delta_{Mar20,<60})$ | $-0.018$ | $-0.043^{**}$ | $-0.043^{**}$ | $-0.043^{**}$ |
| | (0.014) | (0.015) | (0.015) | (0.015) |
| $After_t \times \mathbf{1}\{Month_t = Mar20\} \times \mathbf{1}\{Age_i \geq 60\}(\Delta_{Mar20,\geq 60} + \delta_{Mar20,\geq 60})$ | $-0.086^{***}$ | $-0.085^{***}$ | $-0.085^{***}$ | $-0.085^{***}$ |
| | (0.003) | (0.003) | (0.003) | (0.003) |
| $After_t \times \mathbf{1}\{Month_t = Apr20\} \times \mathbf{1}\{Age_i < 60\}(\Delta_{Apr20,<60} + \delta_{Apr20,<60})$ | $-0.192^{***}$ | $-0.216^{***}$ | $-0.216^{***}$ | $-0.216^{***}$ |
| | (0.016) | (0.016) | (0.016) | (0.016) |
| $After_t \times \mathbf{1}\{Month_t = Apr20\} \times \mathbf{1}\{Age_i \geq 60\}(\Delta_{Apr20,\geq 60} + \delta_{Apr20,\geq 60})$ | $-0.321^{***}$ | $-0.320^{***}$ | $-0.320^{***}$ | $-0.320^{***}$ |
| | (0.003) | (0.003) | (0.003) | (0.003) |
| $After_t \times \mathbf{1}\{Month_t = May20\} \times \mathbf{1}\{Age_i < 60\}(\Delta_{May20,<60} + \delta_{May20,<60})$ | $-0.126^{***}$ | $-0.151^{***}$ | $-0.151^{***}$ | $-0.151^{***}$ |
| | (0.014) | (0.015) | (0.015) | (0.015) |
| $After_t \times \mathbf{1}\{Month_t = May20\} \times \mathbf{1}\{Age_i \geq 60\}(\Delta_{May20,\geq 60} + \delta_{May20,\geq 60})$ | $-0.199^{***}$ | $-0.198^{***}$ | $-0.198^{***}$ | $-0.198^{***}$ |
| | (0.003) | (0.003) | (0.003) | (0.003) |
| $After_t \times \mathbf{1}\{Month_t = Jun20\} \times \mathbf{1}\{Age_i < 60\}(\Delta_{Jun20,<60} + \delta_{Jun20,<60})$ | 0.013 | $-0.012$ | $-0.012$ | $-0.012$ |
| | (0.015) | (0.016) | (0.016) | (0.016) |
| $After_t \times \mathbf{1}\{Month_t = Jun20\} \times \mathbf{1}\{Age_i \geq 60\}(\Delta_{Jun20,\geq 60} + \delta_{Jun20,\geq 60})$ | $-0.047^{***}$ | $-0.046^{***}$ | $-0.046^{***}$ | $-0.046^{***}$ |
| | (0.003) | (0.003) | (0.003) | (0.003) |
| $After_t \times \mathbf{1}\{Month_t = Jul20\} \times \mathbf{1}\{Age_i < 60\}(\Delta_{Jul20,<60} + \delta_{Jul20,<60})$ | 0.023 | $-0.002$ | $-0.002$ | $-0.002$ |
| | (0.016) | (0.017) | (0.017) | (0.017) |
| $After_t \times \mathbf{1}\{Month_t = Jul20\} \times \mathbf{1}\{Age_i \geq 60\}(\Delta_{Jul20,\geq 60} + \delta_{Jul20,\geq 60})$ | $-0.037^{***}$ | $-0.036^{***}$ | $-0.036^{***}$ | $-0.036^{***}$ |
| | (0.003) | (0.003) | (0.003) | (0.003) |
| $After_t \times \mathbf{1}\{Month_t = Aug20\} \times \mathbf{1}\{Age_i < 60\}(\Delta_{Aug20,<60} + \delta_{Aug20,<60})$ | $0.058^{***}$ | $0.033^{*}$ | $0.033^{*}$ | $0.033^{*}$ |
| | (0.016) | (0.016) | (0.016) | (0.016) |
| $After_t \times \mathbf{1}\{Month_t = Aug20\} \times \mathbf{1}\{Age_i \geq 60\}(\Delta_{Aug20,\geq 60} + \delta_{Aug20,\geq 60})$ | $-0.022^{***}$ | $-0.021^{***}$ | $-0.021^{***}$ | $-0.021^{***}$ |
| | (0.003) | (0.003) | (0.003) | (0.003) |
| $After_t \times \mathbf{1}\{Month_t = Sep20\} \times \mathbf{1}\{Age_i < 60\}(\Delta_{Sep20,<60} + \delta_{Sep20,<60})$ | 0.022 | $-0.003$ | $-0.003$ | $-0.003$ |
| | (0.015) | (0.016) | (0.016) | (0.016) |
| $After_t \times \mathbf{1}\{Month_t = Sep20\} \times \mathbf{1}\{Age_i \geq 60\}(\Delta_{Sep20,\geq 60} + \delta_{Sep20,\geq 60})$ | $-0.024^{***}$ | $-0.023^{***}$ | $-0.023^{***}$ | $-0.023^{***}$ |
| | (0.004) | (0.004) | (0.004) | (0.004) |
| $After_t \times \mathbf{1}\{Month_t = Oct20\} \times \mathbf{1}\{Age_i < 60\}(\Delta_{Oct20,<60} + \delta_{Oct20,<60})$ | $-0.076^{***}$ | $-0.101^{***}$ | $-0.101^{***}$ | $-0.101^{***}$ |
| | (0.016) | (0.017) | (0.017) | (0.017) |
| $After_t \times \mathbf{1}\{Month_t = Oct20\} \times \mathbf{1}\{Age_i \geq 60\}(\Delta_{Oct20,\geq 60} + \delta_{Oct20,\geq 60})$ | $-0.151^{***}$ | $-0.149^{***}$ | $-0.149^{***}$ | $-0.149^{***}$ |
| | (0.004) | (0.004) | (0.004) | (0.004) |
| $After_t \times \mathbf{1}\{Month_t = Nov20\} \times \mathbf{1}\{Age_i < 60\}(\Delta_{Nov20,<60} + \delta_{Nov20,<60})$ | $-0.013$ | $-0.038^{*}$ | $-0.038^{*}$ | $-0.038^{*}$ |
| | (0.016) | (0.016) | (0.016) | (0.016) |
| $After_t \times \mathbf{1}\{Month_t = Nov20\} \times \mathbf{1}\{Age_i \geq 60\}(\Delta_{Nov20,\geq 60} + \delta_{Nov20,\geq 60})$ | $-0.106^{***}$ | $-0.105^{***}$ | $-0.105^{***}$ | $-0.105^{***}$ |
| | (0.004) | (0.004) | (0.004) | (0.004) |
| $After_t \times \mathbf{1}\{Month_t = Dec20\} \times \mathbf{1}\{Age_i < 60\}(\Delta_{Dec20,<60} + \delta_{Dec20,<60})$ | $-0.103^{***}$ | $-0.128^{***}$ | $-0.128^{***}$ | $-0.128^{***}$ |
| | (0.018) | (0.018) | (0.018) | (0.018) |
| $After_t \times \mathbf{1}\{Month_t = Dec20\} \times \mathbf{1}\{Age_i \geq 60\}(\Delta_{Dec20,\geq 60} + \delta_{Dec20,\geq 60})$ | $-0.143^{***}$ | $-0.142^{***}$ | $-0.142^{***}$ | $-0.142^{***}$ |
| | (0.004) | (0.004) | (0.004) | (0.004) |
| $After_t \times \mathbf{1}\{Month_t = Jan21\} \times \mathbf{1}\{Age_i < 60\}(\Delta_{Jan21,<60} + \delta_{Jan21,<60})$ | $-0.188^{***}$ | $-0.230^{***}$ | $-0.230^{***}$ | $-0.230^{***}$ |
| | (0.017) | (0.020) | (0.020) | (0.020) |
| $After_t \times \mathbf{1}\{Month_t = Jan21\} \times \mathbf{1}\{Age_i \geq 60\}(\Delta_{Jan21,\geq 60} + \delta_{Jan21,\geq 60})$ | $-0.377^{***}$ | $-0.375^{***}$ | $-0.374^{***}$ | $-0.374^{***}$ |
| | (0.004) | (0.004) | (0.004) | (0.004) |
| $After_t \times \mathbf{1}\{Month_t = Feb21\} \times \mathbf{1}\{Age_i < 60\}(\Delta_{Feb21,<60} + \delta_{Feb21,<60})$ | $-0.066^{***}$ | $-0.108^{***}$ | $-0.109^{***}$ | $-0.109^{***}$ |
| | (0.016) | (0.020) | (0.020) | (0.020) |
| $After_t \times \mathbf{1}\{Month_t = Feb21\} \times \mathbf{1}\{Age_i \geq 60\}(\Delta_{Feb21,\geq 60} + \delta_{Feb21,\geq 60})$ | $-0.201^{***}$ | $-0.199^{***}$ | $-0.199^{***}$ | $-0.199^{***}$ |
| | (0.004) | (0.004) | (0.004) | (0.004) |
| $After_t \times \mathbf{1}\{Month_t = Mar21\} \times \mathbf{1}\{Age_i < 60\}(\Delta_{Mar21,<60} + \delta_{Mar21,<60})$ | 0.019 | $-0.023$ | $-0.023$ | $-0.023$ |
| | (0.018) | (0.021) | (0.021) | (0.021) |
| $After_t \times \mathbf{1}\{Month_t = Mar21\} \times \mathbf{1}\{Age_i \geq 60\}(\Delta_{Mar21,\geq 60} + \delta_{Mar21,\geq 60})$ | $-0.055^{***}$ | $-0.053^{***}$ | $-0.053^{***}$ | $-0.053^{***}$ |
| | (0.004) | (0.004) | (0.004) | (0.004) |
| $After_t \times \mathbf{1}\{Month_t = Apr21\} \times \mathbf{1}\{Age_i >\}(\Delta_{Apr21,<60} + \delta_{Apr21,<60})$ | $0.041^{*}$ | $-0.002$ | $-0.002$ | $-0.002$ |
| | (0.017) | (0.020) | (0.020) | (0.020) |
| $After_t \times \mathbf{1}\{Month_t = Apr21\} \times \mathbf{1}\{Age_i \geq 60\}(\Delta_{Apr21,\geq 60} + \delta_{Apr21,\geq 60})$ | $-0.044^{***}$ | $-0.043^{***}$ | $-0.043^{***}$ | $-0.043^{***}$ |
| | (0.004) | (0.004) | (0.004) | (0.004) |
| Month FE | Yes | Yes | Yes | Yes |
| Individual FE | Yes | Yes | Yes | Yes |
| Age Group$\times Year_t$ $(\Psi_{it})$ | No | Yes | Yes | Yes |
| Income Group $\times Year_t$ $(\Psi_{it})$ | No | No | Yes | Yes |
| Age Group $\times$ Income Group $\times Year_t$ $(\Psi_{it})$ | No | No | No | Yes |
| Observations | 3,583,123 | 3,583,123 | 3,583,123 | 3,583,123 |
| $R^2$ | 0.689 | 0.689 | 0.689 | 0.689 |
| Adjusted $R^2$ | 0.680 | 0.680 | 0.681 | 0.681 |
| Residual Std. Error | 0.776 | 0.776 | 0.775 | 0.775 |
| *Note:* | + p<0.1; * p<0.05; ** p<0.01; *** p<0.001 | | | |
| | Cluster robust standard errors in (); Errors clustered by person | | | |

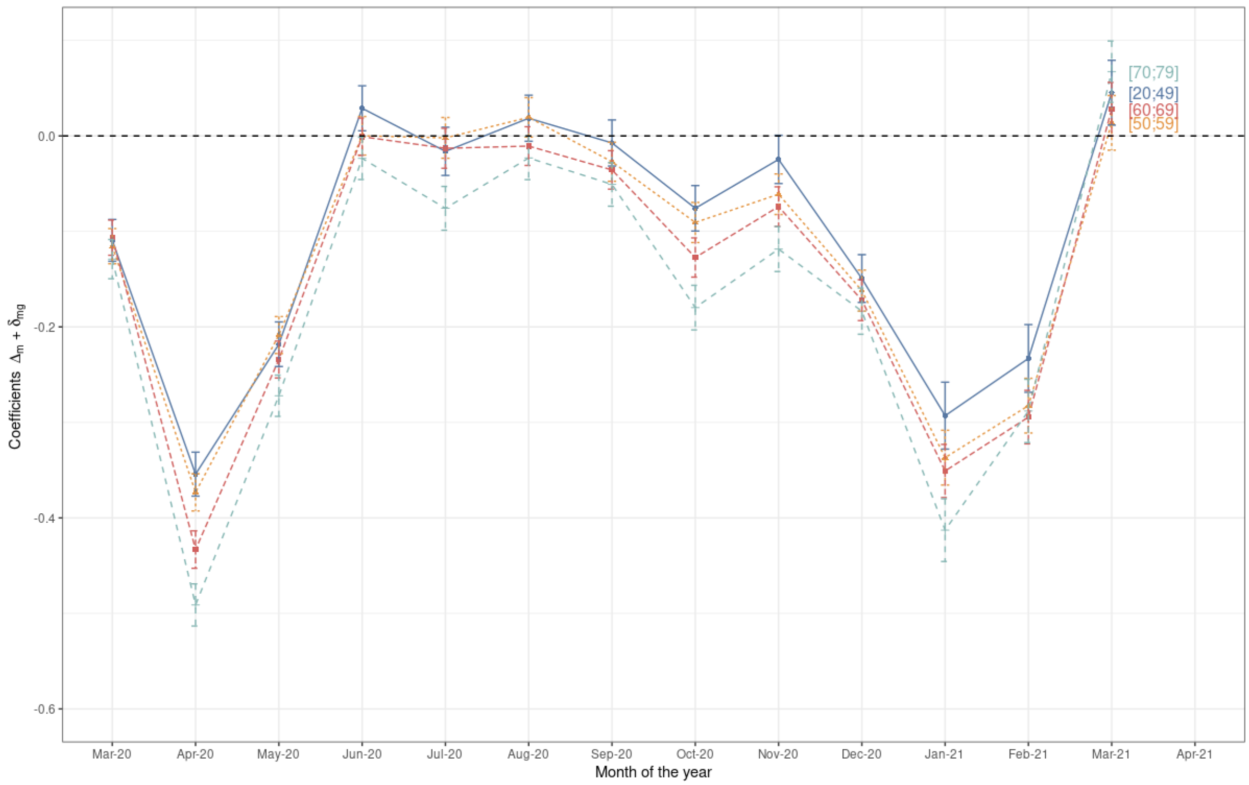


Figure A.3: Estimation results for growth rate specification.

## A.4 The effect of comorbidity

People with underlying health conditions such as heart problems, cancer, obesity and type-2 diabetes are at greater risk of dying from Covid.[A.1] A natural question is whether people with comorbidities react to that risk by reducing consumption more than people who do not have comorbidities.

We do not have the health history of the people in our sample. But we do have data on how much they spend on pharmaceutical drugs. So, we use these expenditures as a proxy for comorbidities. We split the sample into two. The comorbidity sample consists of people whose pharmaceutical drug expenditures are in the top decile of the 2018 distribution of these expenditures for the person's age group. The non-comorbidity sample consists of all of the other people.

Individuals with comorbidities received priority in the Portuguese vaccination process. Most got the two doses of the vaccine before the peak of the third wave at the end of January

[A.1] See the Center for Disease Control (`https://www.cdc.gov/coronavirus/2019-ncov/need-extra-precautions/people-with-medical-conditions.html`) for a thorough review of these comorbidities.

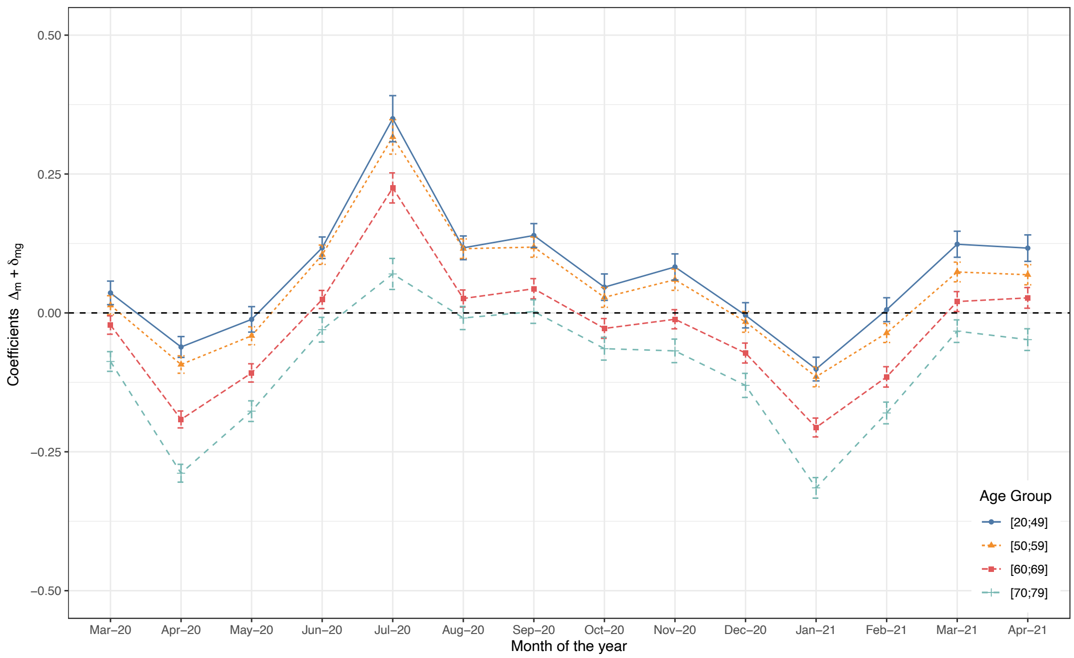


Figure A.4: Changes in expenditures of public servants in the sectors least affected by lockdowns during the epidemic relative to a counterfactual without Covid.

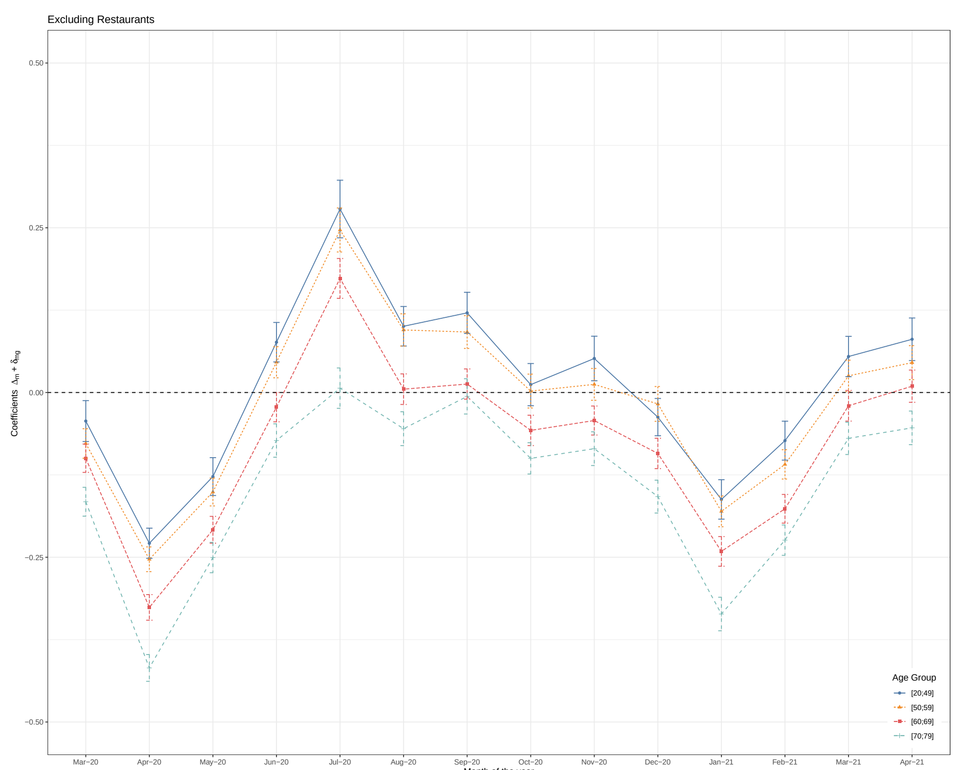


Figure A.5: Estimation results excluding restaurant expenditures.

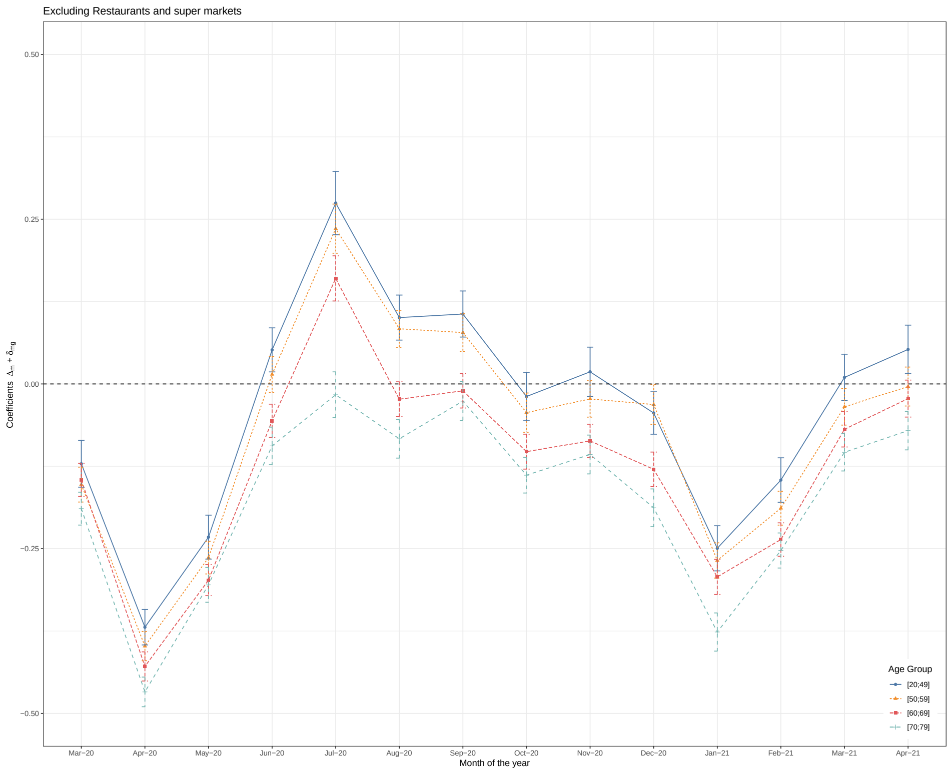


Figure A.6: Estimation results excluding restaurant and supermarket expenditures.

2021. For this reason, we restrict our sample to the period from January 2018 to December 2020.

Table 16 in Appendix A reports our parameter estimates. The key result is displayed in Figure A.7. People with comorbidities cut their consumption by more than people without comorbidities. In April 2020, at the peak of the first wave of infections, people younger than 49 with no comorbidities cut their consumption by 25.5 percent. In contrast, people younger than 49 with comorbidities dropped their consumption expenditures by 32.2 percent.

There are no statistically significant interactions between age and comorbidity: the impact of comorbidity is the same for young and older people.

Interestingly, even after controlling for comorbidity, age remains a key driver of consumption behavior. From March 2019 to December 2020, people younger than 49 with no comorbidities cut their expenditures on average by 7.9 percent. People with no comorbidities who are in their 50s, 60s, and 70s cut consumption expenditures on average during the epidemic dates by an additional 8.2, 12.1, and 15.9 percent, respectively.

These results support the view that people's consumption decisions respond to the perceived risk of dying from Covid.

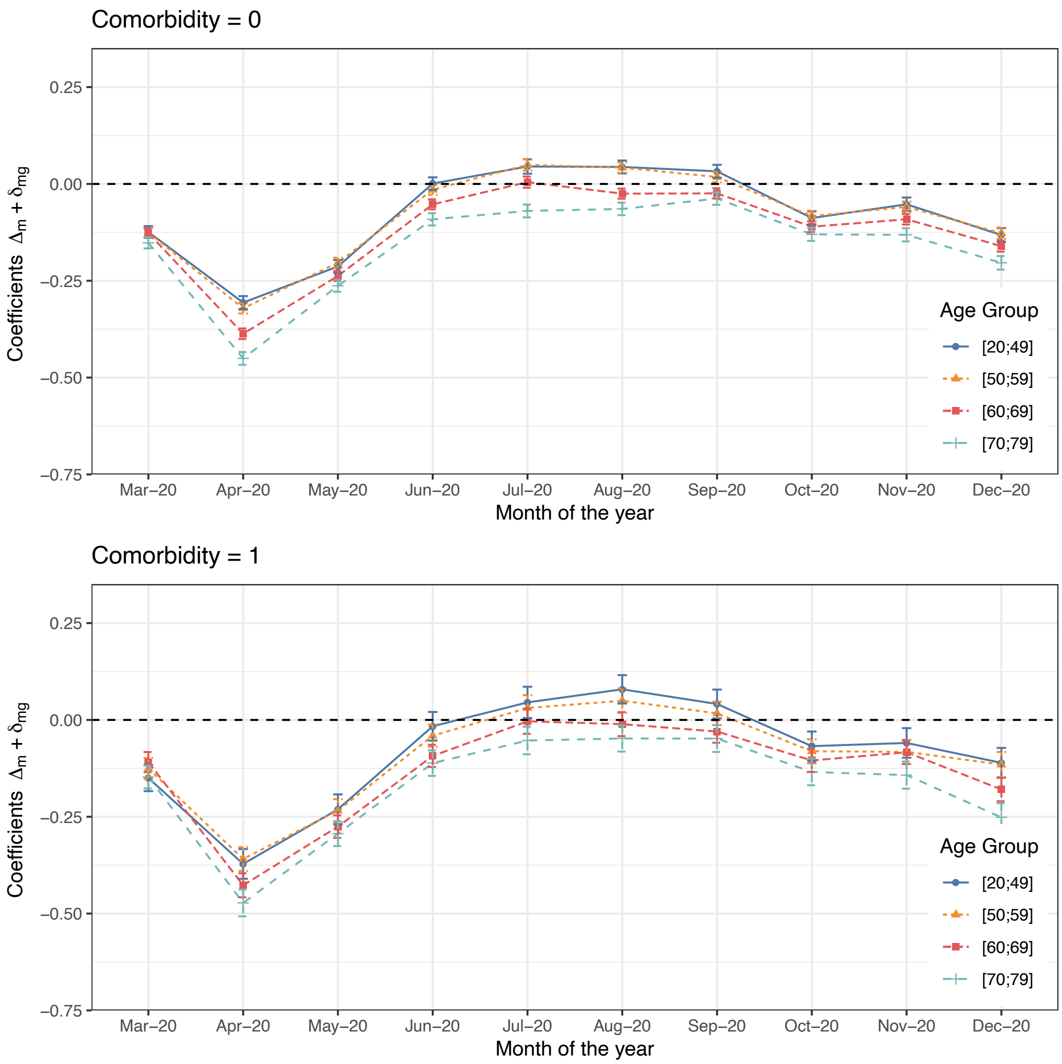


Figure A.7: Changes in expenditures of public servants in different income groups during the epidemic relative to a counterfactual without Covid for people with and without comorbidity.

## A.5 Empirical results for old

In our quantitative model, there are only two groups, old and young. In this subsection, we report our empirical results when people are classified into two age groups: 20-59 and 60-80.

We construct our estimates of $\hat{\psi}$ using the estimated regression parameters, netting out the effects of the time trend, seasonal effects, individual fixed effects, and interactions between seasonal effects and individual characteristics:

$$\begin{aligned}\hat{\psi}_t = \quad & \sum_{m=Mar,2020}^{Apr,2021} \hat{\Delta}_m After_t \times \mathbf{1}\{Month_t = m\} + \\ & \sum_{m=Mar,2020}^{Apr,2021} \hat{\delta}_{mg} After_t \times \mathbf{1}\{Month_t = m\} \times \mathbf{1}\{AgeGroup_i = old\}.\end{aligned} \tag{A.2}$$

Table 12: Impact of age on expenditures (for model estimation).

| | Dependent variable: | | | |
|---|---|---|---|---|
| | $log(Expense_{it})$ | | | |
| | FE | FE | FE | FE |
| | (1) | (2) | (3) | (4) |
| $After_t \times \mathbf{1}\{Month_t = Mar20\}(\Delta_{Mar20})$ | $-0.101^{***}$ | $-0.127^{***}$ | $-0.127^{***}$ | $-0.127^{***}$ |
| | (0.005) | (0.005) | (0.005) | (0.005) |
| $After_t \times \mathbf{1}\{Month_t = Apr20\}(\Delta_{Apr20})$ | $-0.297^{***}$ | $-0.322^{***}$ | $-0.322^{***}$ | $-0.322^{***}$ |
| | (0.005) | (0.005) | (0.005) | (0.005) |
| $After_t \times \mathbf{1}\{Month_t = May20\}(\Delta_{May20})$ | $-0.185^{***}$ | $-0.211^{***}$ | $-0.211^{***}$ | $-0.211^{***}$ |
| | (0.005) | (0.005) | (0.005) | (0.005) |
| $After_t \times \mathbf{1}\{Month_t = Jun20\}(\Delta_{Jun20})$ | $0.014^{**}$ | $-0.012^{*}$ | $-0.012^{*}$ | $-0.012^{*}$ |
| | (0.005) | (0.005) | (0.005) | (0.005) |
| $After_t \times \mathbf{1}\{Month_t = Jul20\}(\Delta_{Jul20})$ | $0.072^{***}$ | $0.046^{***}$ | $0.046^{***}$ | $0.046^{***}$ |
| | (0.006) | (0.006) | (0.006) | (0.006) |
| $After_t \times \mathbf{1}\{Month_t = Aug20\}(\Delta_{Aug20})$ | $0.071^{***}$ | $0.046^{***}$ | $0.046^{***}$ | $0.046^{***}$ |
| | (0.005) | (0.005) | (0.005) | (0.005) |
| $After_t \times \mathbf{1}\{Month_t = Sep20\}(\Delta_{Sep20})$ | $0.050^{***}$ | $0.024^{***}$ | $0.024^{***}$ | $0.024^{***}$ |
| | (0.005) | (0.005) | (0.005) | (0.005) |
| $After_t \times \mathbf{1}\{Month_t = Oct20\}(\Delta_{Oct20})$ | $-0.058^{***}$ | $-0.084^{***}$ | $-0.084^{***}$ | $-0.084^{***}$ |
| | (0.005) | (0.005) | (0.005) | (0.005) |
| $After_t \times \mathbf{1}\{Month_t = Nov20\}(\Delta_{Nov20})$ | $-0.033^{***}$ | $-0.059^{***}$ | $-0.059^{***}$ | $-0.059^{***}$ |
| | (0.005) | (0.005) | (0.005) | (0.005) |
| $After_t \times \mathbf{1}\{Month_t = Dec20\}(\Delta_{Dec20})$ | $-0.101^{***}$ | $-0.127^{***}$ | $-0.127^{***}$ | $-0.127^{***}$ |
| | (0.005) | (0.005) | (0.005) | (0.005) |
| $After_t \times \mathbf{1}\{Month_t = Jan21\}(\Delta_{Jan21})$ | $-0.252^{***}$ | $-0.296^{***}$ | $-0.296^{***}$ | $-0.296^{***}$ |
| | (0.005) | (0.006) | (0.006) | (0.006) |
| $After_t \times \mathbf{1}\{Month_t = Feb21\}(\Delta_{Feb21})$ | $-0.168^{***}$ | $-0.212^{***}$ | $-0.212^{***}$ | $-0.212^{***}$ |
| | (0.005) | (0.006) | (0.006) | (0.006) |
| $After_t \times \mathbf{1}\{Month_t = Mar21\}(\Delta_{Mar21})$ | $-0.039^{***}$ | $-0.083^{***}$ | $-0.083^{***}$ | $-0.083^{***}$ |
| | (0.006) | (0.006) | (0.006) | (0.006) |
| $After_t \times \mathbf{1}\{Month_t = Apr21\}(\Delta_{Apr21})$ | $-0.028^{***}$ | $-0.072^{***}$ | $-0.072^{***}$ | $-0.072^{***}$ |
| | (0.006) | (0.006) | (0.006) | (0.006) |
| $After_t \times \mathbf{1}\{Month_t = Mar20\} \times \mathbf{1}\{Age_i \geq 60\}(\delta_{Mar20,\geq 60})$ | $-0.055^{***}$ | $-0.009$ | $-0.009$ | $-0.009$ |
| | (0.006) | (0.006) | (0.006) | (0.006) |
| $After_t \times \mathbf{1}\{Month_t = Apr20\} \times \mathbf{1}\{Age_i \geq 60\}(\delta_{Apr20,\geq 60})$ | $-0.142^{***}$ | $-0.097^{***}$ | $-0.097^{***}$ | $-0.097^{***}$ |
| | (0.007) | (0.007) | (0.007) | (0.007) |
| $After_t \times \mathbf{1}\{Month_t = May20\} \times \mathbf{1}\{Age_i \geq 60\}(\delta_{May20,\geq 60})$ | $-0.088^{***}$ | $-0.043^{***}$ | $-0.043^{***}$ | $-0.043^{***}$ |
| | (0.006) | (0.006) | (0.006) | (0.006) |
| $After_t \times \mathbf{1}\{Month_t = Jun20\} \times \mathbf{1}\{Age_i \geq 60\}(\delta_{Jun20,\geq 60})$ | $-0.108^{***}$ | $-0.062^{***}$ | $-0.062^{***}$ | $-0.062^{***}$ |
| | (0.006) | (0.006) | (0.006) | (0.006) |
| $After_t \times \mathbf{1}\{Month_t = Jul20\} \times \mathbf{1}\{Age_i \geq 60\}(\delta_{Jul20,\geq 60})$ | $-0.118^{***}$ | $-0.073^{***}$ | $-0.073^{***}$ | $-0.073^{***}$ |
| | (0.007) | (0.007) | (0.007) | (0.007) |
| $After_t \times \mathbf{1}\{Month_t = Aug20\} \times \mathbf{1}\{Age_i \geq 60\}(\delta_{Aug20,\geq 60})$ | $-0.131^{***}$ | $-0.086^{***}$ | $-0.086^{***}$ | $-0.086^{***}$ |
| | (0.006) | (0.007) | (0.007) | (0.007) |
| $After_t \times \mathbf{1}\{Month_t = Sep20\} \times \mathbf{1}\{Age_i \geq 60\}(\delta_{Sep20,\geq 60})$ | $-0.101^{***}$ | $-0.056^{***}$ | $-0.056^{***}$ | $-0.056^{***}$ |
| | (0.006) | (0.007) | (0.007) | (0.007) |
| $After_t \times \mathbf{1}\{Month_t = Oct20\} \times \mathbf{1}\{Age_i \geq 60\}(\delta_{Oct20,\geq 60})$ | $-0.081^{***}$ | $-0.035^{***}$ | $-0.035^{***}$ | $-0.035^{***}$ |
| | (0.006) | (0.007) | (0.007) | (0.007) |
| $After_t \times \mathbf{1}\{Month_t = Nov20\} \times \mathbf{1}\{Age_i \geq 60\}(\delta_{Nov20,\geq 60})$ | $-0.095^{***}$ | $-0.050^{***}$ | $-0.050^{***}$ | $-0.050^{***}$ |
| | (0.007) | (0.007) | (0.007) | (0.007) |
| $After_t \times \mathbf{1}\{Month_t = Dec20\} \times \mathbf{1}\{Age_i \geq 60\}(\delta_{Dec20,\geq 60})$ | $-0.103^{***}$ | $-0.057^{***}$ | $-0.057^{***}$ | $-0.057^{***}$ |
| | (0.007) | (0.007) | (0.007) | (0.007) |
| $After_t \times \mathbf{1}\{Month_t = Jan21\} \times \mathbf{1}\{Age_i \geq 60\}(\delta_{Jan21,\geq 60})$ | $-0.145^{***}$ | $-0.067^{***}$ | $-0.067^{***}$ | $-0.067^{***}$ |
| | (0.007) | (0.008) | (0.008) | (0.008) |
| $After_t \times \mathbf{1}\{Month_t = Feb21\} \times \mathbf{1}\{Age_i \geq 60\}(\delta_{Feb21,\geq 60})$ | $-0.120^{***}$ | $-0.042^{***}$ | $-0.042^{***}$ | $-0.042^{***}$ |
| | (0.007) | (0.008) | (0.008) | (0.008) |
| $After_t \times \mathbf{1}\{Month_t = Mar21\} \times \mathbf{1}\{Age_i \geq 60\}(\delta_{Mar21,\geq 60})$ | $-0.093^{***}$ | $-0.015^{+}$ | $-0.015^{+}$ | $-0.015^{+}$ |
| | (0.006) | (0.008) | (0.008) | (0.008) |
| $After_t \times \mathbf{1}\{Month_t = Apr21\} \times \mathbf{1}\{Age_i \geq 60\}(\delta_{Apr21,\geq 60})$ | $-0.091^{***}$ | $-0.013$ | $-0.013$ | $-0.013$ |
| | (0.006) | (0.008) | (0.008) | (0.008) |
| Month FE | Yes | Yes | Yes | Yes |
| Individual FE | Yes | Yes | Yes | Yes |
| Age Group$\times Year_t$ ($\Psi_{it}$) | No | Yes | Yes | Yes |
| Income Group $\times Year_t$ ($\Psi_{it}$) | No | No | Yes | Yes |
| Age Group $\times$ Income Group $\times Year_t$ ($\Psi_{it}$) | No | No | No | Yes |
| Observations | 2,315,002 | 2,315,002 | 2,315,002 | 2,315,002 |
| $R^2$ | 0.633 | 0.633 | 0.633 | 0.633 |
| Adjusted $R^2$ | 0.623 | 0.623 | 0.624 | 0.624 |
| Residual Std. Error | 0.686 | 0.686 | 0.686 | 0.686 |

*Note:* + p<0.1; * p<0.05; ** p<0.01; *** p<0.001

## A.6 Regression tables used to build the figures

Table 13: Impact of age on consumption expenditures.

| | *Dependent variable:* | | | | |
|---|---|---|---|---|---|
| | $log(Expenses_{it})$ | | | | |
| | (1) | (2) | (3) | (4) | (5) |
| $After_t$ | $-0.138^{***}$ | | | | |
| | (0.002) | | | | |
| $After_t \times \mathbf{1}\{Age_i = [20;49]\}$ | | $-0.067^{***}$ | $-0.103^{***}$ | $-0.103^{***}$ | $-0.103^{***}$ |
| | | (0.004) | (0.005) | (0.005) | (0.005) |
| $After_t \times \mathbf{1}\{Age_i = [50;59]\}$ | | $-0.087^{***}$ | $-0.107^{***}$ | $-0.107^{***}$ | $-0.107^{***}$ |
| | | (0.004) | (0.004) | (0.004) | (0.004) |
| $After_t \times \mathbf{1}\{Age_i = [60;69]\}$ | | $-0.154^{***}$ | $-0.146^{***}$ | $-0.146^{***}$ | $-0.146^{***}$ |
| | | (0.003) | (0.004) | (0.004) | (0.004) |
| $After_t \times \mathbf{1}\{Age_i = [70;79]\}$ | | $-0.223^{***}$ | $-0.187^{***}$ | $-0.187^{***}$ | $-0.187^{***}$ |
| | | (0.004) | (0.005) | (0.005) | (0.005) |
| $\mathbf{1}\{Month_t = Feb\}$ | $-0.050^{***}$ | $-0.050^{***}$ | $-0.050^{***}$ | $-0.050^{***}$ | $-0.050^{***}$ |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| $\mathbf{1}\{Month_t = Mar\}$ | $0.081^{***}$ | $0.081^{***}$ | $0.081^{***}$ | $0.081^{***}$ | $0.081^{***}$ |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| $\mathbf{1}\{Month_t = Apr\}$ | $-0.002$ | $-0.002$ | $-0.002$ | $-0.002$ | $-0.002$ |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| $\mathbf{1}\{Month_t = May\}$ | $0.065^{***}$ | $0.065^{***}$ | $0.065^{***}$ | $0.065^{***}$ | $0.065^{***}$ |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| $\mathbf{1}\{Month_t = Jun\}$ | $0.094^{***}$ | $0.094^{***}$ | $0.094^{***}$ | $0.094^{***}$ | $0.094^{***}$ |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| $\mathbf{1}\{Month_t = Jul\}$ | $0.203^{***}$ | $0.203^{***}$ | $0.203^{***}$ | $0.203^{***}$ | $0.203^{***}$ |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| $\mathbf{1}\{Month_t = Aug\}$ | $0.098^{***}$ | $0.098^{***}$ | $0.098^{***}$ | $0.098^{***}$ | $0.098^{***}$ |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) |
| $\mathbf{1}\{Month_t = Sep\}$ | $0.048^{***}$ | $0.048^{***}$ | $0.048^{***}$ | $0.048^{***}$ | $0.048^{***}$ |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| $\mathbf{1}\{Month_t = Oct\}$ | $0.079^{***}$ | $0.080^{***}$ | $0.080^{***}$ | $0.079^{***}$ | $0.079^{***}$ |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| $\mathbf{1}\{Month_t = Nov\}$ | $0.095^{***}$ | $0.095^{***}$ | $0.095^{***}$ | $0.095^{***}$ | $0.095^{***}$ |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| $\mathbf{1}\{Month_t = Dec\}$ | $0.161^{***}$ | $0.161^{***}$ | $0.161^{***}$ | $0.161^{***}$ | $0.161^{***}$ |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) |
| $Year_t$ | $0.041^{***}$ | $0.041^{***}$ | $0.062^{***}$ | $0.088^{***}$ | $0.105^{***}$ |
| | (0.001) | (0.001) | (0.002) | (0.007) | (0.027) |
| $Year_t \times \mathbf{1}\{Age_i = [50;59]\}$ | | | $-0.009^{**}$ | $-0.008^{*}$ | $-0.071^{+}$ |
| | | | (0.003) | (0.003) | (0.038) |
| $Year_t \times \mathbf{1}\{Age_i = [60;69]\}$ | | | $-0.026^{***}$ | $-0.026^{***}$ | $-0.056^{+}$ |
| | | | (0.003) | (0.003) | (0.029) |
| $Year_t \times \mathbf{1}\{Age_i = [70;79]\}$ | | | $-0.043^{***}$ | $-0.046^{***}$ | $-0.050^{+}$ |
| | | | (0.003) | (0.003) | (0.028) |
| $Year_t \times \mathbf{1}\{Income_i = ]7,091;20,261]\}$ | | | | $-0.007$ | $-0.023$ |
| | | | | (0.007) | (0.027) |
| $Year_t \times \mathbf{1}\{Income_i = ]20,261;40,522]\}$ | | | | $-0.036^{***}$ | $-0.054^{*}$ |
| | | | | (0.007) | (0.027) |
| $Year_t \times \mathbf{1}\{Income_i = ]40,522;80,640]\}$ | | | | $-0.054^{***}$ | $-0.071^{*}$ |
| | | | | (0.007) | (0.028) |
| $Year_t \times \mathbf{1}\{Income_i => 80,640\}$ | | | | $-0.070^{***}$ | $-0.167^{***}$ |
| | | | | (0.010) | (0.036) |
| $Year_t \times \mathbf{1}\{Age_i = [50;59]\} \times \mathbf{1}\{Income_i = ]7,091;20,261]\}$ | | | | | 0.064 |
| | | | | | (0.039) |
| $Year_t \times \mathbf{1}\{Age_i = [60;69]\} \times \mathbf{1}\{Income_i = ]7,091;20,261]\}$ | | | | | 0.028 |
| | | | | | (0.030) |
| $Year_t \times \mathbf{1}\{Age_i = [70;79]\} \times \mathbf{1}\{Income_i = ]7,091;20,261]\}$ | | | | | 0.0002 |
| | | | | | (0.029) |
| $Year_t \times \mathbf{1}\{Age_i = [50;59]\} \times \mathbf{1}\{Income_i = ]20,261;40,522]\}$ | | | | | $0.065^{+}$ |
| | | | | | (0.039) |
| $Year_t \times \mathbf{1}\{Age_i = [60;69]\} \times \mathbf{1}\{Income_i = ]20,261;40,522]\}$ | | | | | 0.033 |
| | | | | | (0.030) |
| $Year_t \times \mathbf{1}\{Age_i = [70;79]\} \times \mathbf{1}\{Income_i = ]20,261;40,522]\}$ | | | | | 0.001 |
| | | | | | (0.029) |
| $Year_t \times \mathbf{1}\{Age_i = [50;59]\} \times \mathbf{1}\{Income_i = ]40,522;80,640]\}$ | | | | | 0.058 |
| | | | | | (0.040) |
| $Year_t \times \mathbf{1}\{Age_i = [60;69]\} \times \mathbf{1}\{Income_i = ]40,522;80,640]\}$ | | | | | 0.032 |
| | | | | | (0.031) |
| $Year_t \times \mathbf{1}\{Age_i = [70;79]\} \times \mathbf{1}\{Income_i = ]40,522;80,640]\}$ | | | | | 0.005 |
| | | | | | (0.030) |
| $Year_t \times \mathbf{1}\{Age_i = [50;59]\} \times \mathbf{1}\{Income_i > 80,640\}$ | | | | | $0.145^{**}$ |
| | | | | | (0.051) |
| $Year_t \times \mathbf{1}\{Age_i = [60;69]\} \times \mathbf{1}\{Income_i > 80,640\}$ | | | | | $0.106^{**}$ |
| | | | | | (0.039) |
| $Year_t \times \mathbf{1}\{Age_i = [70;79]\} \times \mathbf{1}\{Income_i > 80,640\}$ | | | | | $0.108^{**}$ |
| | | | | | (0.040) |
| Individual FE | Yes | Yes | Yes | Yes | Yes |
| Observations | 2,315,002 | 2,315,002 | 2,315,002 | 2,315,002 | 2,315,002 |
| $R^2$ | 0.629 | 0.630 | 0.630 | 0.630 | 0.630 |
| Adjusted $R^2$ | 0.620 | 0.620 | 0.621 | 0.621 | 0.621 |
| Residual Std. Error | 0.689 | 0.689 | 0.689 | 0.688 | 0.688 |
| *Note:* | | | | | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01<br>+ p<0.1; * p<0.05; ** p<0.01; *** p<0.001<br>Cluster robust standard errors in (); Errors clustered by person |

Table 14: Impact of age on consumption expenditures.

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | $log(Expense_{it})$ | | | |
| | FE | FE | FE | FE |
| | (1) | (2) | (3) | (4) |
| $After_t \times \mathbf{1}\{Month_t = Mar20\} \times \mathbf{1}\{Age_i = [20;49]\}(\Delta_{Mar20,[20;49]} + \delta_{Mar20,[20;49]})$ | $-0.094^{***}$ | $-0.128^{***}$ | $-0.128^{***}$ | $-0.128^{***}$ |
| | (0.007) | (0.007) | (0.007) | (0.007) |
| $After_t \times \mathbf{1}\{Month_t = Mar20\} \times \mathbf{1}\{Age_i = [50;59]\}(\Delta_{Mar20,[50;59]} + \delta_{Mar20,[50;59]})$ | $-0.105^{***}$ | $-0.126^{***}$ | $-0.126^{***}$ | $-0.126^{***}$ |
| | (0.006) | (0.006) | (0.006) | (0.006) |
| $After_t \times \mathbf{1}\{Month_t = Mar20\} \times \mathbf{1}\{Age_i = [60;69]\}(\Delta_{Mar20,[60;69]} + \delta_{Mar20,[60;69]})$ | $-0.131^{***}$ | $-0.124^{***}$ | $-0.124^{***}$ | $-0.124^{***}$ |
| | (0.005) | (0.006) | (0.006) | (0.006) |
| $After_t \times \mathbf{1}\{Month_t = Mar20\} \times \mathbf{1}\{Age_i = [70;79]\}(\Delta_{Mar20,[70;79]} + \delta_{Mar20,[70;79]})$ | $-0.188^{***}$ | $-0.151^{***}$ | $-0.151^{***}$ | $-0.151^{***}$ |
| | (0.006) | (0.007) | (0.007) | (0.007) |
| $After_t \times \mathbf{1}\{Month_t = Apr20\} \times \mathbf{1}\{Age_i = [20;49]\}(\Delta_{Apr20,[20;49]} + \delta_{Apr20,[20;49]})$ | $-0.282^{***}$ | $-0.316^{***}$ | $-0.316^{***}$ | $-0.316^{***}$ |
| | (0.008) | (0.008) | (0.008) | (0.008) |
| $After_t \times \mathbf{1}\{Month_t = Apr20\} \times \mathbf{1}\{Age_i = [50;59]\}(\Delta_{Apr20,[50;59]} + \delta_{Apr20,[50;59]})$ | $-0.306^{***}$ | $-0.326^{***}$ | $-0.326^{***}$ | $-0.326^{***}$ |
| | (0.006) | (0.006) | (0.006) | (0.006) |
| $After_t \times \mathbf{1}\{Month_t = Apr20\} \times \mathbf{1}\{Age_i = [60;69]\}(\Delta_{Apr20,[60;69]} + \delta_{Apr20,[60;69]})$ | $-0.399^{***}$ | $-0.393^{***}$ | $-0.393^{***}$ | $-0.393^{***}$ |
| | (0.006) | (0.006) | (0.006) | (0.006) |
| $After_t \times \mathbf{1}\{Month_t = Apr20\} \times \mathbf{1}\{Age_i = [70;79]\}(\Delta_{Apr20,[70;79]} + \delta_{Apr20,[70;79]})$ | $-0.491^{***}$ | $-0.454^{***}$ | $-0.454^{***}$ | $-0.454^{***}$ |
| | (0.007) | (0.008) | (0.008) | (0.008) |
| $After_t \times \mathbf{1}\{Month_t = May20\} \times \mathbf{1}\{Age_i = [20;49]\}(\Delta_{May20,[20;49]} + \delta_{May20,[20;49]})$ | $-0.182^{***}$ | $-0.216^{***}$ | $-0.216^{***}$ | $-0.216^{***}$ |
| | (0.008) | (0.008) | (0.008) | (0.008) |
| $After_t \times \mathbf{1}\{Month_t = May20\} \times \mathbf{1}\{Age_i = [50;59]\}(\Delta_{May20,[50;59]} + \delta_{May20,[50;59]})$ | $-0.187^{***}$ | $-0.208^{***}$ | $-0.208^{***}$ | $-0.208^{***}$ |
| | (0.006) | (0.006) | (0.006) | (0.006) |
| $After_t \times \mathbf{1}\{Month_t = May20\} \times \mathbf{1}\{Age_i = [60;69]\}(\Delta_{May20,[60;69]} + \delta_{May20,[60;69]})$ | $-0.250^{***}$ | $-0.243^{***}$ | $-0.243^{***}$ | $-0.243^{***}$ |
| | (0.006) | (0.006) | (0.006) | (0.006) |
| $After_t \times \mathbf{1}\{Month_t = May20\} \times \mathbf{1}\{Age_i = [70;79]\}(\Delta_{May20,[70;79]} + \delta_{May20,[70;79]})$ | $-0.305^{***}$ | $-0.268^{***}$ | $-0.268^{***}$ | $-0.268^{***}$ |
| | (0.007) | (0.007) | (0.007) | (0.007) |
| $After_t \times \mathbf{1}\{Month_t = Jun20\} \times \mathbf{1}\{Age_i = [20;49]\}(\Delta_{Jun20,[20;49]} + \delta_{Jun20,[20;49]})$ | $0.032^{***}$ | $-0.001$ | $-0.001$ | $-0.001$ |
| | (0.007) | (0.008) | (0.008) | (0.008) |
| $After_t \times \mathbf{1}\{Month_t = Jun20\} \times \mathbf{1}\{Age_i = [50;59]\}(\Delta_{Jun20,[50;59]} + \delta_{Jun20,[50;59]})$ | $0.002$ | $-0.019^{**}$ | $-0.018^{**}$ | $-0.018^{**}$ |
| | (0.006) | (0.006) | (0.006) | (0.006) |
| $After_t \times \mathbf{1}\{Month_t = Jun20\} \times \mathbf{1}\{Age_i = [60;69]\}(\Delta_{Jun20,[60;69]} + \delta_{Jun20,[60;69]})$ | $-0.065^{***}$ | $-0.058^{***}$ | $-0.058^{***}$ | $-0.058^{***}$ |
| | (0.006) | (0.006) | (0.006) | (0.006) |
| $After_t \times \mathbf{1}\{Month_t = Jun20\} \times \mathbf{1}\{Age_i = [70;79]\}(\Delta_{Jun20,[70;79]} + \delta_{Jun20,[70;79]})$ | $-0.132^{***}$ | $-0.095^{***}$ | $-0.095^{***}$ | $-0.095^{***}$ |
| | (0.007) | (0.007) | (0.007) | (0.007) |
| $After_t \times \mathbf{1}\{Month_t = Jul20\} \times \mathbf{1}\{Age_i = [20;49]\}(\Delta_{Jul20,[20;49]} + \delta_{Jul20,[20;49]})$ | $0.079^{***}$ | $0.045^{***}$ | $0.045^{***}$ | $0.045^{***}$ |
| | (0.008) | (0.009) | (0.009) | (0.009) |
| $After_t \times \mathbf{1}\{Month_t = Jul20\} \times \mathbf{1}\{Age_i = [50;59]\}(\Delta_{Jul20,[50;59]} + \delta_{Jul20,[50;59]})$ | $0.067^{***}$ | $0.047^{***}$ | $0.047^{***}$ | $0.047^{***}$ |
| | (0.007) | (0.007) | (0.007) | (0.007) |
| $After_t \times \mathbf{1}\{Month_t = Jul20\} \times \mathbf{1}\{Age_i = [60;69]\}(\Delta_{Jul20,[60;69]} + \delta_{Jul20,[60;69]})$ | $-0.003$ | $0.003$ | $0.003$ | $0.003$ |
| | (0.007) | (0.007) | (0.007) | (0.007) |
| $After_t \times \mathbf{1}\{Month_t = Jul20\} \times \mathbf{1}\{Age_i = [70;79]\}(\Delta_{Jul20,[70;79]} + \delta_{Jul20,[70;79]})$ | $-0.104^{***}$ | $-0.067^{***}$ | $-0.067^{***}$ | $-0.067^{***}$ |
| | (0.007) | (0.008) | (0.008) | (0.008) |
| $After_t \times \mathbf{1}\{Month_t = Aug20\} \times \mathbf{1}\{Age_i = [20;49]\}(\Delta_{Aug20,[20;49]} + \delta_{Aug20,[20;49]})$ | $0.083^{***}$ | $0.049^{***}$ | $0.049^{***}$ | $0.049^{***}$ |
| | (0.007) | (0.008) | (0.008) | (0.008) |
| $After_t \times \mathbf{1}\{Month_t = Aug20\} \times \mathbf{1}\{Age_i = [50;59]\}(\Delta_{Aug20,[50;59]} + \delta_{Aug20,[50;59]})$ | $0.064^{***}$ | $0.043^{***}$ | $0.043^{***}$ | $0.043^{***}$ |
| | (0.006) | (0.006) | (0.006) | (0.006) |
| $After_t \times \mathbf{1}\{Month_t = Aug20\} \times \mathbf{1}\{Age_i = [60;69]\}(\Delta_{Aug20,[60;69]} + \delta_{Aug20,[60;69]})$ | $-0.030^{***}$ | $-0.023^{***}$ | $-0.023^{***}$ | $-0.023^{***}$ |
| | (0.006) | (0.006) | (0.006) | (0.006) |
| $After_t \times \mathbf{1}\{Month_t = Aug20\} \times \mathbf{1}\{Age_i = [70;79]\}(\Delta_{Aug20,[70;79]} + \delta_{Aug20,[70;79]})$ | $-0.099^{***}$ | $-0.062^{***}$ | $-0.062^{***}$ | $-0.062^{***}$ |
| | (0.007) | (0.007) | (0.007) | (0.007) |
| $After_t \times \mathbf{1}\{Month_t = Sep20\} \times \mathbf{1}\{Age_i = [20;49]\}(\Delta_{Sep20,[20;49]} + \delta_{Sep20,[20;49]})$ | $0.067^{***}$ | $0.034^{***}$ | $0.034^{***}$ | $0.034^{***}$ |
| | (0.008) | (0.008) | (0.008) | (0.008) |
| $After_t \times \mathbf{1}\{Month_t = Sep20\} \times \mathbf{1}\{Age_i = [50;59]\}(\Delta_{Sep20,[50;59]} + \delta_{Sep20,[50;59]})$ | $0.038^{***}$ | $0.018^{**}$ | $0.018^{**}$ | $0.018^{**}$ |
| | (0.006) | (0.006) | (0.006) | (0.006) |
| $After_t \times \mathbf{1}\{Month_t = Sep20\} \times \mathbf{1}\{Age_i = [60;69]\}(\Delta_{Sep20,[60;69]} + \delta_{Sep20,[60;69]})$ | $-0.032^{***}$ | $-0.025^{***}$ | $-0.025^{***}$ | $-0.025^{***}$ |
| | (0.006) | (0.006) | (0.006) | (0.006) |
| $After_t \times \mathbf{1}\{Month_t = Sep20\} \times \mathbf{1}\{Age_i = [70;79]\}(\Delta_{Sep20,[70;79]} + \delta_{Sep20,[70;79]})$ | $-0.077^{***}$ | $-0.040^{***}$ | $-0.040^{***}$ | $-0.040^{***}$ |
| | (0.007) | (0.007) | (0.007) | (0.007) |
| $After_t \times \mathbf{1}\{Month_t = Oct20\} \times \mathbf{1}\{Age_i = [20;49]\}(\Delta_{Oct20,[20;49]} + \delta_{Oct20,[20;49]})$ | $-0.052^{***}$ | $-0.085^{***}$ | $-0.085^{***}$ | $-0.085^{***}$ |
| | (0.008) | (0.008) | (0.008) | (0.008) |
| $After_t \times \mathbf{1}\{Month_t = Oct20\} \times \mathbf{1}\{Age_i = [50;59]\}(\Delta_{Oct20,[50;59]} + \delta_{Oct20,[50;59]})$ | $-0.062^{***}$ | $-0.083^{***}$ | $-0.083^{***}$ | $-0.083^{***}$ |
| | (0.006) | (0.006) | (0.006) | (0.006) |
| $After_t \times \mathbf{1}\{Month_t = Oct20\} \times \mathbf{1}\{Age_i = [60;69]\}(\Delta_{Oct20,[60;69]} + \delta_{Oct20,[60;69]})$ | $-0.116^{***}$ | $-0.110^{***}$ | $-0.110^{***}$ | $-0.110^{***}$ |
| | (0.006) | (0.006) | (0.006) | (0.006) |
| $After_t \times \mathbf{1}\{Month_t = Oct20\} \times \mathbf{1}\{Age_i = [70;79]\}(\Delta_{Oct20,[70;79]} + \delta_{Oct20,[70;79]})$ | $-0.168^{***}$ | $-0.131^{***}$ | $-0.131^{***}$ | $-0.131^{***}$ |
| | (0.007) | (0.008) | (0.008) | (0.008) |
| $After_t \times \mathbf{1}\{Month_t = Nov20\} \times \mathbf{1}\{Age_i = [20;49]\}(\Delta_{Nov20,[20;49]} + \delta_{Nov20,[20;49]})$ | $-0.020^{*}$ | $-0.054^{***}$ | $-0.054^{***}$ | $-0.054^{***}$ |
| | (0.008) | (0.008) | (0.008) | (0.008) |
| $After_t \times \mathbf{1}\{Month_t = Nov20\} \times \mathbf{1}\{Age_i = [50;59]\}(\Delta_{Nov20,[50;59]} + \delta_{Nov20,[50;59]})$ | $-0.042^{***}$ | $-0.063^{***}$ | $-0.063^{***}$ | $-0.063^{***}$ |
| | (0.006) | (0.006) | (0.006) | (0.006) |
| $After_t \times \mathbf{1}\{Month_t = Nov20\} \times \mathbf{1}\{Age_i = [60;69]\}(\Delta_{Nov20,[60;69]} + \delta_{Nov20,[60;69]})$ | $-0.097^{***}$ | $-0.090^{***}$ | $-0.090^{***}$ | $-0.090^{***}$ |
| | (0.006) | (0.006) | (0.006) | (0.006) |
| $After_t \times \mathbf{1}\{Month_t = Nov20\} \times \mathbf{1}\{Age_i = [70;79]\}(\Delta_{Nov20,[70;79]} + \delta_{Nov20,[70;79]})$ | $-0.170^{***}$ | $-0.133^{***}$ | $-0.133^{***}$ | $-0.133^{***}$ |
| | (0.008) | (0.008) | (0.008) | (0.008) |
| $After_t \times \mathbf{1}\{Month_t = Dec20\} \times \mathbf{1}\{Age_i = [20;49]\}(\Delta_{Dec20,[20;49]} + \delta_{Dec20,[20;49]})$ | $-0.095^{***}$ | $-0.129^{***}$ | $-0.129^{***}$ | $-0.129^{***}$ |
| | (0.008) | (0.008) | (0.008) | (0.008) |
| $After_t \times \mathbf{1}\{Month_t = Dec20\} \times \mathbf{1}\{Age_i = [50;59]\}(\Delta_{Dec20,[50;59]} + \delta_{Dec20,[50;59]})$ | $-0.105^{***}$ | $-0.125^{***}$ | $-0.125^{***}$ | $-0.125^{***}$ |
| | (0.007) | (0.007) | (0.007) | (0.007) |
| $After_t \times \mathbf{1}\{Month_t = Dec20\} \times \mathbf{1}\{Age_i = [60;69]\}(\Delta_{Dec20,[60;69]} + \delta_{Dec20,[60;69]})$ | $-0.170^{***}$ | $-0.163^{***}$ | $-0.163^{***}$ | $-0.163^{***}$ |
| | (0.006) | (0.007) | (0.007) | (0.007) |
| $After_t \times \mathbf{1}\{Month_t = Dec20\} \times \mathbf{1}\{Age_i = [70;79]\}(\Delta_{Dec20,[70;79]} + \delta_{Dec20,[70;79]})$ | $-0.249^{***}$ | $-0.212^{***}$ | $-0.212^{***}$ | $-0.212^{***}$ |
| | (0.008) | (0.008) | (0.008) | (0.008) |
| $After_t \times \mathbf{1}\{Month_t = Jan21\} \times \mathbf{1}\{Age_i = [20;49]\}(\Delta_{Jan21,[20;49]} + \delta_{Jan21,[20;49]})$ | $-0.238^{***}$ | $-0.296^{***}$ | $-0.296^{***}$ | $-0.296^{***}$ |
| | (0.008) | (0.009) | (0.009) | (0.009) |
| $After_t \times \mathbf{1}\{Month_t = Jan21\} \times \mathbf{1}\{Age_i = [50;59]\}(\Delta_{Jan21,[50;59]} + \delta_{Jan21,[50;59]})$ | $-0.261^{***}$ | $-0.296^{***}$ | $-0.296^{***}$ | $-0.296^{***}$ |
| | (0.007) | (0.007) | (0.007) | (0.007) |
| $After_t \times \mathbf{1}\{Month_t = Jan21\} \times \mathbf{1}\{Age_i = [60;69]\}(\Delta_{Jan21,[60;69]} + \delta_{Jan21,[60;69]})$ | $-0.348^{***}$ | $-0.337^{***}$ | $-0.337^{***}$ | $-0.337^{***}$ |
| | (0.007) | (0.007) | (0.007) | (0.007) |
| $After_t \times \mathbf{1}\{Month_t = Jan21\} \times \mathbf{1}\{Age_i = [70;79]\}(\Delta_{Jan21,[70;79]} + \delta_{Jan21,[70;79]})$ | $-0.462^{***}$ | $-0.399^{***}$ | $-0.398^{***}$ | $-0.398^{***}$ |
| | (0.008) | (0.009) | (0.009) | (0.009) |
| $After_t \times \mathbf{1}\{Month_t = Feb21\} \times \mathbf{1}\{Age_i = [20;49]\}(\Delta_{Feb21,[20;49]} + \delta_{Feb21,[20;49]})$ | $-0.152^{***}$ | $-0.210^{***}$ | $-0.210^{***}$ | $-0.210^{***}$ |
| | (0.008) | (0.009) | (0.009) | (0.009) |
| $After_t \times \mathbf{1}\{Month_t = Feb21\} \times \mathbf{1}\{Age_i = [50;59]\}(\Delta_{Feb21,[50;59]} + \delta_{Feb21,[50;59]})$ | $-0.178^{***}$ | $-0.213^{***}$ | $-0.213^{***}$ | $-0.213^{***}$ |
| | (0.007) | (0.007) | (0.007) | (0.007) |
| $After_t \times \mathbf{1}\{Month_t = Feb21\} \times \mathbf{1}\{Age_i = [60;69]\}(\Delta_{Feb21,[60;69]} + \delta_{Feb21,[60;69]})$ | $-0.264^{***}$ | $-0.252^{***}$ | $-0.252^{***}$ | $-0.252^{***}$ |
| | (0.006) | (0.007) | (0.007) | (0.007) |
| $After_t \times \mathbf{1}\{Month_t = Feb21\} \times \mathbf{1}\{Age_i = [70;79]\}(\Delta_{Feb21,[70;79]} + \delta_{Feb21,[70;79]})$ | $-0.320^{***}$ | $-0.257^{***}$ | $-0.257^{***}$ | $-0.257^{***}$ |
| | (0.008) | (0.009) | (0.009) | (0.009) |
| $After_t \times \mathbf{1}\{Month_t = Mar21\} \times \mathbf{1}\{Age_i = [20;49]\}(\Delta_{Mar21,[20;49]} + \delta_{Mar21,[20;49]})$ | $-0.026^{**}$ | $-0.083^{***}$ | $-0.083^{***}$ | $-0.083^{***}$ |
| | (0.008) | (0.009) | (0.009) | (0.009) |
| $After_t \times \mathbf{1}\{Month_t = Mar21\} \times \mathbf{1}\{Age_i = [50;59]\}(\Delta_{Mar21,[50;59]} + \delta_{Mar21,[50;59]})$ | $-0.048^{***}$ | $-0.083^{***}$ | $-0.083^{***}$ | $-0.083^{***}$ |
| | (0.007) | (0.007) | (0.007) | (0.007) |
| $After_t \times \mathbf{1}\{Month_t = Mar21\} \times \mathbf{1}\{Age_i = [60;69]\}(\Delta_{Mar21,[60;69]} + \delta_{Mar21,[60;69]})$ | $-0.110^{***}$ | $-0.099^{***}$ | $-0.099^{***}$ | $-0.099^{***}$ |
| | (0.007) | (0.007) | (0.007) | (0.007) |
| $After_t \times \mathbf{1}\{Month_t = Mar21\} \times \mathbf{1}\{Age_i = [70;79]\}(\Delta_{Mar21,[70;79]} + \delta_{Mar21,[70;79]})$ | $-0.162^{***}$ | $-0.098^{***}$ | $-0.098^{***}$ | $-0.098^{***}$ |
| | (0.008) | (0.009) | (0.009) | (0.009) |
| $After_t \times \mathbf{1}\{Month_t = Apr21\} \times \mathbf{1}\{Age_i = [20;49]\}(\Delta_{Apr21,[20;49]} + \delta_{Apr21,[20;49]})$ | $-0.008$ | $-0.066^{***}$ | $-0.066^{***}$ | $-0.066^{***}$ |
| | (0.008) | (0.009) | (0.009) | (0.009) |
| $After_t \times \mathbf{1}\{Month_t = Apr21\} \times \mathbf{1}\{Age_i = [50;59]\}(\Delta_{Apr21,[50;59]} + \delta_{Apr21,[50;59]})$ | $-0.041^{***}$ | $-0.076^{***}$ | $-0.076^{***}$ | $-0.076^{***}$ |
| | (0.007) | (0.007) | (0.007) | (0.007) |
| $After_t \times \mathbf{1}\{Month_t = Apr21\} \times \mathbf{1}\{Age_i = [60;69]\}(\Delta_{Apr21,[60;69]} + \delta_{Apr21,[60;69]})$ | $-0.095^{***}$ | $-0.084^{***}$ | $-0.084^{***}$ | $-0.084^{***}$ |
| | (0.007) | (0.007) | (0.007) | (0.007) |
| $After_t \times \mathbf{1}\{Month_t = Apr21\} \times \mathbf{1}\{Age_i = [70;79]\}(\Delta_{Apr21,[70;79]} + \delta_{Apr21,[70;79]})$ | $-0.151^{***}$ | $-0.087^{***}$ | $-0.087^{***}$ | $-0.087^{***}$ |
| | (0.008) | (0.009) | (0.009) | (0.009) |
| Month FE | Yes | Yes | Yes | Yes |
| Individual FE | Yes | Yes | Yes | Yes |
| Age Group$\times Year_t$ ($\Psi_{it}$) | No | Yes | Yes | Yes |
| Income Group $\times Year_t$ ($\Psi_{it}$) | No | No | Yes | Yes |
| Age Group $\times$ Income Group $\times Year_t$ ($\Psi_{it}$) | No | No | No | Yes |
| Observations | 2,315,002 | 2,315,002 | 2,315,002 | 2,315,002 |
| $R^2$ | 0.633 | 0.633 | 0.633 | 0.633 |
| Adjusted $R^2$ | 0.623 | 0.623 | 0.624 | 0.624 |
| Residual Std. Error | 0.686 | 0.686 | 0.686 | 0.686 |
| *Note:* | + p<0.1; * p<0.05; ** p<0.01; *** p<0.001<br>Cluster robust standard errors in (); Errors clustered by person | | | |

Table 15: Impact of age on consumption expenditures by income group.

| | *Dependent variable:* | | |
|---|---|---|---|
| | $Log(Expenses_{it})$ | | |
| | $20,061 \leq$ | $]20,061; 40,522]$ | $\geq 40,522$ |
| | (1) | (2) | (3) |
| $After_t \times \mathbf{1}\{Month_t = Mar20\} \times \mathbf{1}\{Age_i = [20;49]\}(\Delta_{Mar20,[20;49]} + \delta_{Mar20,[20;49]})$ | $-0.100^{***}$ | $-0.148^{***}$ | $-0.153^{***}$ |
| | (0.011) | (0.010) | (0.029) |
| $After_t \times \mathbf{1}\{Month_t = Mar20\} \times \mathbf{1}\{Age_i = [50;59]\}(\Delta_{Mar20,[50;59]} + \delta_{Mar20,[50;59]})$ | $-0.082^{***}$ | $-0.147^{***}$ | $-0.178^{***}$ |
| | (0.010) | (0.007) | (0.017) |
| $After_t \times \mathbf{1}\{Month_t = Mar20\} \times \mathbf{1}\{Age_i = [60;69]\}(\Delta_{Mar20,[60;69]} + \delta_{Mar20,[60;69]})$ | $-0.088^{***}$ | $-0.139^{***}$ | $-0.185^{***}$ |
| | (0.009) | (0.009) | (0.013) |
| $After_t \times \mathbf{1}\{Month_t = Mar20\} \times \mathbf{1}\{Age_i = [70;79]\}(\Delta_{Mar20,[70;79]} + \delta_{Mar20,[70;79]})$ | $-0.110^{***}$ | $-0.185^{***}$ | $-0.237^{***}$ |
| | (0.009) | (0.011) | (0.018) |
| $After_t \times \mathbf{1}\{Month_t = Apr20\} \times \mathbf{1}\{Age_i = [20;49]\}(\Delta_{Apr20,[20;49]} + \delta_{Apr20,[20;49]})$ | $-0.270^{***}$ | $-0.344^{***}$ | $-0.384^{***}$ |
| | (0.013) | (0.010) | (0.031) |
| $After_t \times \mathbf{1}\{Month_t = Apr20\} \times \mathbf{1}\{Age_i = [50;59]\}(\Delta_{Apr20,[50;59]} + \delta_{Apr20,[50;59]})$ | $-0.242^{***}$ | $-0.362^{***}$ | $-0.444^{***}$ |
| | (0.010) | (0.009) | (0.020) |
| $After_t \times \mathbf{1}\{Month_t = Apr20\} \times \mathbf{1}\{Age_i = [60;69]\}(\Delta_{Apr20,[60;69]} + \delta_{Apr20,[60;69]})$ | $-0.303^{***}$ | $-0.451^{***}$ | $-0.495^{***}$ |
| | (0.010) | (0.010) | (0.015) |
| $After_t \times \mathbf{1}\{Month_t = Apr20\} \times \mathbf{1}\{Age_i = [70;79]\}(\Delta_{Apr20,[70;79]} + \delta_{Apr20,[70;79]})$ | $-0.362^{***}$ | $-0.555^{***}$ | $-0.584^{***}$ |
| | (0.010) | (0.014) | (0.020) |
| $After_t \times \mathbf{1}\{Month_t = May20\} \times \mathbf{1}\{Age_i = [20;49]\}(\Delta_{May20,[20;49]} + \delta_{May20,[20;49]})$ | $-0.177^{***}$ | $-0.241^{***}$ | $-0.253^{***}$ |
| | (0.013) | (0.010) | (0.029) |
| $After_t \times \mathbf{1}\{Month_t = May20\} \times \mathbf{1}\{Age_i = [50;59]\}(\Delta_{May20,[50;59]} + \delta_{May20,[50;59]})$ | $-0.136^{***}$ | $-0.238^{***}$ | $-0.303^{***}$ |
| | (0.010) | (0.008) | (0.019) |
| $After_t \times \mathbf{1}\{Month_t = May20\} \times \mathbf{1}\{Age_i = [60;69]\}(\Delta_{May20,[60;69]} + \delta_{May20,[60;69]})$ | $-0.172^{***}$ | $-0.275^{***}$ | $-0.354^{***}$ |
| | (0.009) | (0.009) | (0.015) |
| $After_t \times \mathbf{1}\{Month_t = May20\} \times \mathbf{1}\{Age_i = [70;79]\}(\Delta_{May20,[70;79]} + \delta_{May20,[70;79]})$ | $-0.219^{***}$ | $-0.309^{***}$ | $-0.378^{***}$ |
| | (0.010) | (0.012) | (0.020) |
| $After_t \times \mathbf{1}\{Month_t = Jun20\} \times \mathbf{1}\{Age_i = [20;49]\}(\Delta_{Jun20,[20;49]} + \delta_{Jun20,[20;49]})$ | 0.016 | $-0.015$ | $-0.005$ |
| | (0.012) | (0.010) | (0.030) |
| $After_t \times \mathbf{1}\{Month_t = Jun20\} \times \mathbf{1}\{Age_i = [50;59]\}(\Delta_{Jun20,[50;59]} + \delta_{Jun20,[50;59]})$ | 0.009 | $-0.022^{**}$ | $-0.094^{***}$ |
| | (0.010) | (0.008) | (0.019) |
| $After_t \times \mathbf{1}\{Month_t = Jun20\} \times \mathbf{1}\{Age_i = [60;69]\}(\Delta_{Jun20,[60;69]} + \delta_{Jun20,[60;69]})$ | $-0.020^{*}$ | $-0.080^{***}$ | $-0.109^{***}$ |
| | (0.009) | (0.009) | (0.014) |
| $After_t \times \mathbf{1}\{Month_t = Jun20\} \times \mathbf{1}\{Age_i = [70;79]\}(\Delta_{Jun20,[70;79]} + \delta_{Jun20,[70;79]})$ | $-0.080^{***}$ | $-0.101^{***}$ | $-0.154^{***}$ |
| | (0.010) | (0.012) | (0.020) |
| $After_t \times \mathbf{1}\{Month_t = Jul20\} \times \mathbf{1}\{Age_i = [20;49]\}(\Delta_{Jul20,[20;49]} + \delta_{Jul20,[20;49]})$ | $0.085^{***}$ | $0.029^{*}$ | $-0.077^{*}$ |
| | (0.014) | (0.012) | (0.030) |
| $After_t \times \mathbf{1}\{Month_t = Jul20\} \times \mathbf{1}\{Age_i = [50;59]\}(\Delta_{Jul20,[50;59]} + \delta_{Jul20,[50;59]})$ | $0.066^{***}$ | $0.046^{***}$ | $-0.037^{+}$ |
| | (0.012) | (0.009) | (0.020) |
| $After_t \times \mathbf{1}\{Month_t = Jul20\} \times \mathbf{1}\{Age_i = [60;69]\}(\Delta_{Jul20,[60;69]} + \delta_{Jul20,[60;69]})$ | $0.042^{***}$ | $-0.022^{*}$ | $-0.044^{**}$ |
| | (0.011) | (0.011) | (0.015) |
| $After_t \times \mathbf{1}\{Month_t = Jul20\} \times \mathbf{1}\{Age_i = [70;79]\}(\Delta_{Jul20,[70;79]} + \delta_{Jul20,[70;79]})$ | $-0.035^{**}$ | $-0.085^{***}$ | $-0.135^{***}$ |
| | (0.011) | (0.013) | (0.020) |
| $After_t \times \mathbf{1}\{Month_t = Aug20\} \times \mathbf{1}\{Age_i = [20;49]\}(\Delta_{Aug20,[20;49]} + \delta_{Aug20,[20;49]})$ | $0.038^{**}$ | $0.057^{***}$ | 0.024 |
| | (0.013) | (0.010) | (0.030) |
| $After_t \times \mathbf{1}\{Month_t = Aug20\} \times \mathbf{1}\{Age_i = [50;59]\}(\Delta_{Aug20,[50;59]} + \delta_{Aug20,[50;59]})$ | $0.024^{*}$ | $0.058^{***}$ | 0.029 |
| | (0.011) | (0.008) | (0.021) |
| $After_t \times \mathbf{1}\{Month_t = Aug20\} \times \mathbf{1}\{Age_i = [60;69]\}(\Delta_{Aug20,[60;69]} + \delta_{Aug20,[60;69]})$ | 0.006 | $-0.042^{***}$ | $-0.051^{***}$ |
| | (0.009) | (0.010) | (0.015) |
| $After_t \times \mathbf{1}\{Month_t = Aug20\} \times \mathbf{1}\{Age_i = [70;79]\}(\Delta_{Aug20,[70;79]} + \delta_{Aug20,[70;79]})$ | $-0.032^{**}$ | $-0.082^{***}$ | $-0.139^{***}$ |
| | (0.010) | (0.012) | (0.021) |
| $After_t \times \mathbf{1}\{Month_t = Sep20\} \times \mathbf{1}\{Age_i = [20;49]\}(\Delta_{Sep20,[20;49]} + \delta_{Sep20,[20;49]})$ | $0.038^{**}$ | $0.029^{**}$ | 0.022 |
| | (0.013) | (0.010) | (0.030) |
| $After_t \times \mathbf{1}\{Month_t = Sep20\} \times \mathbf{1}\{Age_i = [50;59]\}(\Delta_{Sep20,[50;59]} + \delta_{Sep20,[50;59]})$ | $0.019^{+}$ | $0.022^{**}$ | $-0.014$ |
| | (0.011) | (0.008) | (0.020) |
| $After_t \times \mathbf{1}\{Month_t = Sep20\} \times \mathbf{1}\{Age_i = [60;69]\}(\Delta_{Sep20,[60;69]} + \delta_{Sep20,[60;69]})$ | 0.002 | $-0.032^{***}$ | $-0.073^{***}$ |
| | (0.010) | (0.009) | (0.014) |
| $After_t \times \mathbf{1}\{Month_t = Sep20\} \times \mathbf{1}\{Age_i = [70;79]\}(\Delta_{Sep20,[70;79]} + \delta_{Sep20,[70;79]})$ | $-0.026^{*}$ | $-0.050^{***}$ | $-0.074^{***}$ |
| | (0.011) | (0.012) | (0.020) |
| $After_t \times \mathbf{1}\{Month_t = Oct20\} \times \mathbf{1}\{Age_i = [20;49]\}(\Delta_{Oct20,[20;49]} + \delta_{Oct20,[20;49]})$ | $-0.063^{***}$ | $-0.094^{***}$ | $-0.144^{***}$ |
| | (0.013) | (0.011) | (0.031) |
| $After_t \times \mathbf{1}\{Month_t = Oct20\} \times \mathbf{1}\{Age_i = [50;59]\}(\Delta_{Oct20,[50;59]} + \delta_{Oct20,[50;59]})$ | $-0.080^{***}$ | $-0.074^{***}$ | $-0.123^{***}$ |
| | (0.011) | (0.009) | (0.019) |
| $After_t \times \mathbf{1}\{Month_t = Oct20\} \times \mathbf{1}\{Age_i = [60;69]\}(\Delta_{Oct20,[60;69]} + \delta_{Oct20,[60;69]})$ | $-0.089^{***}$ | $-0.116^{***}$ | $-0.150^{***}$ |
| | (0.010) | (0.010) | (0.015) |
| $After_t \times \mathbf{1}\{Month_t = Oct20\} \times \mathbf{1}\{Age_i = [70;79]\}(\Delta_{Oct20,[70;79]} + \delta_{Oct20,[70;79]})$ | $-0.138^{***}$ | $-0.107^{***}$ | $-0.175^{***}$ |
| | (0.011) | (0.013) | (0.020) |
| $After_t \times \mathbf{1}\{Month_t = Nov20\} \times \mathbf{1}\{Age_i = [20;49]\}(\Delta_{Nov20,[20;49]} + \delta_{Nov20,[20;49]})$ | 0.001 | $-0.089^{***}$ | $-0.117^{***}$ |
| | (0.013) | (0.011) | (0.034) |
| $After_t \times \mathbf{1}\{Month_t = Nov20\} \times \mathbf{1}\{Age_i = [50;59]\}(\Delta_{Nov20,[50;59]} + \delta_{Nov20,[50;59]})$ | $-0.045^{***}$ | $-0.063^{***}$ | $-0.125^{***}$ |
| | (0.011) | (0.009) | (0.020) |
| $After_t \times \mathbf{1}\{Month_t = Nov20\} \times \mathbf{1}\{Age_i = [60;69]\}(\Delta_{Nov20,[60;69]} + \delta_{Nov20,[60;69]})$ | $-0.063^{***}$ | $-0.096^{***}$ | $-0.145^{***}$ |
| | (0.010) | (0.010) | (0.015) |
| $After_t \times \mathbf{1}\{Month_t = Nov20\} \times \mathbf{1}\{Age_i = [70;79]\}(\Delta_{Nov20,[70;79]} + \delta_{Nov20,[70;79]})$ | $-0.106^{***}$ | $-0.156^{***}$ | $-0.192^{***}$ |
| | (0.011) | (0.013) | (0.021) |
| $After_t \times \mathbf{1}\{Month_t = Dec20\} \times \mathbf{1}\{Age_i = [20;49]\}(\Delta_{Dec20,[20;49]} + \delta_{Dec20,[20;49]})$ | $-0.096^{***}$ | $-0.153^{***}$ | $-0.146^{***}$ |
| | (0.014) | (0.011) | (0.032) |
| $After_t \times \mathbf{1}\{Month_t = Dec20\} \times \mathbf{1}\{Age_i = [50;59]\}(\Delta_{Dec20,[50;59]} + \delta_{Dec20,[50;59]})$ | $-0.110^{***}$ | $-0.138^{***}$ | $-0.138^{***}$ |
| | (0.012) | (0.009) | (0.020) |
| $After_t \times \mathbf{1}\{Month_t = Dec20\} \times \mathbf{1}\{Age_i = [60;69]\}(\Delta_{Dec20,[60;69]} + \delta_{Dec20,[60;69]})$ | $-0.126^{***}$ | $-0.184^{***}$ | $-0.216^{***}$ |
| | (0.010) | (0.010) | (0.015) |
| $After_t \times \mathbf{1}\{Month_t = Dec20\} \times \mathbf{1}\{Age_i = [70;79]\}(\Delta_{Dec20,[70;79]} + \delta_{Dec20,[70;79]})$ | $-0.184^{***}$ | $-0.221^{***}$ | $-0.284^{***}$ |
| | (0.012) | (0.013) | (0.021) |
| $After_t \times \mathbf{1}\{Month_t = Jan21\} \times \mathbf{1}\{Age_i = [20;49]\}(\Delta_{Jan21,[20;49]} + \delta_{Jan21,[20;49]})$ | $-0.270^{***}$ | $-0.298^{***}$ | $-0.413^{***}$ |
| | (0.016) | (0.012) | (0.037) |
| $After_t \times \mathbf{1}\{Month_t = Jan21\} \times \mathbf{1}\{Age_i = [50;59]\}(\Delta_{Jan21,[50;59]} + \delta_{Jan21,[50;59]})$ | $-0.267^{***}$ | $-0.304^{***}$ | $-0.360^{***}$ |
| | (0.013) | (0.009) | (0.022) |
| $After_t \times \mathbf{1}\{Month_t = Jan21\} \times \mathbf{1}\{Age_i = [60;69]\}(\Delta_{Jan21,[60;69]} + \delta_{Jan21,[60;69]})$ | $-0.303^{***}$ | $-0.360^{***}$ | $-0.384^{***}$ |
| | (0.012) | (0.012) | (0.017) |
| $After_t \times \mathbf{1}\{Month_t = Jan21\} \times \mathbf{1}\{Age_i = [70;79]\}(\Delta_{Jan21,[70;79]} + \delta_{Jan21,[70;79]})$ | $-0.382^{***}$ | $-0.408^{***}$ | $-0.441^{***}$ |
| | (0.013) | (0.016) | (0.023) |
| $After_t \times \mathbf{1}\{Month_t = Feb21\} \times \mathbf{1}\{Age_i = [20;49]\}(\Delta_{Feb21,[20;49]} + \delta_{Feb21,[20;49]})$ | $-0.155^{***}$ | $-0.241^{***}$ | $-0.308^{***}$ |
| | (0.015) | (0.012) | (0.038) |
| $After_t \times \mathbf{1}\{Month_t = Feb21\} \times \mathbf{1}\{Age_i = [50;59]\}(\Delta_{Feb21,[50;59]} + \delta_{Feb21,[50;59]})$ | $-0.150^{***}$ | $-0.239^{***}$ | $-0.295^{***}$ |
| | (0.013) | (0.009) | (0.022) |
| $After_t \times \mathbf{1}\{Month_t = Feb21\} \times \mathbf{1}\{Age_i = [60;69]\}(\Delta_{Feb21,[60;69]} + \delta_{Feb21,[60;69]})$ | $-0.175^{***}$ | $-0.297^{***}$ | $-0.352^{***}$ |
| | (0.011) | (0.011) | (0.017) |
| $After_t \times \mathbf{1}\{Month_t = Feb21\} \times \mathbf{1}\{Age_i = [70;79]\}(\Delta_{Feb21,[70;79]} + \delta_{Feb21,[70;79]})$ | $-0.216^{***}$ | $-0.293^{***}$ | $-0.345^{***}$ |
| | (0.013) | (0.015) | (0.023) |
| $After_t \times \mathbf{1}\{Month_t = Mar21\} \times \mathbf{1}\{Age_i = [20;49]\}(\Delta_{Mar21,[20;49]} + \delta_{Mar21,[20;49]})$ | $-0.026^{+}$ | $-0.118^{***}$ | $-0.178^{***}$ |
| | (0.015) | (0.012) | (0.038) |
| $After_t \times \mathbf{1}\{Month_t = Mar21\} \times \mathbf{1}\{Age_i = [50;59]\}(\Delta_{Mar21,[50;59]} + \delta_{Mar21,[50;59]})$ | $-0.022$ | $-0.104^{***}$ | $-0.206^{***}$ |
| | (0.013) | (0.010) | (0.023) |
| $After_t \times \mathbf{1}\{Month_t = Mar21\} \times \mathbf{1}\{Age_i = [60;69]\}(\Delta_{Mar21,[60;69]} + \delta_{Mar21,[60;69]})$ | $-0.038^{***}$ | $-0.128^{***}$ | $-0.191^{***}$ |
| | (0.012) | (0.012) | (0.017) |
| $After_t \times \mathbf{1}\{Month_t = Mar21\} \times \mathbf{1}\{Age_i = [70;79]\}(\Delta_{Mar21,[70;79]} + \delta_{Mar21,[70;79]})$ | $-0.063^{***}$ | $-0.119^{***}$ | $-0.190^{***}$ |
| | (0.013) | (0.015) | (0.024) |
| $After_t \times \mathbf{1}\{Month_t = Apr21\} \times \mathbf{1}\{Age_i = [20;49]\}(\Delta_{Apr21,[20;49]} + \delta_{Apr21,[20;49]})$ | $-0.019$ | $-0.097^{***}$ | $-0.117^{**}$ |
| | (0.016) | (0.012) | (0.039) |
| $After_t \times \mathbf{1}\{Month_t = Apr21\} \times \mathbf{1}\{Age_i = [50;59]\}(\Delta_{Apr21,[50;59]} + \delta_{Apr21,[50;59]})$ | $-0.045^{***}$ | $-0.088^{***}$ | $-0.135^{***}$ |
| | (0.013) | (0.010) | (0.023) |
| $After_t \times \mathbf{1}\{Month_t = Apr21\} \times \mathbf{1}\{Age_i = [60;69]\}(\Delta_{Apr21,[60;69]} + \delta_{Apr21,[60;69]})$ | $-0.049^{***}$ | $-0.099^{***}$ | $-0.134^{***}$ |
| | (0.012) | (0.012) | (0.017) |
| $After_t \times \mathbf{1}\{Month_t = Apr21\} \times \mathbf{1}\{Age_i = [70;79]\}(\Delta_{Apr21,[70;79]} + \delta_{Apr21,[70;79]})$ | $-0.054^{***}$ | $-0.110^{***}$ | $-0.166^{***}$ |
| | (0.013) | (0.016) | (0.024) |
| Month FE | Yes | Yes | Yes |
| Individual FE | Yes | Yes | Yes |
| Age Group$\times Year_t$ ($\Psi_{it}$) | Yes | Yes | Yes |
| Groups | 25838 | 25556 | 7000 |
| Observations | 1,018,346 | 1,017,717 | 278,939 |
| $R^2$ | 0.607 | 0.536 | 0.537 |
| Adjusted $R^2$ | 0.597 | 0.524 | 0.525 |
| Residual Std. Error | 0.717 | 0.658 | 0.668 |

*Note:* + p<0.1; * p<0.05; ** p<0.01; *** p<0.001
All columns estimated with person fixed effects
Cluster robust standard errors in (); Errors clustered by person

Table 16: Impact of age and comorbidity on consumption expenditures (maps to figure A.7).

| | *Dependent variable:* | |
|---|---|---|
| | $log(Expense_{it})$ | |
| | $Comorbidity = 0$ | $Comorbidity = 1$ |
| | (1) | (2) |
| $After_t \times \mathbf{1}\{Month_t = Mar20\} \times \mathbf{1}\{Age_i = [20;49]\}(\Delta_{Mar20,[20;49]} + \delta_{Mar20,[20;49]})$ | $-0.070^{***}$ | $-0.099^{***}$ |
| | (0.007) | (0.016) |
| $After_t \times \mathbf{1}\{Month_t = Mar20\} \times \mathbf{1}\{Age_i = [50;59]\}(\Delta_{Mar20,[50;59]} + \delta_{Mar20,[50;59]})$ | $-0.070^{***}$ | $-0.072^{***}$ |
| | (0.006) | (0.013) |
| $After_t \times \mathbf{1}\{Month_t = Mar20\} \times \mathbf{1}\{Age_i = [60;69]\}(\Delta_{Mar20,[60;69]} + \delta_{Mar20,[60;69]})$ | $-0.060^{***}$ | $-0.046^{***}$ |
| | (0.005) | (0.012) |
| $After_t \times \mathbf{1}\{Month_t = Mar20\} \times \mathbf{1}\{Age_i = [70;79]\}(\Delta_{Mar20,[70;79]} + \delta_{Mar20,[70;79]})$ | $-0.080^{***}$ | $-0.067^{***}$ |
| | (0.007) | (0.014) |
| $After_t \times \mathbf{1}\{Month_t = Apr20\} \times \mathbf{1}\{Age_i = [20;49]\}(\Delta_{Apr20,[20;49]} + \delta_{Apr20,[20;49]})$ | $-0.255^{***}$ | $-0.332^{***}$ |
| | (0.008) | (0.018) |
| $After_t \times \mathbf{1}\{Month_t = Apr20\} \times \mathbf{1}\{Age_i = [50;59]\}(\Delta_{Apr20,[50;59]} + \delta_{Apr20,[50;59]})$ | $-0.268^{***}$ | $-0.317^{***}$ |
| | (0.006) | (0.014) |
| $After_t \times \mathbf{1}\{Month_t = Apr20\} \times \mathbf{1}\{Age_i = [60;69]\}(\Delta_{Apr20,[60;69]} + \delta_{Apr20,[60;69]})$ | $-0.323^{***}$ | $-0.375^{***}$ |
| | (0.006) | (0.014) |
| $After_t \times \mathbf{1}\{Month_t = Apr20\} \times \mathbf{1}\{Age_i = [70;79]\}(\Delta_{Apr20,[70;79]} + \delta_{Apr20,[70;79]})$ | $-0.381^{***}$ | $-0.403^{***}$ |
| | (0.008) | (0.016) |
| $After_t \times \mathbf{1}\{Month_t = May20\} \times \mathbf{1}\{Age_i = [20;49]\}(\Delta_{May20,[20;49]} + \delta_{May20,[20;49]})$ | $-0.148^{***}$ | $-0.173^{***}$ |
| | (0.008) | (0.018) |
| $After_t \times \mathbf{1}\{Month_t = May20\} \times \mathbf{1}\{Age_i = [50;59]\}(\Delta_{May20,[50;59]} + \delta_{May20,[50;59]})$ | $-0.137^{***}$ | $-0.174^{***}$ |
| | (0.006) | (0.014) |
| $After_t \times \mathbf{1}\{Month_t = May20\} \times \mathbf{1}\{Age_i = [60;69]\}(\Delta_{May20,[60;69]} + \delta_{May20,[60;69]})$ | $-0.160^{***}$ | $-0.206^{***}$ |
| | (0.006) | (0.014) |
| $After_t \times \mathbf{1}\{Month_t = May20\} \times \mathbf{1}\{Age_i = [70;79]\}(\Delta_{May20,[70;79]} + \delta_{May20,[70;79]})$ | $-0.180^{***}$ | $-0.207^{***}$ |
| | (0.007) | (0.015) |
| $After_t \times \mathbf{1}\{Month_t = Jun20\} \times \mathbf{1}\{Age_i = [20;49]\}(\Delta_{Jun20,[20;49]} + \delta_{Jun20,[20;49]})$ | $0.066^{***}$ | $0.042^{*}$ |
| | (0.008) | (0.018) |
| $After_t \times \mathbf{1}\{Month_t = Jun20\} \times \mathbf{1}\{Age_i = [50;59]\}(\Delta_{Jun20,[50;59]} + \delta_{Jun20,[50;59]})$ | $0.052^{***}$ | 0.019 |
| | (0.006) | (0.013) |
| $After_t \times \mathbf{1}\{Month_t = Jun20\} \times \mathbf{1}\{Age_i = [60;69]\}(\Delta_{Jun20,[60;69]} + \delta_{Jun20,[60;69]})$ | $0.025^{***}$ | $-0.024^{+}$ |
| | (0.006) | (0.013) |
| $After_t \times \mathbf{1}\{Month_t = Jun20\} \times \mathbf{1}\{Age_i = [70;79]\}(\Delta_{Jun20,[70;79]} + \delta_{Jun20,[70;79]})$ | $-0.009$ | $-0.025$ |
| | (0.007) | (0.015) |
| $After_t \times \mathbf{1}\{Month_t = Jul20\} \times \mathbf{1}\{Age_i = [20;49]\}(\Delta_{Jul20,[20;49]} + \delta_{Jul20,[20;49]})$ | $0.110^{***}$ | $0.103^{***}$ |
| | (0.009) | (0.020) |
| $After_t \times \mathbf{1}\{Month_t = Jul20\} \times \mathbf{1}\{Age_i = [50;59]\}(\Delta_{Jul20,[50;59]} + \delta_{Jul20,[50;59]})$ | $0.116^{***}$ | $0.091^{***}$ |
| | (0.007) | (0.016) |
| $After_t \times \mathbf{1}\{Month_t = Jul20\} \times \mathbf{1}\{Age_i = [60;69]\}(\Delta_{Jul20,[60;69]} + \delta_{Jul20,[60;69]})$ | $0.082^{***}$ | $0.066^{***}$ |
| | (0.007) | (0.016) |
| $After_t \times \mathbf{1}\{Month_t = Jul20\} \times \mathbf{1}\{Age_i = [70;79]\}(\Delta_{Jul20,[70;79]} + \delta_{Jul20,[70;79]})$ | $0.013^{+}$ | $0.034^{*}$ |
| | (0.008) | (0.016) |
| $After_t \times \mathbf{1}\{Month_t = Aug20\} \times \mathbf{1}\{Age_i = [20;49]\}(\Delta_{Aug20,[20;49]} + \delta_{Aug20,[20;49]})$ | $0.109^{***}$ | $0.137^{***}$ |
| | (0.008) | (0.017) |
| $After_t \times \mathbf{1}\{Month_t = Aug20\} \times \mathbf{1}\{Age_i = [50;59]\}(\Delta_{Aug20,[50;59]} + \delta_{Aug20,[50;59]})$ | $0.108^{***}$ | $0.109^{***}$ |
| | (0.006) | (0.015) |
| $After_t \times \mathbf{1}\{Month_t = Aug20\} \times \mathbf{1}\{Age_i = [60;69]\}(\Delta_{Aug20,[60;69]} + \delta_{Aug20,[60;69]})$ | $0.052^{***}$ | $0.058^{***}$ |
| | (0.006) | (0.014) |
| $After_t \times \mathbf{1}\{Month_t = Aug20\} \times \mathbf{1}\{Age_i = [70;79]\}(\Delta_{Aug20,[70;79]} + \delta_{Aug20,[70;79]})$ | $0.018^{*}$ | $0.039^{*}$ |
| | (0.007) | (0.015) |
| $After_t \times \mathbf{1}\{Month_t = Sep20\} \times \mathbf{1}\{Age_i = [20;49]\}(\Delta_{Sep20,[20;49]} + \delta_{Sep20,[20;49]})$ | $0.098^{***}$ | $0.099^{***}$ |
| | (0.008) | (0.017) |
| $After_t \times \mathbf{1}\{Month_t = Sep20\} \times \mathbf{1}\{Age_i = [50;59]\}(\Delta_{Sep20,[50;59]} + \delta_{Sep20,[50;59]})$ | $0.084^{***}$ | $0.077^{***}$ |
| | (0.006) | (0.014) |
| $After_t \times \mathbf{1}\{Month_t = Sep20\} \times \mathbf{1}\{Age_i = [60;69]\}(\Delta_{Sep20,[60;69]} + \delta_{Sep20,[60;69]})$ | $0.053^{***}$ | $0.039^{**}$ |
| | (0.006) | (0.013) |
| $After_t \times \mathbf{1}\{Month_t = Sep20\} \times \mathbf{1}\{Age_i = [70;79]\}(\Delta_{Sep20,[70;79]} + \delta_{Sep20,[70;79]})$ | $0.045^{***}$ | $0.039^{*}$ |
| | (0.007) | (0.015) |
| $After_t \times \mathbf{1}\{Month_t = Oct20\} \times \mathbf{1}\{Age_i = [20;49]\}(\Delta_{Oct20,[20;49]} + \delta_{Oct20,[20;49]})$ | $-0.023^{**}$ | $-0.010$ |
| | (0.008) | (0.017) |
| $After_t \times \mathbf{1}\{Month_t = Oct20\} \times \mathbf{1}\{Age_i = [50;59]\}(\Delta_{Oct20,[50;59]} + \delta_{Oct20,[50;59]})$ | $-0.016^{*}$ | $-0.021$ |
| | (0.006) | (0.014) |
| $After_t \times \mathbf{1}\{Month_t = Oct20\} \times \mathbf{1}\{Age_i = [60;69]\}(\Delta_{Oct20,[60;69]} + \delta_{Oct20,[60;69]})$ | $-0.033^{***}$ | $-0.035^{**}$ |
| | (0.006) | (0.014) |
| $After_t \times \mathbf{1}\{Month_t = Oct20\} \times \mathbf{1}\{Age_i = [70;79]\}(\Delta_{Oct20,[70;79]} + \delta_{Oct20,[70;79]})$ | $-0.047^{***}$ | $-0.048^{**}$ |
| | (0.008) | (0.015) |
| $After_t \times \mathbf{1}\{Month_t = Nov20\} \times \mathbf{1}\{Age_i = [20;49]\}(\Delta_{Nov20,[20;49]} + \delta_{Nov20,[20;49]})$ | 0.013 | $-0.002$ |
| | (0.008) | (0.017) |
| $After_t \times \mathbf{1}\{Month_t = Nov20\} \times \mathbf{1}\{Age_i = [50;59]\}(\Delta_{Nov20,[50;59]} + \delta_{Nov20,[50;59]})$ | 0.007 | $-0.023$ |
| | (0.006) | (0.014) |
| $After_t \times \mathbf{1}\{Month_t = Nov20\} \times \mathbf{1}\{Age_i = [60;69]\}(\Delta_{Nov20,[60;69]} + \delta_{Nov20,[60;69]})$ | $-0.014^{*}$ | $-0.014$ |
| | (0.006) | (0.014) |
| $After_t \times \mathbf{1}\{Month_t = Nov20\} \times \mathbf{1}\{Age_i = [70;79]\}(\Delta_{Nov20,[70;79]} + \delta_{Nov20,[70;79]})$ | $-0.049^{***}$ | $-0.056^{***}$ |
| | (0.008) | (0.015) |
| $After_t \times \mathbf{1}\{Month_t = Dec20\} \times \mathbf{1}\{Age_i = [20;49]\}(\Delta_{Dec20,[20;49]} + \delta_{Dec20,[20;49]})$ | $-0.067^{***}$ | $-0.053^{**}$ |
| | (0.008) | (0.017) |
| $After_t \times \mathbf{1}\{Month_t = Dec20\} \times \mathbf{1}\{Age_i = [50;59]\}(\Delta_{Dec20,[50;59]} + \delta_{Dec20,[50;59]})$ | $-0.061^{***}$ | $-0.055^{***}$ |
| | (0.007) | (0.015) |
| $After_t \times \mathbf{1}\{Month_t = Dec20\} \times \mathbf{1}\{Age_i = [60;69]\}(\Delta_{Dec20,[60;69]} + \delta_{Dec20,[60;69]})$ | $-0.083^{***}$ | $-0.110^{***}$ |
| | (0.006) | (0.014) |
| $After_t \times \mathbf{1}\{Month_t = Dec20\} \times \mathbf{1}\{Age_i = [70;79]\}(\Delta_{Dec20,[70;79]} + \delta_{Dec20,[70;79]})$ | $-0.121^{***}$ | $-0.165^{***}$ |
| | (0.008) | (0.016) |
| Month FE | Yes | Yes |
| Individual FE | Yes | Yes |
| Age Group$\times Year_t$ ($\Psi_{it}$) | Yes | Yes |
| Income Group $\times Year_t$ ($\Psi_{it}$) | Yes | Yes |
| Age Group $\times$ Income Group $\times Year_t$ ($\Psi_{it}$) | Yes | Yes |
| Observations | 1,972,669 | 342,333 |
| $R^2$ | 0.631 | 0.568 |
| Adjusted $R^2$ | 0.621 | 0.557 |
| Residual Std. Error | 0.696 | 0.635 |

*Note:* + p<0.1; * p<0.05; ** p<0.01; *** p<0.001
Cluster robust standard errors in (); Errors clustered by person

# B Appendix B: partial-equilibrium model

In this appendix, we display the value functions of people of different ages and health statuses and our method for computing the aggregate consumption of young and old.

## B.1 Value functions

The value function of a susceptible young person at time $t$ is[B.2]

$$\begin{aligned} U_{y,t}^{s}(b_t) &= \max_{c_{y,t}^{s},b_{t+1}} \Big\{ z + \{(1-\beta)((1-\mu_t)c_{y,t}^{s})^{1-\rho} + \beta[(1-\tau_{y,t})\,(1-\delta_y - v)\left(U_{y,t+1}^{s}(b_{t+1})\right)^{(1-\alpha)} + \\ &\quad (1-\tau_{y,t})\,v\left(U_{o,t+1}^{s}(b_{t+1})\right)^{(1-\alpha)} + \tau_{y,t}(1-\delta_y - v)\left(U_{y,t+1}^{i}(b_{t+1})\right)^{(1-\alpha)} + \\ &\quad \tau_{y,t}v\left(U_{o,t+1}^{i}(b_{t+1})\right)^{1-\alpha} + \delta_y B(b_{t+1})^{1-\alpha}]^{(1-\rho)/(1-\alpha)}\}^{1/(1-\rho)} \Big\}. \end{aligned}$$

The value function of an old, susceptible person at time $t$, $U_{o,t}^{s}(b_t)$, is

$$\begin{aligned} U_{o,t}^{s}(b_t) &= \max_{c_{o,t}^{s},b_{t+1}} \Big\{ z + \{(1-\beta)((1-\mu_t)c_{o,t}^{s})^{1-\rho} + \beta[(1-\tau_{o,t})(1-\delta_o)\left(U_{o,t+1}^{s}(b_{t+1})\right)^{1-\alpha} \\ &\quad +\tau_{o,t}(1-\delta_o)\left(U_{o,t+1}^{i}(b_{t+1})\right)^{1-\alpha} + \delta_o B(b_{t+1})^{1-\alpha}]^{(1-\rho)/(1-\alpha)}\}^{1/(1-\rho)} \Big\}. \end{aligned}$$

With probability $\delta_o$ the person dies of non-Covid causes. With probability $(1-\tau_{o,t})(1-\delta_o)$, this person survives and does not get infected, remaining a susceptible old person. With probability $\tau_{o,t}(1-\delta_o)$, the person survives but gets infected, becoming an infected old person.

The value function of a young, infected person at time $t$, $U_{y,t}^{i}(b_t)$, is

$$\begin{aligned} U_{y,t}^{i}(b_t) &= \max_{c_{y,t}^{i},b_{t+1}} \Big\{ z + \{(1-\beta)((1-\mu_t)c_{y,t}^{i})^{1-\rho} + \beta[(1-\pi_{yr,t}-\pi_{yd,t})(1-\delta_y - v)\left(U_{y,t+1}^{i}(b_{t+1})\right)^{1-\alpha} \\ &\quad +(1-\pi_{yr,t}-\pi_{yd,t})v\left(U_{o,t+1}^{i}(b_{t+1})\right)^{1-\alpha} + \pi_{yr,t}(1-\delta_y - v)\left(U_{y,t+1}^{r}(b_{t+1})\right)^{1-\alpha} \\ &\quad +\pi_{yr,t}v\left(U_{o,t+1}^{r}(b_{t+1})\right)^{1-\alpha} + [\delta_y + \pi_{yd,t}(1-\delta_y)]B(b_{t+1})^{1-\alpha}]^{(1-\rho)/(1-\alpha)}\}^{1/(1-\rho)} \Big\}. \end{aligned}$$

A person who is young and infected at time $t$ remains in that state at time $t+1$ with subjective probability $(1-\pi_{yr,t}-\pi_{yd,t})(1-\delta_y-v)$, remains infected and becomes old with subjective probability $(1-\pi_{yr,t}-\pi_{yd,t})v$, recovers and stays young with probability $\pi_{yr,t}(1-\delta_y-v)$, recovers and ages with probability $\tau_{y,t}v$, and dies of non-Covid causes with probability $\delta_y$.

[B.2] This formulation and the others below involve a slight abuse of notation. The perceived value function $U_{a,t+1}^{h}$ is computed at time $t$ assuming that $\pi_{ad,t+j} = \pi_{ad,t}$ for all $j$. The realized value function at time $t+1$, is computed assuming that $\pi_{ad,t+1+j} = \pi_{ad,t+1}$ for all $j$. Our notation does not distinguish between these two types of value functions. In solving the model, we do take into account this distinction.

The value function of an old infected person at time $t$, $U^i_{o,t}(b_t)$, is

$$\begin{aligned} U^i_{o,t}(b_t) &= \max_{c^i_{o,t},b_{t+1}} \Big\{ z + \{(1-\beta)((1-\mu_t)c^i_{o,t})^{1-\rho} + \beta[(1-\pi_{or,t}-\pi_{od,t})(1-\delta_o)\left(U^i_{o,t+1}(b_{t+1})\right)^{1-\alpha} \\ &\quad +\pi_{or,t}(1-\delta_o)\left(U^r_{o,t+1}(b_{t+1})\right)^{1-\alpha} + [\delta_o + \pi_{od,t}(1-\delta_o)]B(b_{t+1})^{1-\alpha}]^{(1-\rho)/(1-\alpha)}\}^{1/(1-\rho)} \Big\}. \end{aligned}$$

A person who is old and infected at time $t$ remains in that state at time $t+1$ with subjective probability $(1-\pi_{or,t}-\pi_{od,t})(1-\delta_o)$, recovers with probability $\pi_{or,t}(1-\delta_o)$, dies of Covid with probability $(1-\delta_0)\pi_{od,t}$, and dies of non-Covid causes with probability $\delta_o$.

The value function of a young recovered person at time $t$, $U^r_{y,t}(b_t)$, is

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

This person is immune from the virus but still faces two sources of uncertainty: aging with probability $v$ and dying from non-viral causes with probability $\delta_y$.

The value function of an old recovered person at time $t$, $U^r_{o,t}(b_t)$, is

$$U^r_{o,t}(b_t) = \max_{c^r_{o,t},b_{t+1}} \left\{ \begin{array}{c} z + \{(1-\beta)((1-\mu_t)c^r_{o,t})^{1-\rho} \\ +\beta[(1-\delta_o)\left(U^r_{o,t+1}(b_{t+1})\right)^{1-\alpha} + \delta_o B(b_{t+1})^{1-\alpha}]^{(1-\rho)/(1-\alpha)}\}^{1/(1-\rho)} \end{array} \right\}.$$

This person faces only one source of uncertainty, which is dying of non-Covid causes with probability $\delta_o$.

The result of the maximization problems is a set of policy functions of the form $c^h_{a,t}(b)$. To compare the model implications with the data, we need to compute per capita consumption for young ($C_{yt}$) and old ($C_{ot}$). These variables are given by:

$$C_{yt} = \frac{S_{yt}\int c^s_{yt}(b)f^s_{yt}(b)db + I_{yt}\int c^i_{yt}(b)f^i_{yt}(b)db + R_{yt}\int c^r_{yt}(b)f^r_{yt}(b)db}{S_{yt}+I_{yt}+R_{yt}},$$

and

$$C_{ot} = \frac{S_{ot}\int c^s_{yt}(b)f^s_{ot}(b)db + I_{ot}\int c^i_{ot}(b)f^i_{ot}(b)db + R_{ot}\int c^r_{ot}(b)f^r_{ot}(b)db}{S_{ot}+I_{ot}+R_{ot}},$$

where $f^h_{at}(b)$ is the distribution assets at time $t$ among people with age $a$ and health status $h$.

We first solve for the value functions $\bar{U}^h_{a,t}$ for a version of the model with no infections ($I_{yt} = I_{ot} = 0$). As an approximation, we assume that infections are zero at the end of our sample. We use $\bar{U}^h_{a,t}$ as the value functions at the end of our sample and recurse backward. At each point in time, we calculate the value functions conditional on the number of infections inferred from the data. For further details on the computation methods, please consult the replication materials on the authors' websites.

## B.2 Computing consumption per capita in partial equilibrium model

To compare the model's implications with the data, we need to compute per capita consumption for the young ($C_{yt}$) and old ($C_{ot}$). These variables are given by:

$$C_{yt} = \frac{S_{yt} \int c^s_{yt}(b) f^s_{yt}(b) db + I_{yt} \int c^i_{yt}(b) f^i_{yt}(b) db + R_{yt} \int c^r_{yt}(b) f^r_{yt}(b) db}{S_{yt} + I_{yt} + R_{yt}}, \tag{B.3}$$

and

$$C_{ot} = \frac{S_{ot} \int c^s_{yt}(b) f^s_{ot}(b) db + I_{ot} \int c^i_{ot}(b) f^i_{ot}(b) db + R_{ot} \int c^r_{ot}(b) f^r_{ot}(b) db}{S_{ot} + I_{ot} + R_{ot}}. \tag{B.4}$$

To calculate $C_{yt}$ and $C_{ot}$ we need to compute the distributions of assets at time $t$ for people with different ages and health statuses. Characterizing these distributions is feasible but computationally very intensive because asset holdings depend on people's health histories (whether and when they became infected or recovered). As time passes, the number of possible health histories increases dramatically, creating substantial heterogeneity. However, because the three epidemic waves occur over roughly one year, and people can borrow and lend at a fixed interest rate, the asset heterogeneity generated by different health histories is, in practice, quantitatively small.

To estimate the model, we have to solve it numerous times. To make estimation computationally feasible, we use the consumption of a person whose health status remained constant (as susceptible, infected, or recovered) over time to approximate the values of $\int c^s_{yt}(b) f^s_{yt}(b) db$, $\int c^i_{yt}(b) f^i_{yt}(b) db$, and $\int c^r_{yt}(b) f^r_{yt}(b) db$. To show that people with the same current health status but different health histories have very similar consumption, we proceed as follows. We compare the consumption of a person who is infected at time zero and remains infected with a person infected at time $t$. The maximum absolute difference between the consumption of these two people is roughly six euros for young and five euros for old. We also compare the consumption of a person who recovers at time zero with a person who is infected at time $t$ and recovers two weeks later. The maximum absolute difference between the consumption of these two people is roughly nine euros for young and ten euros for old. Since most people in the economy are susceptible and do not change their health status, the effect of our approximation on $C_{yt}$ and $C_{ot}$ is very small, less than two euros according to our calculations.

The equations we use to compute the values of $S_{at}$, $I_{at}$, and $R_{at}$ (for $a = y, o$) are as follows. To simplify, we split the total number of infections observed in the data between young and old according to their population shares, $share_{y,t}$ and $share_{o,t}$:

$$I_{yt} = share_{y,t} I_t,$$

$$I_{ot} = share_{o,t} I_t.$$

The aggregate case fatality rate is

$$\pi^*_{d,t} = share_{y,t}\pi^*_{yd,t} + share_{o,t}\pi^*_{od,t}.$$

Let $D^{covid}_t$ denote cumulative Covid deaths up to time $t$. In period $t+1$ we observe new Covid deaths $(D^{covid}_{t+1} - D^{covid}_t)$. Using these data, we compute the total number of infected people in the economy as:

$$I_t = \frac{D^{covid}_{t+1} - D^{covid}_t}{\pi^*_{d,t}}.$$

Since our sample period is roughly one year, we assume for simplicity that $s_{y,t}$ and $s_{o,t}$ are constant and equal to their values at the beginning of the sample.

Using the fact that $R_{y,0} = R_{o,0} = D^{covid}_{y,0} = D^{covid}_{o,0} = 0$, we compute $R_{y,t+1}$, $R_{o,t+1}$, $D^{covid}_{y,t+1}$, $D^{covid}_{o,t+1}$ recursively as follows:

$$R_{y,t+1} = R_{y,t}(1 - \delta_y - v) + I_{y,t}\pi^*_{yr}(1 - \delta_y - v),$$

$$R_{o,t+1} = R_{o,t}(1 - \delta_o) + R_{y,t}v + I_{y,t}\pi^*_{yr}v + I_{o,t}\pi^*_{or,t}(1 - \delta_o),$$

$$D^{covid}_{y,t+1} = D^{covid}_{y,t} + \pi^*_{yd,t} I_{y,t},$$

$$D^{covid}_{o,t+1} = D^{covid}_{o,t} + \pi^*_{od,t} I_{o,t}.$$

Finally, we compute the number of young and old susceptible people as a residual

$$S_{yt} = share_{y,t} - I_{y,t} - R_{y,t} - D^{covid}_{y,t},$$

$$S_{ot} = share_{o,t} - I_{o,t} - R_{o,t} - D^{covid}_{o,t}.$$

## B.3 Equivalence between two ways of modeling containment

In this subsection, we consider two models. In both models, there is containment in period one. In the first model, households cannot consume a fraction $1 - n$ of the goods in period one because of containment measures. In the second model, containment takes the form of a wedge in the utility function that reduces the utility of consumption in period one. We show, in a simple setting, that these two ways of modeling containment are equivalent.

**Model where some goods cannot be consumed in period one** Consider a simple two-period problem where the objective is to maximize,

$$U = \log(C_1) + \beta \log(C_2),$$

Consumption is given by a continuum of differentiated goods combined according to a Dixit-Stiglitz aggregator,

$$C_t = \left( \int_0^{n_t} x_{it}^{\alpha} di \right)^{1/\alpha},$$

where $\alpha < 1$. The household's budget constraint is

$$\int_0^{n_1} p_{i1} x_{i1} di + (1+r)^{-1} \int_0^1 p_{i2} x_{i2} di = Y,$$

where $Y$ denotes household income. In period 1, there is containment, so households can only consume the first $n_1 < 1$ goods. There is no containment in period 2, so $n_2 = 1$.

To simplify, we assume that $\beta = (1+r)^{-1}$ and that

$$p_{i1} = p_{i2} = p.$$

In this case,

$$C_1 = {n_1}^{1/\alpha} x_1$$

$$C_2 = x_2$$

We can rewrite the utility function as,

$$U = \log\left(n_1^{1/\alpha} x_1\right) + \beta \log(x_2),$$

and the budget constraint as,

$$n_1 p x_1 + (1+r)^{-1} p x_2 = Y.$$

The first-order conditions for $x_1$ and $x_2$ are

$$x_1^{-1} = \lambda n_1 p,$$

$$\beta x_2^{-1} = \lambda (1+r)^{-1} p,$$

where $\lambda$ is the Lagrange multiplier associated with the budget constraint.

Combining,

$$\frac{x_2}{x_1} = n_1$$

Using the budget constraint, we obtain,

$$x_1 = \frac{1}{1+(1+r)^{-1}} \frac{Y}{n_1 p},$$

$$x_2 = \frac{1}{1+(1+r)^{-1}} \frac{Y}{p},$$

$$\frac{C_2}{C_1} = n_1^{1-1/\alpha}.$$

**Model with a wedge in utility** The objective is to maximize

$$U = (1-\mu)\log(C_1) + \beta\log(C_2),$$

subject to the budget constraint

$$C_1 + (1+r)^{-1} C_2 = Y.$$

The first-order conditions are

$$\frac{1-\mu}{C_1} = \lambda,$$

$$\beta\frac{1}{C_2} = \lambda(1+r)^{-1}.$$

Combining these two equations,

$$\frac{C_2}{C_1} = \frac{1}{1-\mu}.$$

For each value of $n$ in the first economy, we can always choose a wedge $\mu$ in the second economy such that households choose the same consumption in the two economies,

$$(1-\mu)^{-1} = n_1^{1-1/\alpha}.$$

We can rewrite this expression as,

$$\mu = 1 - n_1^{1/\alpha - 1} > 0.$$

The smaller is $n$, the fraction of goods that can be consumed in the first economy, the larger is $\mu$, the utility wedge in the second economy. These results can easily be generalized to other environments.

## B.4 Calibration of case-fatality rates

Sorensen et al. (2022) estimate the population-wide time trend in the infection-fatality rate from April 2020 to January 2021 for Portugal. According to Table 2 (page 1479) in Sorensen et al. (2022), the point estimates for the infection fatality rates on April 15, 2020, July 15, 2020, October 15, 2020, and January 1, 2021, are 2.683%, 2.085%, 1.805% and 1.708%, respectively. We discuss below how we convert infection-fatality rates into case-fatality rates.

Given that our sample ranges from March 1, 2020 through May 15, 2021, we assume that the infection-fatality rate on March 1 is the same as on April 15, 2020, i.e., 2.683%. Likewise, we assume that the infection-fatality rate after May 15, 2021 (the last date of our sample) is the same as on January 1, 2021, i.e., 1.708%.

We assume that the weekly time profile of the infection-fatality rates is flat, i.e., the infection-fatality rates decline stepwise over time with discrete steps at the above dates. We normalize the resulting time series of the infection fatality rates by its value on July 26, 2020. The resulting time series has the value of unity on July 26, a value of 1.2868 on March 1, 2020, and a value of 0.8192 on May 15, 2021, with discrete stepwise declines at the dates listed above and flat time profiles in between the dates listed above.

Note that $100 \times (1 - 0.8192/1.2868) = 36.3382$ implies that the infection fatality rate on May 15, 2021, is about 36% lower than on March 1, 2020. Finally, we multiply the normalized time series for infection fatality rates from Sorensen et al. (2022) with the July 26, 2020 estimates of the case-fatality rates for young and old $\pi^*_{yd}$ and $\pi^*_{od}$. This calculation results in time series for $\pi^*_{yd,t}$ and $\pi^*_{od,t}$ that have a downward trend (with stepwise declines at the dates listed above and flat time profiles in between the dates). The blue-dashed lines in Figure 7 show the resulting time series for $\pi^*_{yd,t}$ and $\pi^*_{od,t}$. Finally, we assume that the values of $\pi^*_{yd,t}$ and $\pi^*_{od,t}$ are such that, on average, infected people recover or die in two weeks ($\pi^*_{or,t} + \pi^*_{od,t} = \pi^*_{yr,t} + \pi^*_{yd,t} = 7/14$). We make the same assumption for the beliefs of case-fatality rates, i.e., $\pi_{or,t} + \pi_{od,t} = \pi_{yr,t} + \pi_{yd,t} = 7/14$.

## B.5 Perfect foresight solution

This figure corresponds to a version of the model in which people know about the second and third waves at the beginning of the epidemic.

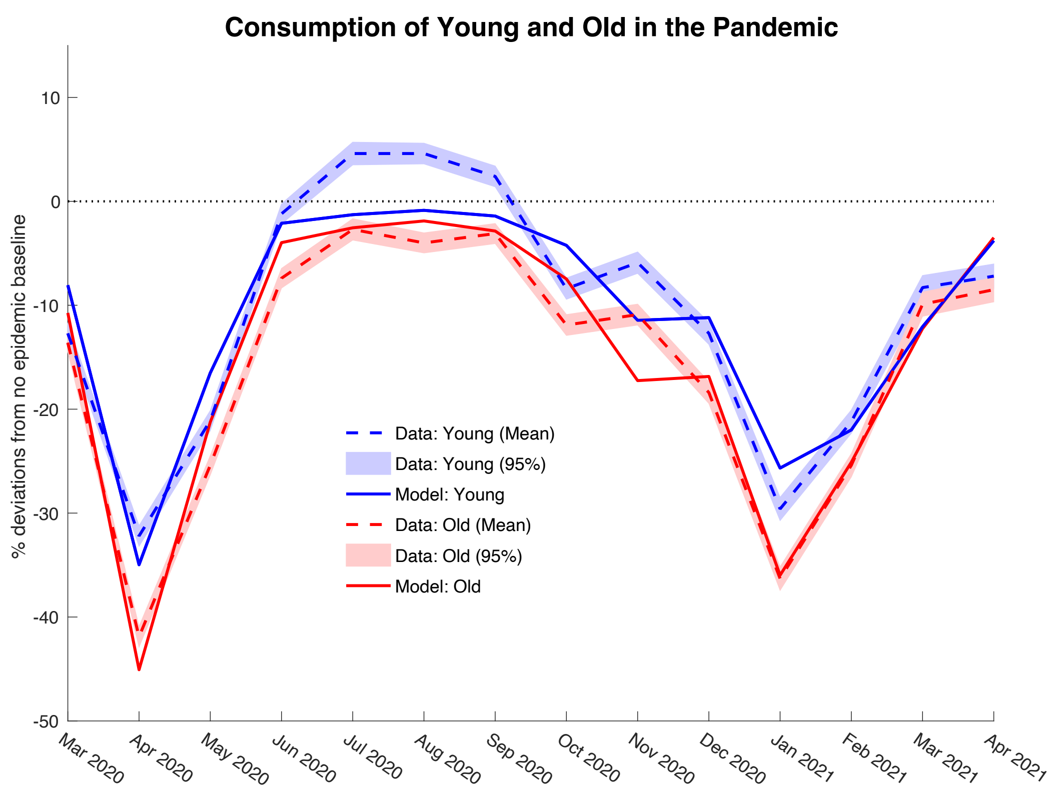


Figure B.8: Perfect foresight solution.

## B.6 Gauging the effect of alpha variant

The figure below illustrates the impact of assuming that the alpha variant was fifty percent more contagious than the ancestral Covid virus. This variant was detected in Portugal in the week of December 7, 2020, so we assume that $\pi_1$ and $\pi_2$ increase by 50 percent from that week on.

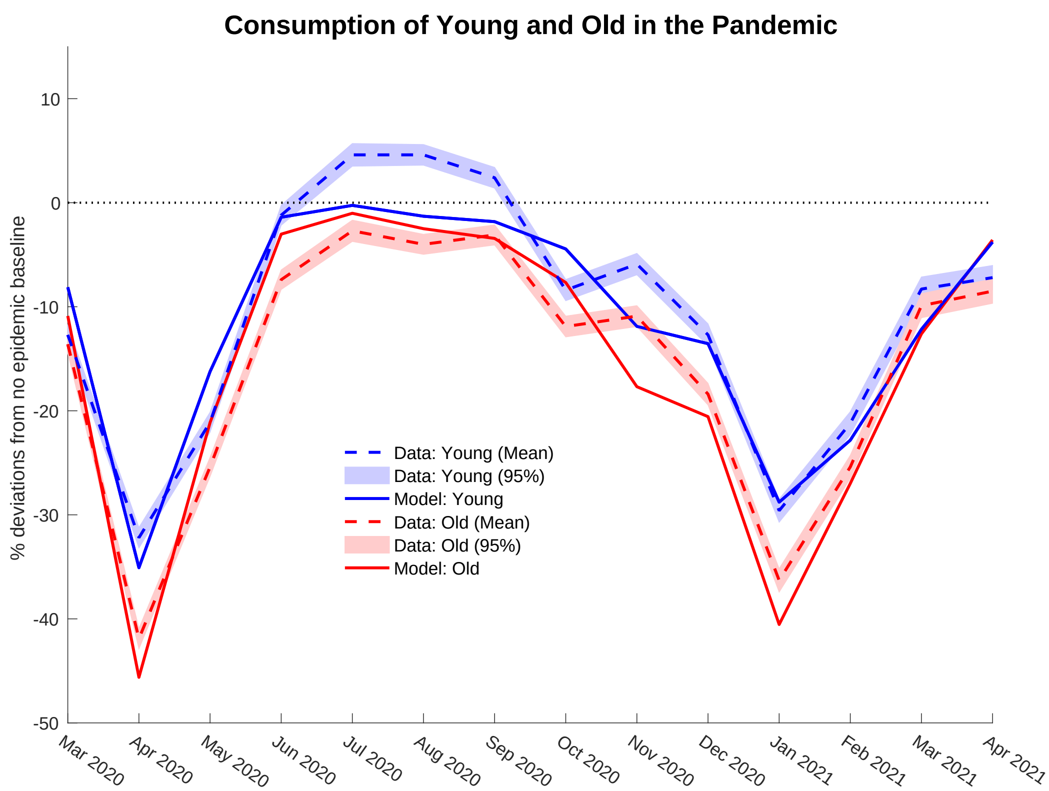


Figure B.9: Higher infectiousness starting in the week of December 6, 2020.

## B.7 Model with constant case-fatality rate

The figure below shows results for a version of the model in which the true case-fatality rates are constant over time.

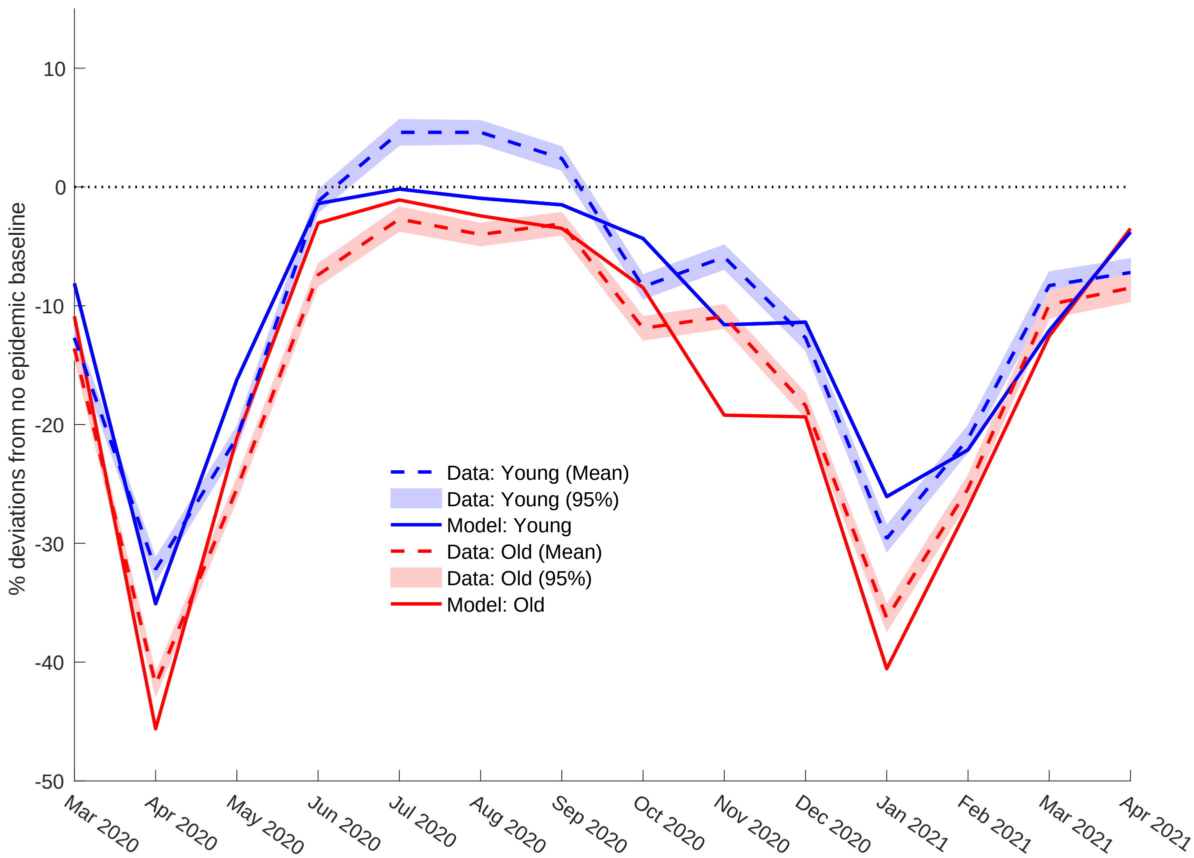


Figure B.10: Consumption of young and old in the epidemic. Model with constant case fatality rates and data implications for changes in expenditures of young and old during the epidemic relative to a counterfactual without Covid.

# C Appendix C: Model of endemic Covid

In this appendix, we first describe the model of endemic Covid. Then we discuss the computational algorithm and the model parameterization.

## C.1 Model

In our partial-equilibrium analysis, we abstract from births because we focus on a short period. Here we study steady-state properties, so we modify the model to ensure that the total population and the shares of younger and older people are constant. We assume that in each period $\mathfrak{B}_{y,t}$ young people without comorbidities are born. In addition, $\mathfrak{B}_{o,t}$ people are born with comorbidities.

The number of newly infected people with age $a$ is given by the following transmission function

$$T_{a,t} = \pi_1 S_{a,t}(1-\phi_a)C^s_{a,t}(I_{y,t}C^i_{y,t} + I_{o,t}C^i_{o,t}) + \pi_2 S_{a,t}(1-\phi_a)N^s_{a,t}(I_{y,t}N^i_{y,t} + I_{o,t}N^i_{o,t}) \quad \text{(C.5)}$$
$$+\pi_3 S_{a,t}(1-\phi_a)\left(I_{y,t} + I_{o,t}\right).$$

The variables $C^s_{a,t}$ and $C^i_{a,t}$ represent the consumption of susceptible and infected people of age $a$, respectively. The variables $N^s_t$ and $N^i_t$ represent the total hours worked by susceptible and infected people of age $a$, respectively. Susceptible people of age $a$ are vaccinated with probability $\phi_a$. Susceptible people who are vaccinated acquire immunity to the virus without becoming infected. Critically, we assume that both people who have been vaccinated and have acquired immunity by becoming infected lose, on average, their immunity after $1/\pi_s$ weeks, becoming susceptible again.

The number of newly infected people with age $a$ that results from consumption-related interactions is given by $\pi_1 S_{a,t}(1-\phi_a)C^s_{a,t}(I_{y,t}C^i_{y,t} + I_{o,t}C^i_{o,t})$. The term $S_{a,t}(1-\phi_a)C^s_{a,t}$ is the total consumption of susceptible people with age $a$ who have not been vaccinated. The term $I_{y,t}C^i_{y,t} + I_{o,t}C^i_{o,t}$ represents total consumption of infected people. The parameter $\pi_1$ reflects both the amount of time spent in consumption activities and the probability of becoming infected due to those activities.

The number of newly infected people that results from interactions at work is given by $\pi_2 S_{a,t}(1-\phi_a)N^s_{a,t}(I_{y,t}N^i_{y,t} + I_{o,t}N^i_{o,t})$. The term $S_{a,t}(1-\phi_a)N^s_{a,t}$ is the total hours worked by susceptible people with age $a$ who have not been vaccinated. The term $I_{y,t}N^i_{y,t} + I_{o,t}N^i_{o,t}$ represents total hours worked by infected people. The parameter $\pi_2$ reflects the probability of infection due to work interactions.

Susceptible and infected people can meet in ways unrelated to consuming or working. The number of random meetings between susceptible people with age $a$ who have not been vaccinated and infected people is $S_{a,t}(1-\phi_a)\left(I_{y,t} + I_{o,t}\right)$. These meetings result in $\pi_3 S_{a,t}(1-\phi_a)\left(I_{y,t} + I_{o,t}\right)$ newly infected people with age $a$.

The timing is as follows. The changes in health status caused by the epidemic occur at the beginning of the period. Aging and natural death occur at the end of the period.

The number of young and old susceptible people at time $t+1$ is given by:

$$S_{y,t+1} = [S_{y,t}(1-\phi_y) - T_{y,t}](1-\delta_y - v) + \pi_s R_{y,t} + \mathfrak{B}_{y,t}, \quad \text{(C.6)}$$

$$S_{o,t+1} = [S_{o,t}(1-\phi_o) - T_{o,t}](1-\delta_o) + [S_{y,t}(1-\phi_y) - T_{y,t}]v + \pi_s R_{o,t} + \mathfrak{B}_{o,t}. \quad \text{(C.7)}$$

The number of young and old infected people at time $t+1$ is given by:

$$I_{y,t+1} = I_{y,t}(1 - \pi_{yr} - \pi^*_{yd})(1 - \delta_y - v) + T_{y,t}(1 - \delta_y - v), \tag{C.8}$$

$$I_{o,t+1} = I_{o,t}(1 - \pi_{or} - \pi^*_{od})(1 - \delta_o) + T_{y,t}v + T_{o,t}(1 - \delta_o) + I_{y,t}(1 - \pi_{yr} - \pi^*_{yd})v. \tag{C.9}$$

The number of young and old recovered people at time $t+1$ is given by:

$$R_{y,t+1} = R_{y,t}(1 - \delta_y - v - \pi_s) + \phi_y S_{y,t}(1 - \delta_y - v) + I_{y,t}\pi_{yr}(1 - \delta_y - v), \tag{C.10}$$

$$R_{o,t+1} = R_{o,t}(1 - \delta_o - \pi_s) + \phi_o S_{o,t}(1 - \delta_o) + v\phi_y S_{y,t} + R_{y,t}v + I_{y,t}\pi_{yr}v + I_{o,t}\pi_{or}(1 - \delta_o). \tag{C.11}$$

New deaths at the end of period $t$ are given by

$$D_{y,t+1} - D_{y,t} = I_{y,t}\pi^*_{yd} - \pi^*_{yd}vI_{y,t} + \delta_y[S_{y,t} + I_{y,t}(1 - \pi^*_{yd}) + R_{y,t}],$$

$$D_{o,t+1} - D_{o,t} = \delta_o S_{o,t} + \delta_o I_{o,t}(1 - \pi^*_{od}) + \pi^*_{od}I_{o,t} + \delta_o R_{o,t} + I_{y,t}\pi^*_{yd}v.$$

The number of births that keeps the population constant is

$$\mathfrak{B}_{y,t} = D_{y,t+1} - D_{y,t},$$

$$\mathfrak{B}_{o,t} = D_{o,t+1} - D_{o,t}.$$

### C.1.1 The household problem

For tractability, we assume that people are organized into households, each with a continuum of identical members. This household structure introduces limited sharing of health risks. Without the household structure, the asset holdings of a person would depend on how long they had a particular health status. As time goes by, we would have to keep track of an increasing number of types of people.

At time zero, a household has a continuum of measure one of family members. The law of large numbers applies and has two implications. First, the demographic composition of the household is the same as the composition of the population, i.e., it includes the same fraction of people of different ages and health statuses. Second, the household problem is deterministic.

We modify the utility specification in Section 6 to allow for endogenous labor supply. The household's lifetime utility is given by

$$U_t = z + m_t + \beta \left(E_t U_{t+1}^{1-\alpha}\right)^{1/(1-\alpha)}, \tag{C.12}$$

where $m_t$ is a weighted average of the momentary utility of the household members:

$$m_t = \sum_{a \in \{o,y\}} [s_{a,t} u(c^s_{a,t}, n^s_{a,t}) + i_{a,t} u(c^i_{a,t}, n^i_{a,t}) + r_{a,t} u(c^r_{a,t}, n^r_{a,t})].$$

The variables $s_{a,t}$, $i_{a,t}$, and $r_{a,t}$ denote the number of family members with age $a$ who are susceptible, infected, and recovered, respectively. The variables $c^h_{a,t}$ and $n^h_{a,t}$ denote the consumption and hours worked by people with age $a$ and health status $h$, respectively. The utility function of a person with age $a$ and health status $h$ is

$$u(c^h_{a,t}, n^h_{a,t}) = \frac{\left(c^h_{a,t}\right)^{1-\rho} - 1}{1-\rho} - \frac{\theta}{2} \left(n^h_{a,t}\right)^2 .$$

Since the household faces no uncertainty, $U_{t+1} = \left(E_t U^{1-\alpha}_{t+1}\right)^{1/(1-\alpha)}$, and we can rewrite household utility as

$$U_t = z + m_t + \beta U_{t+1}.$$

The household budget constraint is given by

$$\sum_{a \in \{o,y\}} (s_{a,t} c^s_{a,t} + i_{a,t} c^i_{a,t} + r_{a,t} c^r_{a,t}) + k_{t+1} - (1-\delta_k) k_t = w_t \sum_{a \in \{o,y\}} (s_{a,t} n^s_{a,t} + i_{a,t} n^i_{a,t} + r_{a,t} n^r_{a,t}) + R^k_t k_t. \tag{C.13}$$

Here, $k_t$ denotes the stock of capital, $\delta_k$ the depreciation rate, $w_t$ the real wage rate, and $R^k_t$ the real rental rate of capital.

The number of newly infected people of age $a$ is given by:

$$\begin{aligned} \tau_{a,t} &= \pi_1 s_{a,t}(1-\phi_a) c^s_{a,t} (I_{y,t} C^i_{y,t} + I_{o,t} C^i_{o,t}) + \pi_2 s_{a,t}(1-\phi_a) n^s_{a,t} (I_{y,t} N^i_{y,t} + I_{o,t} N^i_{o,t}) \qquad (C.14) \\ &\quad + \pi_3 s_{a,t} (1-\phi_a) \left(I_{y,t} + I_{o,t}\right). \end{aligned}$$

The household can affect $\tau_{a,t}$ through its choice of $c^s_{a,t}$ and $n^s_{a,t}$. However, the household takes economy-wide aggregates $I_{y,t} C^i_{y,t} + I_{o,t} C^i_{o,t}$, and $I_{y,t} N^i_{y,t} + I_{o,t} N^i_{o,t}$ as given, i.e., it does not internalize the impact of its choices on economy-wide infection rates.

To simplify, we assume that a fraction $\phi_o$ of old susceptibles and a fraction $\phi_y$ of young susceptibles get vaccinated. The fraction of the initial family that is susceptible, infected, and recovered at time $t+1$ is given by:

$$s_{y,t+1} = [s_{y,t}(1-\phi_y) - \tau_{y,t}](1 - \delta_y - \upsilon) + \pi_s r_{y,t} + \mathfrak{b}_{y,t}, \tag{C.15}$$

$$s_{o,t+1} = [s_{o,t}(1-\phi_o) - \tau_{o,t}](1 - \delta_o) + [s_{y,t}(1-\phi_y) - \tau_{y,t}]\upsilon + \pi_s r_{o,t} + \mathfrak{b}_{o,t}, \tag{C.16}$$

$$i_{y,t+1} = i_{y,t}(1 - \pi_{yr} - \pi^*_{yd})(1 - \delta_y - v) + \tau_{y,t}(1 - \delta_y - v), \tag{C.17}$$

$$i_{o,t+1} = i_{o,t}(1 - \pi_{or} - \pi^*_{od})(1 - \delta_o) + \tau_{y,t}v + \tau_{o,t}(1 - \delta_o) + i_{y,t}(1 - \pi_{yr} - \pi^*_{yd})v, \tag{C.18}$$

$$r_{y,t+1} = r_{y,t}(1 - \delta_y - v - \pi_s) + \phi_y s_{y,t}(1 - \delta_y - v) + i_{y,t}\pi_{yr}(1 - \delta_y - v), \tag{C.19}$$

$$r_{o,t+1} = r_{o,t}(1 - \delta_o - \pi_s) + s_{o,t}\phi_o(1 - \delta_o) + v\phi_y s_{y,t} + r_{y,t}v + i_{y,t}\pi_{yr}v + i_{o,t}\pi_{or}(1 - \delta_o). \tag{C.20}$$

The household maximizes (C.12) subject to the budget constraint (C.13) and to the laws of motion for the health status of family members (equations (C.14)-(C.20)).

### C.1.2 The firms' problem

Output is produced by a continuum of measure one of competitive firms, each of whom produces the final good with a Cobb-Douglas production function that combines capital ($K_t$) and labor ($N_t$). Firms maximize their profits, given by

$$\pi = AK_t^{1-\gamma}N_t^{\gamma} - R_t^k K_t - w_t N_t.$$

The first-order conditions for the firm's problem are:

$$(1-\gamma)AK_t^{-\gamma}N_t^{\gamma} = R_t^k,$$

$$\gamma AK_t^{1-\gamma}N_t^{\gamma-1} = w_t.$$

### C.1.3 Equilibrium in goods and factor markets

In equilibrium, households and firms solve their maximization problems and the market for consumption, hours worked, and output clear,

$$\begin{aligned} C_t &= \sum_{a\in\{o,y\}} \left[S_{a,t}C^s_{a,t} + I_{a,t}C^i_{a,t} + R_{a,t}C^r_{a,t}\right], \\ N_t &= \sum_{a\in\{o,y\}} \left[S_{a,t}N^s_{a,t} + I_{a,t}N^i_{a,t} + R_{a,t}N^r_{a,t}\right], \\ C_t + K_{t+1} &= AK_t^{1-\gamma}N_t^{\gamma} + (1-\delta_k)K_t. \end{aligned}$$

The fraction of people in the family with age $a$ who are susceptible, infected and recovered is the same as the corresponding fraction in the population:

$$s_{a,t} = S_{a,t},\ i_{a,t} = I_{a,t},\ \text{and}\ r_{a,t} = R_{a,t}.$$

The market for physical capital clears

$$K_t = k_t.$$

### C.1.4 Calibration of endemic Covid model

With one exception, parameters common to the partial- and general-equilibrium model are set to the values discussed in Section 6.1. The exception is $z$, the constant in the utility function. This parameter is reset to $-1.125$ so that, as in our partial-equilibrium model, the value of life in a pre-epidemic steady state is roughly 900 thousand euros.

Moving to general equilibrium introduces a new set of parameters that we must calibrate. We set $\gamma = 2/3$, which is consistent with recent estimates by Lopes et al. (2021) of the labor share inclusive of the income received by self-employed workers attributable to labor. The weekly rate of capital depreciation $\delta_k$ is $0.1/52$.

Consistent with our estimates in Section (7), we set $\pi_1$ so that the fraction of infections in the pre-epidemic steady state due to consumption is 4.6 percent. We set $\pi_2$ so that the fraction of infections in the pre-epidemic steady state due to work activities is also 4.6 percent. We set $\pi_3$ so that the basic reproduction rate, $\mathcal{R}_0$, is 2.5. Recall that this estimate of $\mathcal{R}_0$ is close to the one that the Center for Disease Control prefers. The resulting parameter values are $\pi_1 = 7.8210 \times 10^{-7}$, $\pi_2 = 7.3822 \times 10^{-5}$ and $\pi_3 = 1.1342$. We choose $\pi_s = 1/26$, which is consistent with the notion that immunity lasts, on average, for six months.

Recall that the weekly probabilities of dying once infected ($\pi^*_{od,t}$ and $\pi^*_{yd,t}$) decline over time, consistent with the time trend in Sorensen et al. (2022). We choose the values of $\pi^*_{od,t}$ and $\pi^*_{yd,t}$ equal to those obtained at the end of our sample. Consistent with our estimated model, we assume that the values of $\pi_{or,t}$ and $\pi_{yr,t}$ are such that, on average, infected people recover or die in two weeks ($\pi_{or,t} + \pi^*_{od,t} = \pi_{yr,t} + \pi^*_{yd,t} = 7/14$).

We set $\phi_y = \phi_o = 1/26$, which implies that roughly 4 percent of the population gets vaccinated each week. This value is approximately the weekly fraction of the population vaccinated between April 1 and September 1, 2021. We set the probability of aging $v = 0.000634$ so that the population's pre-epidemic share of old people is 0.3.

According to the Statistics Portugal 1999 Survey of Time Use, employed people spend roughly 7 hours per day at work. The fraction of the population employed in 2019 is 57.6 percent. So, the average hours worked per week in the population is 28 ($7 \times 7 \times 0.576$). We set $\theta = 0.007401$, so people work 28 hours per week in the pre-epidemic steady state. We set $A = 1.086265$ so that, as in Section 6.1, annual income is $19,000$ Euros in the pre-epidemic steady state.

For the population of young and old to be constant in the steady state, we require an inflow of newborns. Given our other assumptions, this requirement implies that: $\mathfrak{B}_{y,t} = 0.000711$ and $\mathfrak{B}_{o,t} = 0.000054$. Recall that $\mathfrak{B}_{o,t}$ and $\mathfrak{B}_{y,t}$ represent newborns with and without comorbidities, respectively.

The steady-state distribution of people across age and health status for an economy with endemic Covid is as follows: 57 percent of the population is recovered, 42 percent is susceptible, and 1 percent is infected. The fraction of people that die weekly from all causes is 0.08 of 1 percent. Covid accounts for 7.6 percent of these deaths. A fraction 0.006 of 1 percent of the population dies from Covid each week. Average life expectancy at birth falls on a log-percentage basis by 1.5 percent, from 66.7 to 65.6 years.[C.3]

## C.2 First-order conditions and computational algorithm

The state variables of the household problem are $\Omega_t = \{s_t, i_t, r_t, k_t\}$. We will omit them to simplify the notation.

Lifetime utility is given by:

$$U_t = z + m_t + \beta \left(E_t U_{t+1}^{1-\alpha}\right)^{1/(1-\alpha)}$$

The household problem is deterministic because the law of large numbers applies: the fraction of family members in each health state follows a deterministic path. Since risk does not play a role, we can rewrite lifetime utility as

$$U_t = z + m_t + \beta U_{t+1}$$

$$m_t = \sum_{a\in\{o,y\}} s_{a,t} u(c^s_{a,t}, n^s_{a,t}) + i_{a,t} u(c^i_{a,t}, n^i_{a,t}) + r_{a,t} u(c^r_{a,t}, n^r_{a,t}).$$

$$u(c^h_{a,t}, n^h_{a,t}) = \frac{\left(c^h_{a,t}\right)^{1-\rho} - 1}{1-\rho} - \frac{\theta}{2}\left(n^h_{a,t}\right)^2.$$

Budget constraint

$$\sum_{a\in\{o,y\}} (s_{a,t}c^s_{a,t} + i_{a,t}c^i_{a,t} + r_{a,t}c^r_{a,t}) + k_{t+1} - (1-\delta_k)k_t = w_t \sum_{a\in\{o,y\}} (s_{a,t}n^s_{a,t} + i_{a,t}n^i_{a,t} + r_{a,t}n^r_{a,t}) + R^k_t k_t$$

Transmission function for age $a$

$$\begin{aligned}\tau_{a,t} &= \pi_1 s_{a,t}(1-\phi_a)c^s_{a,t}(I_{y,t}C^I_{y,t} + I_{o,t}C^I_{o,t}) + \pi_2 s_{a,t}(1-\phi_a)n^s_{a,t}(I_{y,t}N^i_{y,t} + I_{o,t}N^i_{o,t}) \\ &\quad + \pi_3 s_{a,t}(1-\phi_a)\left(I_{y,t} + I_{o,t}\right)\end{aligned}$$

[C.3] Recall that we exclude people younger than 20 from our analysis which reduces life expectancy.

Social dynamics

$$s_{y,t+1} = [s_{y,t}(1-\phi_y) - \tau_{y,t}](1-\delta_y - \upsilon) + \pi_s r_{y,t} + \mathfrak{b}_{y,t}, \tag{C.21}$$

$$s_{o,t+1} = [s_{o,t}(1-\phi_o) - \tau_{o,t}](1-\delta_o) + [s_{y,t}(1-\phi_y) - \tau_{y,t}]\upsilon + \pi_s r_{o,t} + \mathfrak{b}_{o,t}, \tag{C.22}$$

$$i_{y,t+1} = i_{y,t}(1-\pi_{yr} - \pi_{yd})(1-\delta_y - \upsilon) + \tau_{y,t}(1-\delta_y - \upsilon), \tag{C.23}$$

$$i_{o,t+1} = i_{o,t}(1-\pi_{or} - \pi_{od})(1-\delta_o) + \tau_{y,t}\upsilon + \tau_{o,t}(1-\delta_o) + i_{y,t}(1-\pi_{yr} - \pi_{yd})\upsilon, \tag{C.24}$$

$$r_{y,t+1} = r_{y,t}(1-\delta_y - \upsilon - \pi_s) + \phi_y s_{y,t}(1-\delta_y - \upsilon) + i_{y,t}\pi_{yr}(1-\delta_y - \upsilon), \tag{C.25}$$

$$r_{o,t+1} = r_{o,t}(1-\delta_o - \pi_s) + s_{o,t}\phi_o(1-\delta_o) + \upsilon\phi_y s_{y,t} + r_{y,t}\upsilon + i_{y,t}\pi_{yr}\upsilon + i_{o,t}\pi_{or}(1-\delta_o). \tag{C.26}$$

FOCs for consumption

$$\left(c^s_{a,t}\right)^{-\rho} - \lambda^b_t + \lambda^\tau_{a,t}\pi_1(1-\phi_a)(I_{y,t}C^i_{y,t} + I_{o,t}C^i_{o,t}) = 0$$

$$\left(c^i_{a,t}\right)^{-\rho} - \lambda^b_t = 0$$

$$\left(c^r_{a,t}\right)^{-\rho} - \lambda^b_t = 0$$

FOCs for labor

$$-\theta n^s_{a,t} + w_t\lambda^b_t + \lambda^\tau_{a,t}\pi_2(1-\phi_a)(I_{y,t}N^i_{y,t} + I_{o,t}N^i_{o,t}) = 0$$

$$-\theta n^i_{a,t} + w_t\lambda^b_t = 0$$

$$-\theta n^r_{a,t} + w_t\lambda^b_t = 0$$

FOC for $k_{t+1}$

$$\lambda^b_t = \beta\lambda^b_{t+1}[R^k_{t+1} + 1 - \delta_k]$$

$$\frac{dU_t}{ds_{a,t}} = \frac{\left(c^s_{a,t}\right)^{1-\rho} - 1}{1-\rho} - \frac{\theta}{2}\left(n^s_{a,t}\right)^2$$

$$\frac{dU_t}{di_{a,t}} = \frac{\left(c^i_{a,t}\right)^{1-\rho} - 1}{1-\rho} - \frac{\theta}{2}\left(n^i_{a,t}\right)^2$$

$$\frac{dU_t}{dr_{a,t}} = \frac{\left(c^r_{a,t}\right)^{1-\rho} - 1}{1-\rho} - \frac{\theta}{2}\left(n^r_{a,t}\right)^2$$

$$\frac{dU_t}{dU_{t+1}} = \beta$$

The first-order condition for $s_{y,t+1}$, $s_{o,t+1}$, $i_{y,t+1}$, $i_{o,t+1}$, $r_{y,t+1}$, $r_{o,t+1}$, $\tau_{y,t}$, and $\tau_{o,t}$ are

$$\begin{aligned}
& \frac{dU_t}{dU_{t+1}}\frac{dU_{t+1}}{ds_{y,t+1}} + \beta\lambda^b_{t+1}(w_{t+1}n^s_{y,t+1} - c^s_{y,t+1}) - \lambda^s_{y,t} + \beta\lambda^s_{y,t+1}(1-\phi_y)(1-\delta_y - v) \\
& +\beta\lambda^r_{y,t+1}\phi_y(1-\delta_y - v) + \beta\lambda^r_{o,t+1}v\phi_y + \\
& \beta\lambda^s_{o,t+1}(1-\phi_y)v + \beta\lambda^\tau_{y,t+1}(1-\phi_y)[\pi_1 c^s_{y,t+1}(I_{y,t+1}C^i_{y,t+1} + I_{o,t+1}C^i_{o,t+1}) \\
& +\pi_2 n^s_{y,t+1}(I_{y,t+1}N^i_{y,t+1} + I_{o,t+1}N^i_{o,t+1}) + \pi_3\left(I_{y,t+1} + I_{o,t+1}\right)] \\
= \; & 0,
\end{aligned}$$

$$\begin{aligned}
& \frac{dU_t}{dU_{t+1}}\frac{dU_{t+1}}{ds_{o,t+1}} + \beta\lambda^b_{t+1}(w_{t+1}n^s_{o,t+1} - c^s_{o,t+1}) - \lambda^s_{o,t} + \beta\lambda^s_{o,t+1}(1-\phi_o)(1-\delta_o) \\
& +\beta\lambda^r_{o,t+1}\phi_o(1-\delta_o) \\
& +\beta\lambda^\tau_{o,t+1}(1-\phi_o)\left[\begin{array}{c} \pi_1 c^s_{o,t+1}(I_{y,t+1}C^i_{y,t+1} + I_{o,t+1}C^i_{o,t+1}) \\ +\pi_2 n^s_{o,t+1}(I_{y,t+1}N^I_{y,t+1} + I_{o,t+1}N^i_{o,t+1}) + \pi_3\left(I_{y,t+1} + I_{o,t+1}\right) \end{array}\right] \\
= \; & 0,
\end{aligned}$$

$$\begin{aligned}
& \frac{dU_t}{dU_{t+1}}\frac{dU_{t+1}}{di_{y,t+1}} + \beta\lambda^b_{t+1}(w_{t+1}n^i_{y,t+1} - c^i_{y,t+1}) \\
& -\lambda^i_{y,t} + \beta\lambda^i_{y,t+1}(1-\pi_{yr}-\pi_{yd})(1-\delta_y - v) + \\
& \beta\lambda^i_{o,t+1}(1-\pi_{yr}-\pi_{yd})v + \beta\lambda^r_{y,t+1}\pi_{yr}(1-\delta_y - v) + \beta\lambda^r_{o,t+1}\pi_{yr}v = 0,
\end{aligned}$$

$$\begin{aligned}
& \frac{dU_t}{dU_{t+1}}\frac{dU_{t+1}}{di_{o,t+1}} + \beta\lambda^b_{t+1}(w_{t+1}n^i_{o,t+1} - c^i_{o,t+1}) - \lambda^i_{o,t} \\
& +\beta\lambda^i_{o,t+1}(1-\pi_{or}-\pi_{od})(1-\delta_o) + \beta\lambda^r_{o,t+1}\pi_{or}(1-\delta_o) = 0,
\end{aligned}$$

$$\begin{aligned}
\frac{dU_t}{dU_{t+1}}\frac{dU_{t+1}}{dr_{y,t+1}} + \beta\lambda^b_{t+1}(w_{t+1}n^r_{y,t+1} - c^r_{y,t+1}) + \beta\lambda^s_{y,t+1}\pi_s - \lambda^r_{y,t} \\
+\beta\lambda^r_{y,t+1}(1-\delta_y - v - \pi_s) + \beta\lambda^r_{o,t+1}v = 0,
\end{aligned}$$

$$\begin{aligned}
\frac{dU_t}{dU_{t+1}}\frac{dU_{t+1}}{dr_{o,t+1}} + \beta\lambda^b_{t+1}(w_{t+1}n^r_{o,t+1} - c^r_{o,t+1}) + \beta\lambda^s_{o,t+1}\pi_s \\
-\lambda^r_{o,t} + \beta\lambda^r_{o,t+1}(1-\delta_o-\pi_s) = 0,
\end{aligned}$$

$$-\lambda^s_{y,t}(1-\delta_y - v) - \lambda^s_{o,t}v + \lambda^i_{y,t}(1-\delta_y - v) + \lambda^i_{o,t}v - \lambda^\tau_{y,t} = 0,$$

$$-\lambda^s_{o,t}(1-\delta_o) + \lambda^i_{o,t}(1-\delta_o) - \lambda^\tau_{o,t} = 0.$$

### C.2.1 Firm problem

$$\pi = AK_t^{1-\gamma}N_t^{\gamma} - R^k_t K_t - w_t N_t$$

$$(1-\gamma)AK_t^{-\gamma}N_t^{\gamma} = R^k_t$$

$$\gamma AK_t^{1-\gamma}N_t^{\gamma-1} = w_t$$

### C.2.2 Equilibrium in goods and factor markets

$$N_t = \sum_{a\in\{o,y\}} \left[S_{a,t}N^s_{a,t} + I_{a,t}N^i_{a,t} + R_{a,t}N^r_{a,t}\right]$$
$$C_t = \sum_{a\in\{o,y\}} \left[S_{a,t}C^s_{a,t} + I_{a,t}C^i_{a,t} + R_{a,t}C^r_{a,t}\right]$$

$$C_t + K_{t+1} = AK_t^{1-\gamma}N_t^{\gamma} + (1-\delta_k)K_t$$

### C.2.3 Population dynamics

$$\begin{aligned} T_{a,t} &= \pi_1 S_{a,t}(1-\phi_a)C^s_{a,t}(I_{y,t}C^i_{y,t} + I_{o,t}C^i_{o,t}) + \pi_2 S_{a,t}(1-\phi_a)N^s_{a,t}(I_{y,t}N^i_{y,t} + I_{o,t}N^i_{o,t}) \\ &\quad + \pi_3 S_{a,t}(1-\phi_a)\left(I_{y,t} + I_{o,t}\right). \end{aligned}$$

Social dynamics

$$S_{y,t+1} = \left(S_{y,t}(1-\phi_y) - T_{y,t}\right)(1-\delta_y - \upsilon) + \pi_s R_{y,t} + \mathfrak{B}_{y,t}$$

$$S_{o,t+1} = \left(S_{o,t}(1-\phi_o) - T_{o,t}\right)(1-\delta_o) + \left(S_{y,t}(1-\phi_y) - T_{y,t}\right)\upsilon + \pi_s R_{o,t} + \mathfrak{B}_{o,t}$$

$$I_{y,t+1} = I_{y,t}(1-\pi_{yr} - \pi_{yd})(1-\delta_y - \upsilon) + T_{y,t}(1-\delta_y - \upsilon)$$

$$I_{o,t+1} = I_{o,t}(1-\pi_{or} - \pi_{od})(1-\delta_o) + T_{y,t}\upsilon + T_{o,t}(1-\delta_o) + I_{y,t}(1-\pi_{yr} - \pi_{yd})\upsilon$$

$$R_{y,t+1} = R_{y,t}(1-\delta_y - \upsilon - \pi_s) + \phi_y S_{y,t}(1-\delta_y - \upsilon) + I_{y,t}\pi_{yr}(1-\delta_y - \upsilon)$$

$$R_{o,t+1} = R_{o,t}(1-\delta_o - \pi_s) + \phi_o S_{o,t}(1-\delta_o) + \upsilon\phi_y S_{y,t} + R_{y,t}\upsilon + I_{y,t}\pi_{yr}\upsilon + I_{o,t}\pi_{or}(1-\delta_o)$$

### C.2.4 Steady state

In the steady state, we impose

$$\begin{aligned} S_y + R_y + I_y &= \omega_y \\ S_o + I_o + R_o &= \omega_o \\ \omega_y + \omega_o &= 1 \end{aligned}$$

Calculate:

$$R^k = \frac{1}{\beta} - 1 + \delta_k$$

Guess $\mathfrak{B}_y$ and $\mathfrak{B}_o$. Calculate

$$I_y = \frac{\mathfrak{B}_y - (\upsilon + \delta_y)\,\omega_y}{(1-\upsilon-\delta_y)\,\pi_{dy}}$$

$$T_y = \frac{1-(1-\pi_{yr}-\pi_{yd})(1-\delta_y-v)}{1-\delta_y-v} I_y$$
$$R_y = \frac{1-v-\delta_y}{v+\delta_y+\pi_s+\phi_y\left(1-v-\delta_y\right)}\left(I_y\pi_{ry}+\phi_y\left(\omega_y-I_y\right)\right)$$
$$S_y = \omega_y - I_y - R_y$$

and

$$I_o = \frac{\mathfrak{B}_o + v\left(R_y+S_y+\left(1-\pi_{dy}\right)I_y\right)}{\left(1-\delta_o\right)\pi_{do}} - \frac{\delta_o\omega_o}{\left(1-\delta_o\right)\pi_{do}}$$
$$T_o = \frac{\left(1-(1-\pi_{or}-\pi_{od})(1-\delta_o)\right)I_o - v\left(T_y+I_y(1-\pi_{yr}-\pi_{yd})\right)}{1-\delta_o}$$
$$R_o = \frac{v\left(R_y+I_y\pi_{ry}+\phi_y S_y\right)+\left(1-\delta_o\right)\left(I_o\pi_{or}+\phi_o\left(\omega_o-I_o\right)\right)}{\delta_o+\pi_s+\phi_o\left(1-\delta_o\right)}$$
$$S_o = \omega_o - R_o - I_o$$

Guess $N$

$$K = \left(\frac{(1-\gamma)AN^\gamma}{R^k}\right)^{\frac{1}{\gamma}}$$
$$w = \gamma A K^{1-\gamma}N^{\gamma-1}$$

Guess $C_y^i$

$$\lambda^b = \left(C_y^i\right)^{-\rho}$$
$$C_o^i = C_y^i$$
$$C_o^r = C_y^i$$
$$C_y^r = C_y^i$$
$$N_y^i = \frac{w\lambda^b}{\theta}$$
$$N_o^i = N_y^i$$
$$N_y^r = N_y^i$$
$$N_o^r = N_y^i$$
$$C = AK^{1-\gamma}N^\gamma - \delta_k K$$

Guess $C_y^s$ and $N_y^s$

$$\begin{aligned}
N_o^s &= \frac{N-\sum_{a\in\{o,y\}}\left[I_aN_a^i+R_aN_a^r\right]-S_yN_y^s}{S_o}\\
C_o^s &= \frac{C-\sum_{a\in\{o,y\}}\left[I_aC_a^i+R_aC_a^r\right]-S_yC_y^s}{S_o}
\end{aligned}$$

$$u(C_a^h, N_a^h) = \frac{\left(C_a^h\right)^{1-\rho} - 1}{1-\rho} - \frac{\theta}{2}\left(N_a^h\right)^2$$

$$m = \sum_{a \in \{o,y\}} S_a u(C_a^s, N_a^s) + I_a u(C_a^i, N_a^i) + R_a u(C_a^r, N_a^r)$$

$$U = \frac{1}{1-\beta}(z+m)$$

$$\frac{dU}{dS_a} = \frac{(C_a^s)^{1-\rho} - 1}{1-\rho} - \frac{\theta}{2}(N_a^s)^2$$

$$\frac{dU}{dI_a} = \frac{(C_a^i)^{1-\rho} - 1}{1-\rho} - \frac{\theta}{2}(N_a^i)^2$$

$$\frac{dU}{dR_a} = \frac{(C_a^r)^{1-\rho} - 1}{1-\rho} - \frac{\theta}{2}(N_a^r)^2$$

Guess $\lambda_o^\tau$, $\lambda_y^\tau, \lambda_o^r$ and $\lambda_y^r$:

$$\begin{aligned}\lambda_o^s &= \frac{\beta \frac{dU}{dS_o} + \beta\lambda^b(wN_o^s - C_o^s) + \beta\lambda_o^r\phi_o(1-\delta_o)}{1-\beta(1-\phi_o)(1-\delta_o)} \\ &+ \frac{\beta\lambda_o^\tau(1-\phi_o)\left[\pi_1 C_o^s(I_y C_y^i + I_o C_o^i) + \pi_2 N_o^s(I_y N_y^I + I_o N_o^I) + \pi_3\left(I_y + I_o\right)\right]}{1-\beta(1-\phi_o)(1-\delta_o)}\end{aligned}$$

$$\lambda_y^s = \frac{\begin{pmatrix} \beta\frac{dU}{dS_y} + \beta\lambda^b(wN_y^s - C_y^s) + \beta\lambda_o^s(1-\phi_y)v + \beta\lambda_y^r\phi_y(1-\delta_y - v) \\ +\beta\lambda_o^r v\phi_y + \beta\lambda_y^\tau(1-\phi_y)[\pi_1 C_y^s(I_y C_y^i + I_o C_o^i) + \pi_2 N_y^s(I_y N_y^I + I_o N_o^I) + \pi_3\left(I_y + I_o\right)] \end{pmatrix}}{1-\beta(1-\phi_y)(1-\delta_y - v)}$$

$$\lambda_o^i = \frac{\lambda_o^\tau + \lambda_o^s(1-\delta_o)}{1-\delta_o}$$

$$\lambda_y^i = \frac{\lambda_y^\tau - \lambda_o^i v + \lambda_o^s v + \lambda_y^s(1-\delta_y - v)}{1-\delta_y - v}$$

Adjust guesses for $\mathfrak{B}_y, \mathfrak{B}_o, N, C_y^i, C_y^s, N_y^s, \lambda_o^\tau$,$\lambda_y^\tau$, $\lambda_o^r$ and $\lambda_y^r$ to make the following equations hold:

$$1)\ T_y = (1-\phi_y)\left(\pi_1 S_y C_y^s(I_y C_y^i + I_o C_o^i) + \pi_2 S_y N_y^s(I_y N_y^i + I_o N_o^i) + \pi_3 S_y\left(I_y + I_o\right)\right)$$

$$2)\ T_o = (1-\phi_o)\left(\pi_1 S_o C_o^s(I_y C_y^i + I_o C_o^i) + \pi_2 S_o N_o^s(I_y N_y^i + I_o N_o^i) + \pi_3 S_o\left(I_y + I_o\right)\right)$$

$$3)\ \left(C_y^s\right)^{-\rho} - \lambda^b + \lambda_y^\tau\pi_1(1-\phi_y)(I_y C_y^i + I_o C_o^i) = 0$$

$$4)\ (C_o^s)^{-\rho} - \lambda^b + \lambda_o^\tau\pi_1(1-\phi_o)(I_y C_y^i + I_o C_o^i) = 0$$

$$5)\ -\theta N_y^s + w\lambda^b + \lambda_y^\tau\pi_2(1-\phi_y)(I_y N_y^i + I_o N_o^i) = 0$$

$$6)\ -\theta N_o^s + w\lambda^b + \lambda_o^\tau \pi_2 (1-\phi_o)(I_y N_y^i + I_o N_o^i) = 0$$

$$7)\qquad \beta \frac{dU}{dI_y} + \beta\lambda^b (wN_y^i - C_y^i) - \lambda_y^i + \beta\lambda_y^i (1-\pi_{yr}-\pi_{yd})(1-\delta_y - v) + \beta\lambda_o^i (1-\pi_{yr}-\pi_{yd}) v + \beta\lambda_y^r \pi_{yr}(1-\delta_y - v) + \beta\lambda_o^r \pi_{yr} v = 0$$

$$8)\ \beta \frac{dU}{dI_o} + \beta\lambda^b (wN_o^i - C_o^i) - \lambda_o^i + \beta\lambda_o^i (1-\pi_{or}-\pi_{od})(1-\delta_o) + \beta\lambda_o^r \pi_{or}(1-\delta_o) = 0,$$

$$9)\ \lambda_o^r = \frac{\beta \frac{dU}{dR_o} + \beta\lambda^b (wN_o^r - C_o^r) + \beta\lambda_o^s \pi_s}{1-\beta(1-\delta_o-\pi_s)}$$

$$10)\ \lambda_y^r = \frac{\beta \frac{dU}{dR_y} + \beta\lambda^b (wN_y^r - C_y^r) + \beta\lambda_y^s \pi_s + \beta\lambda_o^r v}{1-\beta(1-\delta_y - v-\pi_s)}$$

### C.2.5 Pre-epidemic steady state

Assume no vaccines and no re-infections. Set

$$S_y = \omega_y$$

Then

$$S_o = 1 - S_y$$

Set $\mathfrak{B}_o = 0$. Then

$$v = \frac{S_o \delta_o}{S_y}$$

$$\mathfrak{B}_y = S_y(\delta_y + v)$$

Also

$$R^k = \frac{1}{\beta} - 1 + \delta_k$$

Fix income per capita (unit mass of population in pre-epidemic steady state):

$$inc = AK^{1-\gamma}N^\gamma$$

Calculate

$$A = \left[ \frac{inc}{\left(\frac{1-\gamma}{R^k}\right)^{\frac{1-\gamma}{\gamma}} N} \right]^\gamma$$

$$K = \left[\frac{(1-\gamma)AN^{\gamma}}{R^k}\right]^{\frac{1}{\gamma}}$$
$$C = AK^{1-\gamma}N^{\gamma} - \delta_k K$$
$$w = \gamma AK^{1-\gamma}N^{\gamma-1}$$

$$\begin{aligned} N &= N_y^s \\ N &= N_o^s \\ C &= C_y^s \\ C &= C_o^s \end{aligned}$$

$$C^{-\rho} = \lambda^b$$
$$\theta = \frac{w\lambda^b}{N}$$
$$u(C_a^s, N_a^s) = \frac{(C_a^s)^{1-\rho} - 1}{1-\rho} - \frac{\theta}{2}(N_a^s)^2$$
$$m = \sum_{a\in\{o,y\}} S_a u(C_a^s, N_a^s)$$
$$U = \frac{1}{1-\beta}(z+m)$$

### C.2.6 Calibration of transmission function parameters

Recall that the transmission functions take the form:

$$T_y = (1-\phi_y)\left(\pi_1 S_y C_y^s(I_y C_y^i + I_o C_o^i) + \pi_2 S_y N_y^s(I_y N_y^i + I_o N_o^i) + \pi_3 S_y (I_y + I_o)\right)$$
$$T_o = (1-\phi_o)\left(\pi_1 S_o C_o^s(I_y C_y^i + I_o C_o^i) + \pi_2 S_o N_o^s(I_y N_y^i + I_o N_o^i) + \pi_3 S_o (I_y + I_o)\right)$$

Evaluate at pre-epidemic steady state (also assuming no vaccines):

$$T_y = \pi_1 S_y C^2(I_y + I_o) + \pi_2 S_y N^2(I_y + I_o) + \pi_3 S_y (I_y + I_o),$$

$$T_o = \pi_1 S_o C^2(I_y + I_o) + \pi_2 S_o N^2(I_y + I_o) + \pi_3 S_o (I_y + I_o).$$

Calibrate $\pi_1, \pi_2$ and $\pi_3$:

$$\begin{aligned} 1/6 &= \frac{\pi_1 C^2}{\pi_1 C^2 + \pi_2 N^2 + \pi_3}, \\ 1/6 &= \frac{\pi_2 N^2}{\pi_1 C^2 + \pi_2 N^2 + \pi_3}, \\ 2.5 &= R_0 = \frac{\frac{T_0}{I_0}}{S_y\pi_{ry} + S_o\pi_{ro} + S_y\pi_{dy} + S_o\pi_{do}} = \frac{\pi_1 C^2 + \pi_2 N^2 + \pi_3}{S_y\pi_{ry} + S_o\pi_{ro} + S_y\pi_{dy} + S_o\pi_{do}}. \end{aligned}$$

Solving:

$$
\begin{aligned}
\pi_1 &= \frac{1/6 \times 2.5\,(S_y\pi_{ry} + S_o\pi_{ro} + S_y\pi_{dy} + S_o\pi_{do})}{C^2}, \\
\pi_2 &= \frac{1/6 \times 2.5\,(S_y\pi_{ry} + S_o\pi_{ro} + S_y\pi_{dy} + S_o\pi_{do})}{N^2}, \\
\pi_3 &= 2.5 \times (S_y\pi_{ry} + S_o\pi_{ro} + S_y\pi_{dy} + S_o\pi_{do}) - \pi_1 C^2 - \pi_2 N^2.
\end{aligned}
$$